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# The Social Ecology of Public Space: Active Streets and Violent Crime in Urban Neighborhoods1

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## Abstract

Drawing on one element of Jacobs' (1961) discussion of the social control benefits of "eyes on the street," this paper explores the link between the prevalence of active streets and violence in urban neighborhoods. Three distinct data sources from the Project on Human Development in Chicago Neighborhoods are merged to explore the functional form and potential contingency of the active streets-violence relationship: (1) video data capturing the presence of people on neighborhood streets; (2) longitudinal data on adolescents (ages 11 to 16) and their self-reports of witnessing severe violence; and (3) community survey data on neighborhood social organizational characteristics. Results from multilevel models indicate that the proportion of neighborhood streets with adults present exhibits a nonlinear association with exposure to severe violence. At low prevalence, the increasing prevalence of active streets is positively associated with violence exposure. Beyond a threshold, however, increases in the prevalence of active streets serves to reduce the likelihood of violence exposure. The analyses offer no evidence that the curvilinear association between active streets and violence varies by levels of collective efficacy, and only limited evidence that it varies by anonymity. Analyses of data on homicide and violent victimization corroborate these findings.

"The street" has long been vilified as the origin of urban vice—a locale in which deviant inclinations are cultivated, expressed, and transmitted. Mid-20th century Modernist architects and planners envisioned the restructuring of physical space away from the perceived chaos of the traditional urban street (Le Corbusier 1925), influencing subsequent "urban renewal" efforts in the 1950's and '60s. This powerful current of distrust surrounding the street was fundamentally challenged in the latter half of the 20th century, inspired by the publication of Jane Jacobs' (1961) classic, *The Death and Life of Great American Cities*. Overturning the prevailing Modernist-inspired approach to community design, Jacobs emphasized the positive aspects of organically developing neighborhoods. In her view, dense population and mixed commercial and residential land use serve to promote ongoing and spatially distributed street activity. The resulting "eyes on the street" enhance the monitoring and associated informal social control capacity of urban neighborhoods.

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Despite decades of debate regarding street life and street safety, there remains little if any neighborhood-based research directly addressing the link between social ecologies of public space and crime (Reynald 2011). The recent resurgence of interest in “neighborhood effects” has drawn principally on normative and social capital theories of neighborhood influence, largely neglecting the role of street ecologies in contributing to neighborhood social control capacity. In what follows, we develop a model of the informal social control capacity of active streets, drawing on one key element of Jacobs' model—the *prevalence* of active streets. The proportion of a neighborhood's streets that are active captures Jacobs focus on the distribution (as opposed to the concentration) of "eyes on the street." Second, we examine the potential for a contingent influence of neighborhood street ecologies depending on social organizational conditions, including anonymity and collective efficacy (Taylor 1988).

The analysis considers the link between active street prevalence in the neighborhood and exposure to (i.e., witnessing) severe violence among urban youth as well as independently collected data on the prevalence of homicide and violent victimization. Hypotheses regarding the street ecology-crime relationship are tested using data from the Project on Human Development in Chicago Neighborhoods (PDHCN) and administrative resources. In addition to high quality self-report data on urban neighborhoods, the PHDCN provides some of the first systematically collected video data on the social and physical conditions of urban public space. These data thus offer an unprecedented opportunity to address longstanding questions regarding the influence of street social ecologies on urban crime.

## BACKGROUND

### SOCIAL ORGANIZATION AND SOCIAL ECOLOGY APPROACHES TO NEIGHBORHOOD INFLUENCE

Recent decades have seen a resurgence of interest in the consequences of neighborhood environments for a variety of outcomes (Baumer and South 2001; Boardman et al. 2005; Browning, Leventhal and Brooks-Gunn 2005; Harding 2003; Ross, Reynolds and Geis 2000), including crime (Sampson 2012). This research builds on a long tradition of inquiry into the processes by which urban social contexts shape human experience. Social disorganization theory, first articulated by Shaw and McKay (1969), has been among the more resilient approaches to the influence of neighborhood context. As elaborated by Kornhauser (1978) and Sampson and colleagues (1997), among others, the social disorganization perspective points to the role of structural features of neighborhood disadvantage—including poverty, residential instability, and ethnic heterogeneity—in limiting the social network and normative resources necessary to control crime and promote other collective goals. In an important theoretical advance, Sampson and colleagues have emphasized the critical intervening role of *collective efficacy*—that is, the combination of neighborhood-level trust and normative expectations for pro-social action—in linking structural conditions to crime.

Despite a strong emphasis on the role of space in recent articulations of social disorganization and collective efficacy theory, attention to potentially criminogenic and protective patterns of public space use has been limited. Collective efficacy theory points to the relative strength of intervention norms as an important dimension of neighborhood mobilization capacity. Neighborhoods are better-suited to manage the prevalence of criminal activity when they exhibit stronger expectations that residents will intervene in public neighborhood places to control criminogenic conditions. Yet the conditions under which such intervention might take place are dependent not only on the strength of supporting norms, but on the social dynamics of local public places. Theorizing such conditions requires attention *social ecological* approaches to neighborhood influence.

Urban ecological theory refers broadly to the study of person-environment interactions and has been a mainstay of urban sociology for decades (Hawley 1950). The following discussion offers a social ecological approach emphasizing the dynamics of social occupation of urban public space, specifically the prevalence of active urban streets. Focus on the social dynamics of public spaces allows for hypotheses regarding the role of active streets in informal social control. Does the presence (vs. absence) of people on the street encourage or deter crime? Under what conditions? This approach also calls attention to the possible mechanisms through which norms promoting the control of public space are enacted. Do high collective efficacy neighborhoods manage criminogenic conditions through leveraging active social ecologies for informal social control? Is the role of social ecology dependent upon typical levels of anonymity characterizing people on the street? An emphasis on social ecology highlights the conceptual distinction between norms of public space use and the ecological dynamics of streets, which may or may not be composed of neighborhood residents. These issues are central to the debate regarding the protective or criminogenic role of active streets.

## THE INFORMAL SOCIAL CONTROL CAPACITY OF ACTIVE STREETS

According to Jacobs, densely populated, mixed-use neighborhoods draw pedestrians onto the street. Neighborhoods with residential density and prevalent, diverse, spatially distributed commerce will tend to draw foot traffic across a large proportion of neighborhood streets. Throughout the day, such neighborhoods will be more likely to experience pedestrians traversing city streets on the way to work, running errands, and going to restaurants or other entertainment venues. The ecological dynamics generated by diverse, mixed-use neighborhoods provide a foundation for effective informal social control of public space through encouraging a steady stream of “eyes on the street.”

Drawing on one element of Jacobs’ social ecological approach, we emphasize the importance of widely distributed street activity throughout neighborhoods. Specifically, we focus on the *prevalence* of active streets (operationalized here as those with one or more adults present). Consistent with Jacobs, we argue that neighborhoods with a high proportion of active streets will benefit from the regulatory effects of spatially dispersed monitoring. Such neighborhoods will avoid “grey area” streets with minimal or no traffic. In contrast, concentrated or uneven distribution of active streets may have adverse implications for overall levels of crime. Active streets in areas characterized by highly concentrated commercial activity, for instance, may provide social control benefits on those streets but lead to a thinning out of active streets on the commercial periphery. These marginal streets may have insufficient pedestrian presence to promote effective monitoring, offering little more than opportunities for victimization and potentially offsetting the social control benefits experienced on nearby active streets (Brantingham and Brantingham 1995). In this view, moving from few if any active streets to activity on a small proportion of neighborhood streets may actually serve to increase crime levels. At low levels, the increasing prevalence of active streets may simply increase the pool of potential victims. Since nearby streets are less likely to be occupied, they will also be less likely to serve as a source of potential witnesses. Beyond a threshold, however, increases in the proportion of streets that are active will likely exert a regulatory effect because the prevalence of potential witnesses offsets the criminogenic effect of available targets.

To be clear, the model emphasizes social ecological conditions at the neighborhood level as opposed to the street level under the assumption that individuals move throughout neighborhood spaces as part of their daily routines and—consistent with Jacobs—the routine, spatially distributed traversing of urban streets provides an organic source of monitoring. Informal social control benefits arise as neighborhood streets feed "eyes" onto one another. From this standpoint, a model of the effects of pedestrian presence on crime at the street level would be inadequate in the absence of information on the larger ecological conditions—the prevalence of active streets in the neighborhood as whole—that may impinge on a given street's dynamics. Ideally, we would also consider the total number of people on the street alongside our emphasis on the prevalence of active streets. Although we do not examine this aspect of Jacobs' model in the current analyses, we partially address this issue with sensitivity analyses reported below.

The foregoing discussion drew on Jacobs' approach to develop a nonlinear expectation regarding the effect of active streets on crime. In what follows, we consider possible contingencies in active street effects, depending on the strength of neighborhood-level trust and intervention norms in public space as well as levels of anonymity. Finally, we describe a situationally rational approach to offending that hypothesizes a regulatory effect of active street prevalence (at high levels) independent of other aspects of neighborhood social organization.

## POTENTIAL CONTINGENCIES IN THE REGULATORY IMPACT OF ACTIVE STREETS

Jacobs highlights the interaction of active streets and informal social control in the supervision of public space. Specifically, Jacobs argues that without the expectation that others will back one up in an intervention effort, the monitoring benefits of eyes on the street are unlikely to translate into effective social control. As she states, street monitoring must be accompanied by trust and a "reassurance of general street support" (Jacobs 1961:42) in order for street control to be realized. The combination of trust and generalized expectations for pro-social action implicit in Jacobs' work anticipates the concept of collective efficacy (Sampson, Raudenbush and Earls 1997). The model thus suggests an interaction between active street prevalence and collective efficacy such that their regulatory benefits are expected to be mutually reinforcing.

Taylor's (1998) *territoriality* model—which in part builds on Jacobs' street control model—points to the potential role of anonymity in moderating the influence of active streets. Taylor distinguishes between the street presence of residents engaged in territorial behaviors—such as street monitoring, gardening, and neighborhood upkeep—from that of strangers or "outsiders" who may have little inclination to maintain behavioral standards. Although Taylor hypothesizes that the former will function in a similar manner to that expected by Jacobs (in addition to maintaining visible cues of respect for order and safety), the presence of the latter may actually be criminogenic. Indeed, Taylor argues that dense, mixed-use neighborhoods tend to increase outsider pedestrian traffic, reducing the likelihood that street occupants will know one another. Anonymity, in turn, induces withdrawal among neighborhood residents, diminishing social control inclinations and effectiveness. Since effective informal social control emanates almost exclusively from residents' territorial inclinations, the withdrawal of neighborhood residents from public space is accompanied by enhanced opportunity for victimization. Although Taylor challenges Jacobs' claims regarding the consequences of social ecologies produced by mixed land use neighborhoods, both Taylor and Jacobs agree that active street effects on crime are contingent on the level of social organization characterizing the neighborhood. Lower levels of anonymity and higher levels of collective efficacy are likely to amplify the benefits of active street prevalence for the control of crime. In contrast, more prevalent active streets in neighborhoods characterized by minimal social control and streets dominated by strangers may experience more widespread crime.

Finally, a high proportion of active streets within a neighborhood may function as a deterrent from the standpoint of the offender independent of the intervention inclinations of potential witnesses. Active streets offer a stream of potential witnesses. From the standpoint of the potential offender—and consistent with criminal opportunity theory's emphasis on strategic offending (Cook 1986)—active streets are likely to serve as a deterrent to more overt crimes, such as violence.[1] The actual relationship among bystanders and the potential "diffusion of responsibility" is of less concern in this instance than is their capacity to witness criminal activity.[2] Although the probability of bystander intervention is unknown, the potential presence of witnesses in any number compared to no witnesses increases the possibility that a crime will (later) be reported to the police (Wilkinson 2007) and that the offender will be identified. Thus, all else equal, active street prevalence is likely to lead to the situationally rational avoidance of crime—particularly overt, severe forms of violence—on the part of prospective offenders (Felson 1994). This *autonomous* (vs. contingent) street control model suggests a regulatory role of active streets independent of bystander willingness to intervene.[3]

[1]Active streets may not serve as a deterrent against more covert crimes, such as some forms of property crime. Indeed, a large public crowd within which to disappear after stealing from a street-located commercial establishment may actually facilitate property crime (Felson 1994).

[2]The bystander literature proposes that the presence of a large crowd discourages bystander intervention to stop or mitigate violence (Latane and Darley 1969). Yet research finds that even when perceived bystander willingness to intervene is marginal, police involvement is more likely when bystanders are present (Wilkinson 2007), and the presence of bystanders also may provide a favorable, nonviolent resolution (Wilkinson and Carr 2008). Hence, we argue that even in the absence of willingness to intervene in conflict already in progress, the prevalence of active streets nevertheless may deter the occurrence of crime in public places.

[3]Although the regulatory role of active streets may exist independent of bystander willingness to intervene, the deterrent effect of active streets nonetheless may be stronger if prospective offenders perceive that pedestrians would be more willing to intervene on behalf of a victim (Meares and Kahn 1998)—for example, if they believe the neighborhood has higher degree of collective efficacy. Hence, in addition to a growing pool of witnesses, increased prevalence of active streets when combined with elevated levels of collective efficacy may increase the costs of criminal offending thereby making it less likely.

## SUMMARY

In what follows, we examine the association between active street prevalence and exposure to severe violence in urban neighborhoods, testing hypotheses regarding the potential nonlinearity and contingency of the active streets-violence association. Exposure to violence has emerged as an important public health concern because understanding of the prevalence and consequences of both violent victimization *and* witnessing violence in urban communities has improved. The experience of witnessing severe violence is both more common and more readily measured in social surveys of urban youth than is severe violent victimization, and it increasingly is recognized to have significant negative consequences (Overstreet and Mazza 2003). Like physical victimization, witnessing violence has been linked with Posttraumatic Stress Disorder (Buka et al. 2001; Dempsey 2002), and with internalizing (Flannery, Singer and Wester 2001) and externalizing behaviors (Guerra, Huesmann and Spindler 2003). Moreover, the experience of witnessing violence may be more difficult to control than the experience of violent victimization. Evidence suggests that urban youth acquire differential levels of “street efficacy” that shape their likelihood of experiencing victimization in their neighborhoods (Sharkey 2006). Such selection processes, however, are less likely to influence the experience of witnessing violence. Nevertheless, we examine links between active street prevalence and alternative measures of violence—homicide and violent victimization—to corroborate findings from the analysis of exposure to violence.

We test approaches to the social ecology-crime link using unprecedented data from the Project on Human Development in Chicago Neighborhoods on neighborhood social organization and street conditions. We focus first on estimating the functional form (i.e., linearity) and statistical significance of the relationship between active street prevalence and exposure to violence among urban youth. We then examine active street effects on measures of homicide and violent victimization from independent data sources. Finally, we consider the hypothesis that any observed effect of active streets prevalence on exposure to violence is contingent on neighborhood social organizational conditions, specifically, on levels of anonymity and collective efficacy. These tests offer the first evidence based on systematic, objectively collected data regarding the role of active streets in the spatial distribution of urban crime.

## DATA AND MEASURES

We draw on unique Project on Human Development in Chicago Neighborhoods (PHDCN) Systematic Social Observation data on active streets, PHDCN Community Survey data on social organization and violent victimization, and administrative data resources (the Chicago Homicide Data and the 1990 Census). We use the PHDCN Longitudinal Cohort data to estimate multilevel models of the effect of active street prevalence on violence exposure among urban youth. Examining data on violence from multiple sources and at both individual and neighborhood levels of aggregation provides an opportunity to more comprehensively investigate the role of active streets in regulating crime.

## DESIGN

For the Longitudinal Cohort Study (LCS), Chicago's 847 census tracts were combined into 343 neighborhood clusters (NCs). NCs were constructed in order to maximize population homogeneity with respect to racial/ethnic, socioeconomic, housing, and family structure characteristics (NCs average roughly 8,000 people). NCs were bounded by identifying, where possible, ecologically meaningful borders, such as railroad tracks. Next, a two-stage sampling procedure was employed that included selecting a random sample of 80 of the 343 Chicago NCs stratified by racial/ethnic composition (7 categories) and SES (high, medium, and low). The study design was constructed in order to capture an equal number of NCs in all 21 cells (varying by racial/ethnic composition and SES). Within these 80 NCs, children falling within 7 age cohorts (3, 6, 9, 12, 15, and 18) were sampled from randomly selected households. Extensive in-home interviews and assessments were conducted with these children and with their primary caregivers twice over a 4-year period, at roughly 2-year intervals (Wave 1 in 1995–1996 and Wave 2 in 1998–1999).

The Community Survey (CS) is a probability sample of 8,782 residents of Chicago emphasizing respondent evaluations of their communities. The CS was conducted in 1994–1995, overlapping with the first wave of the LCS. These samples were independently collected, however, minimizing problems of shared source bias that may afflict studies that employ neighborhood assessments from respondents who also are reporting on the dependent variable. The CS used a three-stage sampling strategy: First, city blocks were randomly selected within each of the identified 343 NCs; second, dwelling units within blocks were randomly selected; and third, one adult respondent within each dwelling unit was randomly selected to complete the survey. The final response rate was 75%. The CS sampling strategy achieved sufficient within-neighborhood sample sizes to estimate neighborhood characteristics based on aggregated individual-level data. The overall within-tract sample size averaged about 20 for those tracts also sampled for the LCS.

The PHDCN Systematic Social Observation (SSO) was designed to observe various land use, commercial, and other physical and social characteristics of Chicago communities directly through the use of videotape and observer logs (Raudenbush and Sampson 1999). The study was conducted between June and September of 1995. National Opinion Research Center observers drove a sport utility vehicle at five miles an hour down every street within the 80 NCs included in the LCS sample. A videographer and two observers recorded events and conditions for each block face (i.e., one side of a street block), which is the original unit of observation for the study. A total of 23,816 block faces were observed and videotaped (an average of 298 per NC). For those variables that were derived from videotapes (as opposed to observer logs), a subsample of 15,141 face-blocks was selected for viewing and coding (an average of 77 per census tract)—the baseline sample from which the indicator of active streets was constructed for the current analysis.[4]

[4]The advantages of using slow-moving SUVs to collect the PHDCN-SSO data are discussed in Carter et al. (1996). One advantage was more feasible intercoder reliability, which was assessed by independently recoding approximately 10% of video-recorded block faces. The discrepancy rate was 0.8%.

## SAMPLE

This study uses 176 census tracts represented in both the CS and the SSO (i.e., within the 80 NCs sampled for the LCS).[5] Analyses of exposure to violence are based on 1,135 LCS respondents representing 157 of the census tracts (due to sampling). For the exposure to violence analysis, Wave 1 LCS data on subject and primary caregiver characteristics are used to predict Wave 2 exposure to violence among respondents from the age 12 and 15 cohorts. Sample retention across waves was 82%. Analyses of homicide and violent victimization use data from 176 census tracts.

## MEASURES

**Dependent Variables—**The measure of *exposure to violence* is based on three items from the LCS asking respondents whether they had witnessed any of three severe forms of violence in the last year: 1) someone attacked with a weapon, 2) someone shot at, or 3) someone shot. Among the sample of adolescents, 24% reported having seen someone attacked with a weapon, 17% had seen someone shot at, and 11% had seen someone shot. Corroborative analyses of alternative violence outcomes are based on two measures. First, the 1995–97 *homicide rate* is based on the Chicago Homicide Data (Block, Block and Illinois Criminal Justice Information Authority 2005). For analytic purposes, the dependent variable is the empirical Bayes (EB) log homicide rate per 1,000 population from a two-level Poisson model (adjusting tract-specific counts for reliability [Morenoff, Sampson and Raudenbush 2001]; mean = −1.322, SD = .504). *Violent victimization* is based on 1995 PHDCN CS reports. Specifically, victimization was assessed by asking CS respondents: “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?” (yes/no; mean = .127, N=2,946).[6] Unfortunately, it is impossible to disaggregate the specific forms of violent victimization using these data. But to the extent that the CS measure of violent victimization also captures domestic and other assaults perhaps confined within the home, our results likely are conservative estimates of the effect of active street prevalence on victimization.

**Independent Variables—**Independent variables used in the analysis include measures of active street prevalence, land use, and business presence. Analyses also include two measures of social organization—collective efficacy and anonymity—as well as key neighborhood controls. Finally, individual-level variables are included in the analysis analyses of exposure to violence and violent victimization. Table 1 reports descriptive statistics on independent variables.

*Active street* prevalence is based on video data from the PHDCN SSO and measures the proportion of sampled block faces with adults present. The SSO observed streets between 7 AM and 7 PM. The active streets variable captures the proportion of block faces within a

[5]Although it is impossible to compare our sample of tracts to all tracts represented in the CS along our social ecology measures, we emphasize that the subsample of 80 LCS-NCs were selected according to a stratified probability sample based on the 21 strata reflecting the racial/ethnic and SES compositions characteristic of Chicago neighborhoods.

[6]Respondents were given the following definition of “neighborhood:” “By neighborhood…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."

tract on which adults are observed. This measure is adjusted for the time of day using a two-level logistic regression of block faces nested within census tracts. A dichotomous indicator of whether adults were observed on the block face was regressed on the grand-mean centered time of day and its square at level one. We employ this quadratic specification of time of day because dummy variable indicators of the hour of street observation produced an essentially curvilinear pattern, with the likelihood of adult presence increasing over the course of the day until mid- to late-afternoon, and then declining somewhat. The active streets measure is the model-based predicted proportion of active streets. Among the 176 tracts used in our analyses, the average proportion of sampled block faces within a tract on which adults were observed is .43 (the variable is approximately normally distributed). The centered (around zero) variable and its square are included in the statistical models described below in order to capture the hypothesized inverted U-shape association between active streets prevalence and violence.

Of block faces with people present, 86% were coded as having adults present, 22% had teens present, and 31% had children present. Blocks faces also were coded for the presence of teenage peer groups that resemble gangs, fighting adults, homeless people or those who are begging, prostitutes, people selling drugs, and people who are drinking or who appear intoxicated. Less than 1% of face blocks exhibited any of these activities. Excluding them from the construction of the active streets variable did not alter the results of the analysis (see also Duneier [1999] for a discussion of the potential for homeless people to promote street control).

In separate models, we also assess the influence of two additional variables that capture an active social ecology. *Mixed land use* is the proportion of block faces within a tract that have both residential and commercial land use. *Business Presence* is the mean number of businesses per block face within a tract.

*Collective efficacy* combines information from two scales administered as part of the CS: First, a social cohesion scale was constructed from a cluster of conceptually related items measuring the respondent’s level of agreement (on a five-point scale) with the following statements: 1) “People around here are willing to help their neighbors,” 2) “This is a close-knit neighborhood,” 3) “People in this neighborhood can be trusted,” 4) “People in this neighborhood generally don’t get along with each other,” and 5) “People in this neighborhood do not share the same values.” The latter two items were reverse coded. An informal social control scale captures respondents' expectations regarding residents’ willingness to intervene on behalf of the public good with a focus on bystander intervention to control criminogenic conditions (Sampson et al. 1997). The informal social control scale is constructed from respondent assessments of the likelihood that their neighbors could be counted on to intervene if 1) “Children were skipping school and hanging out on a street corner,” 2) “Children were spray-painting graffiti on a local building,” 3) Children were “showing disrespect to an adult,” 4) “There was a fight in front of your house and someone was being beaten or threatened,” or 5) “The fire station closest to your home was going to be closed down by the city” due to budget cuts. Responses were given on a five-point scale from “very unlikely” to “very likely.” A principal component analysis suggests that these 10 items likely define one factor, with factor loadings lowest for the getting along and sharing values items, each at about .47, and other loadings ranging from .63 to .76. The collective efficacy scale is constructed using a three-level Item Response Theory (IRT) model with scale items at level one, individuals at level two, and tracts at level three. The final variable is the level-three empirical Bayes (EB) corrected intercept (Raudenbush and Sampson 1999). The multilevel reliability of the collective efficacy scale is .60.[7]

The *anonymity* scale combines responses to three questions from the CS. Response categories for the first two questions—"How many adults do you know or recognize by sight in this neighborhood?" and "How many children do you recognize or know by sight in this neighborhood?"—were 1-"a great many," 2-"many," 3-"a few," or 4-"none," and categories for the third question—"How easy is it for you to pick out people who are outsiders or who obviously don't live in this area?"—were 1-"very easy," 2-"somewhat easy," 3-"somewhat difficult," or 4-"very difficult." A principal component analysis suggests these items load well into one factor. For each respondent, we calculate an anonymity score that is the mean of the four standardized items (alpha = .717). The final measure is the level-two EB corrected intercept from an IRT model of individual anonymity scores nested within tracts. Higher values on this scale tap greater levels of anonymity.

**Neighborhood-level controls:** Neighborhood-level social composition scales are constructed from the 1990 decennial census. Scale definitions are based on prior theory, research on the structural antecedents of violent crime, and existing studies based on PHDCN data (Land et al. 1990; Morenoff et al. 2001). Principal components analysis yielded three key scales. C*oncentrated poverty* is defined by the percentage below the poverty line, receiving public assistance, unemployed, and the percentage of families headed by a female. A second scale—*residential stability*—is defined by the percentage living in the same residence since 1985 and the percent of homes occupied by owners. A third scale—*immigrant concentration*—is defined by the percentage Latino and the percentage foreign born. *Population density* is the number of persons per square kilometer in the census tract. Because this variable's distribution is skewed, we use a log transformation. A control for prior homicide rates is included to address possible endogeneity in the association between active streets and violence at the neighborhood level. The prior homicide measure is the 1991-93 EB log homicide rate per 1,000 persons at the tract level.

**Individual-level controls:** For the analyses of exposure to violence, we include a number of demographic and background measures including age, sex, race/ethnicity (African American and Latino vs. white/other), and immigrant status (first, second, vs. third or greater generation). Family background measures include family socioeconomic status (the first principal component of annual household income, education [highest education level achieved by primary caregiver in the household], and the occupation of the adolescent's primary caregiver[8]), and a dummy variable indicating the presence of two biological parents in the household.

[7]Of the 8,713 CS respondents, 59% responded to all 10 scale items, and over 98% responded to at least one item. The IRT approach uses information from all individuals with a response on at least one scale item. Empirical Bayes estimates regress OLS residuals toward the grand mean by a factor proportional to their unreliability, thereby adjusting neighborhood-level intercepts (Raudenbush and Bryk 2002).

Two measures of family social process are included. Family attachment and support is comprised of five items tapping adolescents agreement with the following statements: (1) “No matter what happens, I know that my family will always be there for me should I need them,” (2) “My family lets me know they think I’m a worthwhile (valuable) person,” (3) “People in my family have confidence in me,” (4) “People in my family help me find solutions to my problems,” and (5) “I know my family will always stand by me” (reliability = .540) (Turner et al. 1987). Second, supervision is a 24-item scale based on an expanded version of the supervision subscale of the Home Observation for Measurement of the Environment (HOME) (Bradley et al. 2000). Items were based on primary caregiver reports and include dichotomous (yes/no) responses to questions asking whether, for example, the subject has a set time (i.e., curfew) to be home on school nights, and whether the subject is not allowed to wander in public places without adult supervision for more than two hours (reliability = .626). The final measures are the EB adjusted intercepts from two-level Rasch models of each set of items (Cheong and Raudenbush 2000; Raudenbush, Johnson and Sampson 2003).

**Individual risk factors:** The analyses incorporate measures of prior violence exposure and delinquency to control for the propensity to witness violence. A wave 1 exposure to violence measure added the number of three violent acts the respondent reported ever witnessing: (1) someone shoved, kicked, or punched; (2) someone attacked with a knife; and (3) someone shot. The items from the prior exposure to violence scale do not overlap precisely with the wave 2 items. But by including a more common violent event, the measure captures at an early age youth who may be at risk of experiencing more severe events during their adolescent years. Prior problem behavior was assessed by adolescents’ reported participation (yes/no) in 19 activities involving violent behavior, property crime, and use of illegal drugs (reliability = .667). The scale was constructed using a two-level Rasch model.

## ANALYTIC STRATEGY

The three exposure to violence items are modeled simultaneously using a three-level Rasch model with random intercepts. The model takes the following form: First, let $Y_{ijk}$ take on a value of unity if the $i$-th exposure to violence item is endorsed by respondent $j$ of neighborhood k (otherwise $Y_{ijk} = 0$) and let $\mu_{\mathrm{ijk}}$ denote the probability $Y_{ijk} = 1$. At level 1, the log odds of endorsement on response $i$ are modeled as follows:

$$\ln\left(\frac{\mu_{ijk}}{1-\mu_{ijk}}\right) = \pi_{jk} + \sum_{\mathrm{m}=1}^{\mathrm{M}-1} \alpha_{mjkDmijk}$$

where $\pi_{jk}$ is the intercept, $D_{mijk}$ are indicator variables representing the exposure to violence items (with one omitted reference item), and $\alpha_{mjk}$ reflects the relative level of severity represented by item $m$. Thus, $\pi_{0k}$ is the log odds of endorsing the omitted reference item (in this case, the dummy variable indicator of whether the respondent witnessed someone being

8Occupational prestige was based on a coding strategy developed by Nakao and Treas (1994) using the updated 1990 Census Occupational Classification System.

attacked with a weapon in the last year), and $\pi_{0k} + \alpha_m$ is the log odds of endorsing item $m$. At level two (between individuals), individual demographic background, family, and individual characteristics are included in models of the subject's adjusted latent exposure to violence score (intercepts from the level one equation) as follows:

$$\pi_{\mathrm{jk}} = \beta_{0\mathrm{k}} + \sum_{\mathrm{q}=1}^{\mathrm{Q}} \beta_q X_{qjk} + r_{jk} \qquad r_{jk} \sim \mathrm{N}(0, \sigma^2)$$

where $\beta_{0k}$ is the intercept, $X_{qjk}$ is the value of person level predictor $q$ for individual $j$ in neighborhood $k$, $\beta_q$ is the effect of $q$ on individual $j$'s expected exposure to violence score, and $r_{jk}$ is an independently, normally distributed error term with variance $\sigma^2$. Finally, adjusted intercepts $\beta_{0k}$ are modeled at the neighborhood level:

$$\beta_{0k} = \gamma_0 + \sum_{s=1}^{S} \gamma_s Z_{sk} + u_k \qquad u_k \sim \mathrm{N}(0, \tau_\beta)$$

Here, $\beta_{0\kappa}$ is the exposure to violence score for neighborhood $j$ adjusted for demographic, family, peer, and individual characteristics and item severity, $\gamma_0$ is the grand mean, $Z_{sk}$ is the value of covariate $s$ (including active streets and neighborhood controls) for neighborhood $k$, $\gamma_s$ is the effect of covariate $s$ on neighborhood exposure to violence scores, and $u_k$ is an independent, normally distributed error term with variance $\tau_\beta$. Accordingly, the intraclass correlation (ICC) for the exposure to violence scale is $\tau_\beta/(\tau_\beta + \sigma^2)$.

We employ Ordinary Least Squares regression with robust standard errors to investigate the relationship between active streets and EB homicide rates. Models of respondent self-reports of violent victimization from the CS are modeled using two-level hierarchical nonlinear models. In all analyses, person- and neighborhood-level variables are grand-mean centered.

# RESULTS

## EXPOSURE TO VIOLENCE

We begin by fitting the three-level model of exposure to violence without predictors (the unconditional model), calculating the ICC based on variances from the level-two (individual) and level-three (neighborhood) models. Estimated variances for $\tau_\beta$ (.12) and $\sigma^2$ (1.29) from the unconditional model indicate that about 8% of the variance in exposure to violence is at the neighborhood level.

Table 2 presents coefficients from three-level Rasch models of severe violence exposure among PHDCN adolescents. Model 1 includes individual and family variables at the person level, as well as the active streets measure and its square at the neighborhood level. The results from Model 1 reveal findings consistent with previous research on the antecedents of exposure to violence. African American and Latino children are significantly more likely to witness severe violence as are males and older adolescents. First generation immigrants, however, are less likely to witness severe violence. Supervision and family attachment and support each is negatively and significantly associated with violence exposure. At the neighborhood level, we test whether the coefficients on the linear and quadratic active streets variables both are equal to zero. Based on a multiparameter test, we reject the null hypothesis; the coefficients on the linear and quadratic terms are jointly significant. Furthermore, the significant negative coefficient on the squared term suggests a concave association between active streets and exposure to violence.

In Model 2 we add the mixed land use measure, which is not significantly associated with exposure to violence. Because mixed land use is dependent upon business presence, we also tested the influence of business presence in separate models. It was not significantly associated with the outcome in analyses of exposure to violence or of violent victimization.

In the more inclusive Model 2, we also find, the coefficient on first generation immigrant status no longer reaches statistical significance. The other individual- and neighborhood-level findings from Model 1, however, persist. Building on Model 2, Model 3 also includes neighborhood structural controls. The curvilinear effect of active streets persists, but the coefficients on residential stability and immigrant concentration fail to reach statistical significance. In contrast, we find that concentrated disadvantage is positively and significantly associated with exposure to severe violence. We also find population density is negatively associated with exposure to violence. This finding is consistent with Jacobs' expectation regarding the protective effects of concentrated population.

**Final Model—**Model 4 is the most inclusive model of exposure to severe violence. In addition to the variables included in Model 3, we also add measures of prior problem behavior and Wave 1 exposure to violence at the individual level, and the 1991-93 homicide rate at the neighborhood level. At the individual level, all findings from Model 3 save for the negative effect of family attachment and support and positive effect of age persist in this more inclusive model. We also find that prior problem behavior and Wave 1 exposure to violence each is positively associated with Wave 2 exposure to violence. At the neighborhood level, both concentrated disadvantage and population density continue to be associated with exposure to violence. Finally, we again find a nonlinear association between active streets and exposure to violence.

## CORROBORATIVE ANALYSES OF HOMICIDE AND VIOLENT VICTIMIZATION

The theory linking active streets and violence exposure on which the analyses are based is rooted in neighborhood-level dynamics, as opposed to individual-level processes that may lead to selection into violent experience (Sharkey 2006). Consequently, the link between active streets and violence should be observed when other measures of neighborhood-level severe violence are considered. In order to examine the robustness of the active streets-violence link to alternative violence measures, Table 3 presents models of 1995–1997 EB homicide rate and of violent victimization.

**Homicide—**Results from the OLS regression of homicide on only active streets is presented in Model 1 of Table 3. As expected, the coefficients on the active streets variable and its square are jointly significant. Consistent with the findings from analyses of exposure to violence, the negative and significant quadratic term suggests a concave relationship between active streets and homicide. We find this relationship persists once additional controls are added in Model 2. In addition to active streets, the results suggest business presence is positively associated with homicide, which is consistent with research on busy places and hotspots (Bernasco and Block 2011; Rountree, Land and Miethe 1994) (in a separate model not shown, we replace business presence with the measure of mixed land use and find it is not significantly associated with homicide). We also find concentrated disadvantage is positively associated with homicide. In Model 3 we add a control for the prior homicide rate and find that it is positively associated with the subsequent homicide rate, and find that concentrated disadvantage continues to be significantly associated with homicide (although the coefficient on business presence no longer reaches statistical significance). Active streets again exert a nonlinear effect on homicide that resembles an inverted-U shape.

**Violent Victimization—**Analyses of violent victimization employ two-level logit models that adjust for gender, age, race/ethnicity (black, Latino vs. white), education, income, employment status (employed vs. not employed), marital status (never married, other vs. married), homeownership, years residing in the neighborhood, and number of moves in the last five years. Results are presented in Table 3 (parameter estimates for level-one controls are omitted from the table but available upon request). Model 4 includes only the active streets variable and its square at the neighborhood level. The coefficients are jointly significant, and the significant and negative coefficient on the squared term indicates a concave association with the outcome. We find this association persists when additional neighborhood-level controls are included in Model 5. Finally, in Model 6 we add a control for the prior homicide rate. Although this measure fails to reach statistical significance, we find the effect of active streets persists. The association between active streets and violent victimization resembles an inverted-U shape. Thus, these results and those from the analyses of homicide corroborate our initial findings regarding the nonlinear association between active streets and exposure to violence.

## SUMMARY OF NONLINEAR EFFECTS OF ACTIVE STREETS

The nonlinear associations between active streets and each outcome—exposure to severe violence, violent victimization, and homicide—are depicted in Figures 1, 2, and 3, respectively. As shown in Figure 1, the association between active streets and exposure to violence is positive until 53.49% ($72^{nd}$ percentile) of block faces in the tract are active. This corresponds to a .29 predicted probability of exposure to violence along the omitted violence item when all other covariates from Model 4, Table 2 are held at their grand means. Beyond this point, the association between active streets and exposure to violence becomes negative. For violent victimization, this peak occurs at a slightly lower level of active streets—43.12% ($51^{st}$ percentile) active block faces in the tract. This corresponds to a .12 predicted probability of violent victimization when all other covariates from Model 6, Table 3 are held at their grand means. Finally, for homicide this peak occurs at an even lower level of active streets—28.14% ($20^{th}$ percentile) active block faces. This corresponds to a .29 predicted homicide rate per 1,000 population when all other covariates from Model 3, Table 3 are held at their grand means. The results therefore suggest that for more severe offenses, active streets begins to exert a protective effect at lower levels. The higher estimated vertex for exposure to violence may be due to exposure processes associated with the risk of this outcome. Specifically, some youth may not spend as much time outdoors as others, reducing their likelihood of observing community violence. We control for parental supervision, capturing perhaps the key factor related to time use patterns that would place a youth at risk of exposure to community violence. Nevertheless, additional unobserved factors may still be operating. This might explain, in part, relatively lower levels of violence exposure at low levels of active streets (i.e., parents are less likely to allow youth to spend time outside).

## CONTINGENT EFFECTS OF ACTIVE STREETS ON EXPOSURE TO VIOLENCE

Is the relationship between active streets and violence dependent upon levels of neighborhood social organization? Specifically, are neighborhoods with lower levels of anonymity or higher collective efficacy more capable of translating more prevalent active streets into social control? These hypotheses are assessed by considering the interactive effects of active streets and measures of the two social organizational factors on exposure to violence and on homicide.

Table 4 presents neighborhood-level coefficients for models examining the interactive effects of active streets with anonymity and collective efficacy. The baseline specifications for analyses of exposure to violence (Models 1 and 2) are Model 3 of Table 2, and for homicide (Models 3 and 4) are Model 2 of Tables 3, modified to include both the main and interactive (with active streets) effects of social organizational characteristics. Statistically significant neighborhood-level interactive effects may be difficult to observe due both to the neighborhood-level sample size and the compounding of measurement error associated with product term interactions (Cohen and Cohen 1983). Consequently, we include only controls for demographic and family structural background at level one, and neighborhood structural background at level two. Thus, the models are less conservative estimates of the joint impact of social organization and active streets effects (i.e., favoring their detection; results are comparable, however, with additional controls included).

Models include two interactive terms—the interaction between the social organization characteristic considered and both the active streets linear and quadratic effects. The interaction with the linear active streets variable indicates the degree to which the social organization characteristic modifies the inflection point on the nonlinear active streets effect. The interaction with the quadratic active streets variable indicates the degree to which changes in the social organization characteristic deflect the curve describing the nonlinear effect of active streets. In analyses of exposure to violence, no evidence of differential effects of active streets by social organizational conditions emerges. That is, the interactions between each social organizational characteristic and the linear and quadratic active streets variables do not achieve significance even at the p<.10 level. Corroborative analyses of violent victimization (analyses not presented but available upon request) also reveal no evidence of contingent active street effects.

The interactive effects of active streets by social organizational characteristics on homicide are displayed in in Models 3 and 4. The negative and significant coefficient on the A*nonymity*Active Streets*$^2$ interaction term in Model 3 suggests that at higher levels of neighborhood anonymity, the decline in the homicide rate associated with more prevalent active streets is less pronounced. Consistent with the findings from analyses of exposure to violence, we fail to find that collective efficacy modifies the association between active streets and homicide.

In additional models otherwise equivalent to those presented in Table 4, we find that the association between active streets and each outcome persists when controling for anonymity or collective efficacy.

### ADDITIONAL CONSIDERATIONS

To further examine the nonlinear association between active streets and each of the three outcomes, we tested cubic specifications of active streets in models otherwise analogous to Model 4 (Table 3) for exposure to violence, and Models 3 and 6 (Table 4) for homicide and violent victimization, respectively. In each instance, the cubed term failed to reach statistical significance. An exploratory analysis using splines equally spaced at four intervals across the range of values for the active streets variable also reveals nonlinear effects that are consistent with the quadratic specfication (see Figure S-1 in the online supplement).

We also tested an alternative measure of active streets that is the tract mean number of block faces per block-face dyad on which adults were observed (i.e., adults observed on 0, 1, or 2 sides of the street for a given block-face pair). In addition to the prevalence of active streets, this measure also incorporates the *level* of activity on a given street by tapping whether one or both sides of a block-face pair are active. We find similar concave relationships between this dyad measure and the three outcomes (see Figure S-2 in the online supplement).

Finally, we explored whether the presence of certain groups influences exposure to violence. Merry (1981) observes that places often are understood as “dangerous” based on the type of people—for example, street youth—who frequent the location, and their comportment. But it is unclear whether these sentiments reflect an actual risk of (exposure to) violence. The SSO data include binary indicators of whether any adults or men were loitering/ congregating/hanging out, or if peer groups of three or more teens or of male teens were observed on the block face. On average adults loitering only were observed on 7.8 % of block faces within a tract. The percentages were much lower for men loitering, teen peer groups, and male teen peer group presence, with most tracts reporting less than 2% block face presence for each measure. We find that inclusion of either a continuous measure of adults loitering or indicators for whether tracts had relatively high levels (i.e., above 2%) of men loitering, teen peer groups, or male teen peer groups in separate models (now shown) did not change the quadratic effects of active streets on any of the three outcomes.

## DISCUSSION

Despite decades of theory incorporating the role of socially occupied public space in influencing the prevalence of crime, few if any studies have examined this link directly. The debate about the functioning of public space has taken on new relevance, particularly in the aftermath of natural disasters such as hurricane Katrina that have wrought widespread devastation and required substantial rebuilding efforts. New Urbanist planners and architects have played a significant role in conceiving the development of post-Katrina New Orleans, highlighting the importance of examining Jacobs-inspired claims about the role of neighborhood walkability and active streets (Calthorpe and Fulton 2001). Similarly, the spate of urban redevelopment efforts that are currently being negotiated as urban renewal-based public housing projects come down calls for careful study of the conditions that yield optimal collective control of public space.

This study focused on the influence of a central feature of urban social ecology—active streets—on the prevalence of severe violent crime in a large urban area. Two key questions motivated the analysis. First, to what extent (and how) do active streets influence violent crime rates at the neighborhood level? Second, is the relationship between active streets and violent crime conditional on neighborhood social organization, specifically, levels of anonymity and collective efficacy within urban neighborhoods?

Jacobs' (1961) highly influential discussion of "eyes on the street" as a social control mechanism in urban neighborhoods points to an important regulatory role of active streets. A key feature of Jacobs' model, however, is its recognition that neighborhoods benefit only when a sufficient density of active streets has been achieved. At very low levels, increases in the prevalence of active streets may offer little more than additional potential targets for victimization. Jacobs' expectation regarding the neighborhood-level benefits of active street prevalence (a social control effect occurring beyond a threshold) has not been widely acknowledged and, to date, no study has systematically tested this aspect of Jacobs' model of street control.

Analyses of unprecedented PHDCN Systematic Social Observation data on active streets and self-report data on exposure to severe violence among urban youth revealed evidence consistent with Jacobs' expectation of a nonlinear relationship between active street prevalence and violence. The pattern of association between active streets and exposure to violence held even in the presence of controls for prior exposure to violence, problem behavior, and a control for prior homicide rates at the neighborhood level. The nonlinear relationship between active streets and exposure to violence was reproduced in analyses of both administrative data on homicide and independently collected data on household-level victimization. The analyses thus revealed strong and consistent evidence of a criminogenic effect of active street prevalence at low levels, but a regulatory effect beyond a threshold.

The nonlinear relationship between active street prevalence and crime has potentially important implications for the process of urban redevelopment and neighborhood change. In communities that experience residential repopulation and commercial reinstitutionalization (Wilson 1996), associated social ecological changes may actually increase violence as active streets become more prevalent but still not sufficient to generate social control benefits. Increases in criminal activity might lead to retrenchment of development efforts in the absence of information about the nature of the relationship between active street prevalence and crime. Indeed, the current findings suggest that increases in street activity-generating residential and commercial densities may produce short-term increases in violent crime that hold the potential to be more enduring if not accompanied by ongoing and more spatially dispersed development efforts. Such efforts may produce conditions necessary to foster a sufficient presence of people on the street for a social control benefit to emerge. Future analyses incorporating longitudinal information on changes in active streets over time and significantly more detailed information on the spatial and temporal distribution of urban street use will offer important insight into the role of changing social ecologies in influencing the prevalence of urban violence.

A second question concerned the potential for contingency in the relationship between active streets and crime. Jacobs, for instance, suggests that active streets are likely to produce better monitoring and street control only when neighborhood residents share the value of a crime-free public realm and maintain confidence that neighbors will back them up when intervention becomes necessary. As a forerunner to collective efficacy theory, Jacobs' model integrates social organizational characteristics of urban neighborhoods (informal social control norms) with explicit attention to the social ecologies necessary for neighborhood social organization to exert regulatory effects on crime. Similarly, Taylor argues that active streets accompanied by high levels of anonymity may actually increase crime as opposed to providing informal social control benefits. The implication of Jacobs' and Taylor's theoretical approaches is that the prevalence of active streets interacts with social organization, with each dependent upon the presence of the other for the realization of social control benefits. In contrast, an autonomous street control model views active streets as a potentially independent source of urban social control. People on the street may serve as a situational deterrent to criminal activity, given that potential offenders are uncertain regarding the intervention capacity of the social environment.

Findings from models that interacted measures of neighborhood-level anonymity and collective efficacy with active streets offered limited evidence of a contingent effect of the latter on the prevalence of violence. The results failed to show an interactive effect of collective efficacy on any of the three outcomes. Only anonymity was found to slightly mitigate the protective effects of high prevalence of active streets on homicide, but not on exposure to violence or violent victimization. This suggests that although social organizational factors may modify the effects of active street prevalence in limited instances, the informal social control benefits of active streets may operate largely independent of the strength of neighborhood social organization.

The implications of evidence in support of the autonomous street control model are potentially important for allocating research attention related to neighborhood effects. For decades, neighborhood effects research has focused, both theoretically and empirically, on the "parochial" realm—that is the realm of friendship, acquaintanceship, informal ties, and the associated resident-based normative order—as the key source of variability in local social control of crime. Attention to the functioning of the parochial realm has yielded important findings on the collective dynamics of crime control and other aspects of neighborhood well-being (Browning et al. 2005; Bursik 1993; Sampson et al. 1999). But insufficient attention to the functioning of the public realm—that is, that dominated by "strangers" (Lofland 1995)—may limit understanding of how contemporary urban neighborhoods regulate the prevalence of crime even in the absence of effective parochial control (Carr 2003). Although the findings of the current analysis require replication on additional and larger samples of neighborhoods with more precise information on the quantitative and qualitative aspects of urban street use, they nevertheless suggest the importance of understanding social ecological dynamics as a potentially unique source of informal social control.

An important goal of future research will be the collection of more detailed, longitudinal data on public space use at the neighborhood level. A key limitation of the current analysis was the relative dearth of information on the extent and characteristics of people on the street within Chicago neighborhoods. Although unprecedented in scope and methodological rigor, the PHDCN SSO data were not coded for the total number of individuals present on urban block faces. Consequently, the analyses relied only on an assessment of the presence or absence of people across neighborhood block faces (although analyses including assessment of the presence of adults on one or both sides of the street revealed comparable results). More information on the nature of street activity—including the number and comportment of people on the street in addition to their dispersion within a neighborhood—also would help shed light on possible differences in the impact of active streets.

Although the SSO data are unique in that they contain extensive measures of the *observed* prevalence of active streets, land use, and business presence down to the block-face level, they were collected over 15 years ago. Nonetheless, our theoretical arguments are not period-specific, so we have no reason to expect that the associations found here would be different if we used comparable data collected more recently. Still, it would be informative to examine whether and how street dynamics have changed, and how these changes influence crime. To this end, longitudinal data on neighborhood street activity might be used to track changes in social ecologies over time. Increasingly, household-based surveys are incorporating basic data collection on physical and social ecologies of respondent micro-neighborhoods (face blocks or small clusters of face blocks) through interviewer-based systematic social observations (Sastry and Pebley 2004). The collection of such data on a variety of urban contexts—including more decentralized, automobile-oriented cities—would provide information on the nature and consequences of social ecologies across a range of urban conditions.

Another limitation is that our active streets measure captures daytime activity whereas much of violent crime may occur at night. Unfortunately, pretests of SSO data collection indicated that adequate street observations by video or first-hand were not possible at night (Sampson and Raudenbush 1999). Nonetheless, in supplemental analyses not shown, we find that, at high prevalence, our measure of active streets is negatively associated with the perceived risk of walking alone in the neighborhood after dark (net of population density, concentrated disadvantage, residential stability, immigrant concentration, prior homicide, and a range of individual-level controls). Although this finding suggests that our approach to measuring active streets may be capturing crime-relevant social ecological dynamics at night as well as during the daytime, we cannot adequately assess this claim without information on nighttime street ecologies.

Ideally, our analyses also would have included information on specific types of violent crime (beyond homicide). For instance, prior research has found evidence that factors associated with dense social ecologies are positively predictive of robberies (perhaps due to the inclusion in this offense type of highly premeditated, rapidly occurring crimes that may benefit from a crowd in which to disappear; Browning, et al. 2010). Thus, our results may obscure a stronger protective effect of active streets for other forms of violent victimization.

To date, neighborhood research largely has relied on characteristics of residents and their survey-based reports to evaluate neighborhood social environments. Although resident-based data are a critical tool for assessing neighborhoods, they are likely to be less effective for accurately characterizing aspects of public space (Sampson and Raudenbush 2004). Incorporating attention to the observed characteristics of urban public space and their potentially unique role in influencing neighborhood outcomes moves neighborhood research further toward a recognition of the true significance of "place" in social life.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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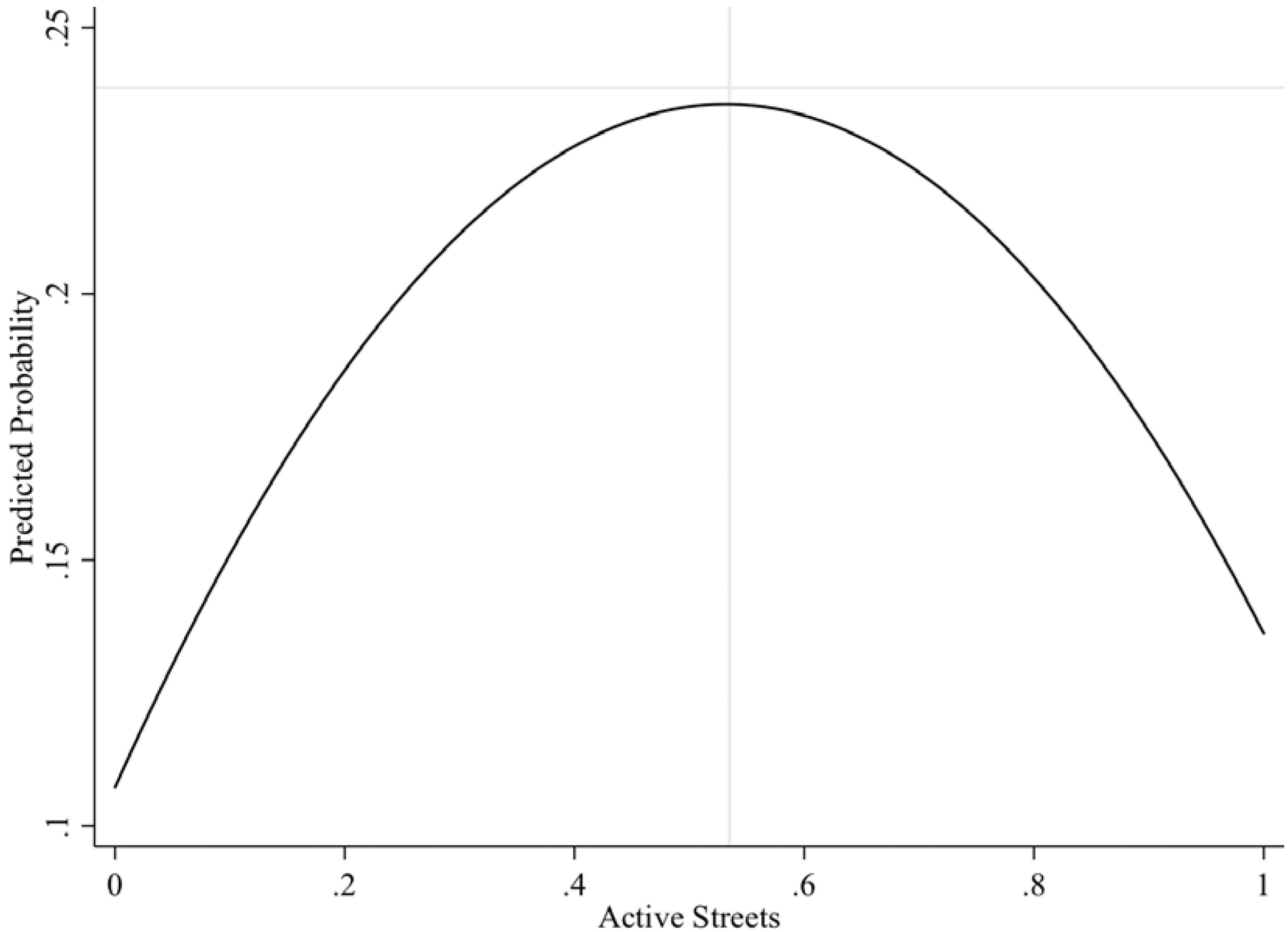


**Figure 1.**
Predicted Probability of Exposure to Severe Violence by Proportion of Active Streets (predictions are based on Model 4 results in Table 2 and refer to the probability of witnessing someone attacked with a weapon [i.e., the omitted item at level one]; all other variables are held at their grand means).

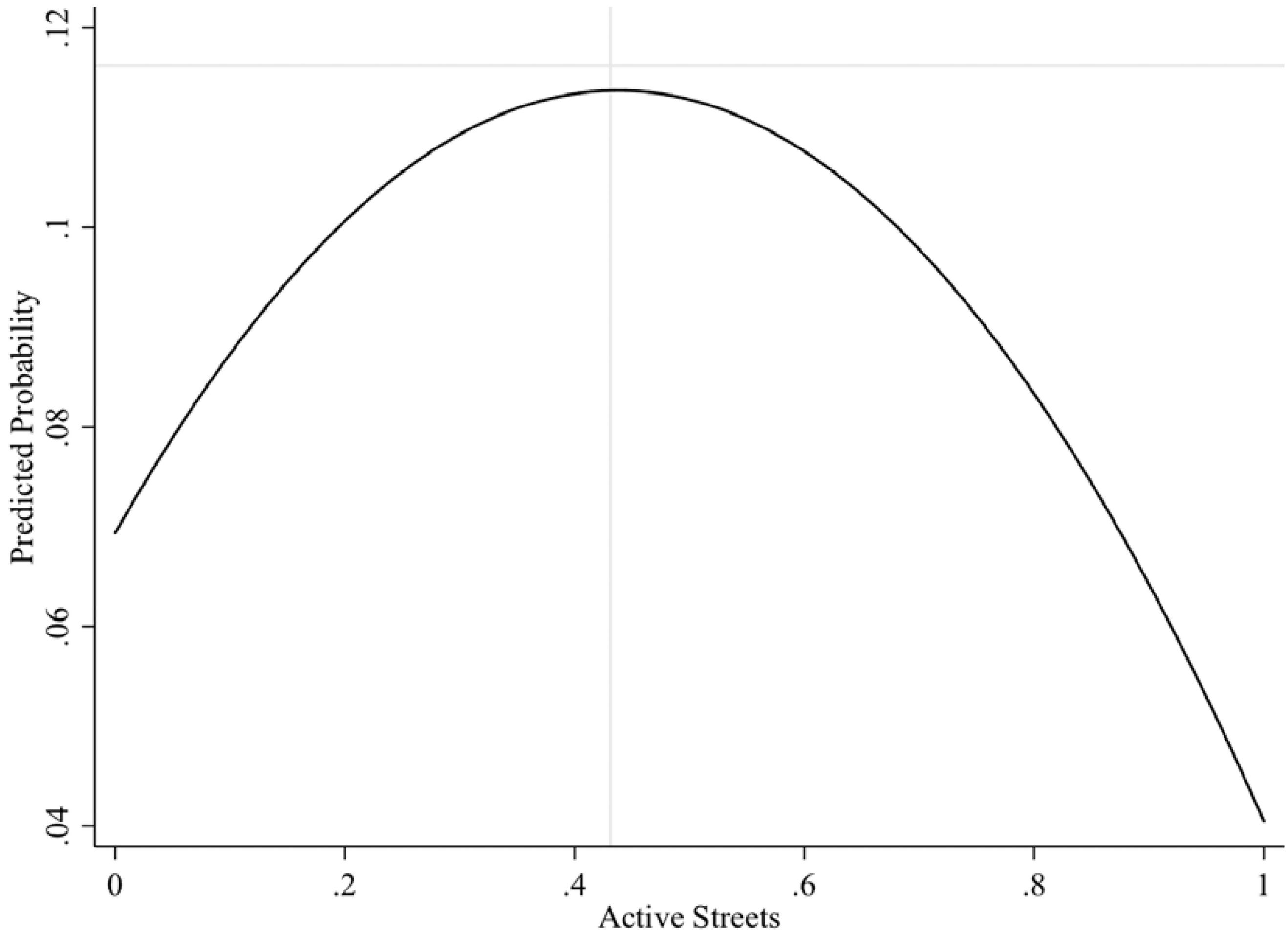


**Figure 2.**
Predicted Probability of Violent Victimization by Proportion of Active Streets (predictions are based on Model 6 results in Table 3 and refer to the probability when all other variables are held at their grand means).

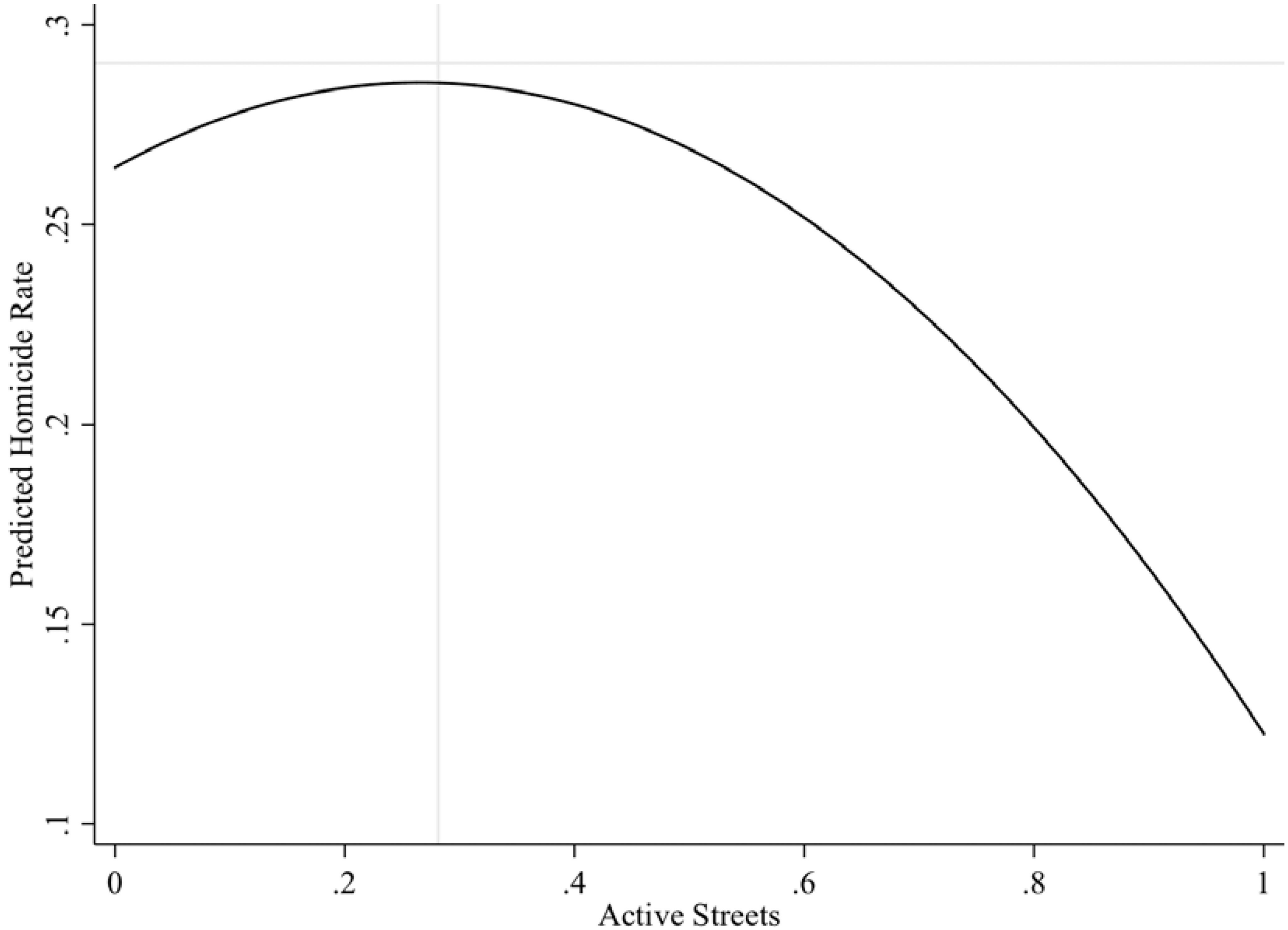


**Figure 3.**

Predicted Homicide Rate Per 1,000 by Proportion of Active Streets (predictions are based on Model 3 results in Table 3 and refer to the homicide rate when all other variables are held at their grand means).

## Table 1

Descriptive Statistics for Analyses of Exposure to Violence (Neighborhood-level N=157; Person-level N=1,135).

| Independent Variables | Mean | Std. Dev. |
|---|---|---|
| *Individual/Family Level* | | |
| Race/Ethnicity (vs. White/Other) | | |
| African American | .3436 | |
| Latino | .4714 | |
| Immigrant Generation (vs. Third) | | |
| First | .1357 | |
| Second | .2758 | |
| Male | .4837 | |
| Family Socioeconomic Status | −.1202 | 1.4181 |
| Two Biological Parents | .4934 | |
| Family Supervision | 4.8838 | .6869 |
| Family Attachment & Support | .0002 | .6948 |
| Prior Problem Behavior | 2.4947 | 1.1127 |
| Wave 1 Exposure to Violence | 1.2159 | .7501 |
| *Neighborhood Level* | | |
| Active Streets | .4251 | .1811 |
| Mixed Land Use | .2201 | .14985 |
| Business Presence | .9063 | .6480 |
| Concentrated Disadvantage | .2934 | .8183 |
| Residential Stability | −.2625 | .9004 |
| Immigrant Concentration | .6337 | 1.3459 |
| Ln. Population Density | 8.7389 | .7222 |
| 1991-93 Homicide Rate | −.2340 | .7805 |
| Collective Efficacy | 3.4641 | .2578 |
| Anonymity | −.0396 | .2538 |

**Table 2**

Three-Level Rasch Models of Exposure to Severe Violence by Individual, Family, and Neighborhood Characteristics (Neighborhood-level N=157; Person-level N=1,135).[a]

| Independent Variables | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| *Individual Level* | | | | |
| Race/Ethnicity | | | | |
| African American | .8695*** (.1952) | .8466*** (.1965) | .6652** (.1847) | .4782* (.1839) |
| Latino | .5708** (.2105) | .5908** (.2084) | .5118* (.2191) | .4525* (.2127) |
| Age | .1722*** (.0396) | .1714*** (.0396) | .1766*** (.0394) | .0646 (.0419) |
| Immigrant Generation | | | | |
| First | −.5306* (.2648) | −.5224 (.2693) | −.3718 (.2787) | −.1402 (.2743) |
| Second | −.1707 (.2337) | −.1734 (.2336) | −.0780 (.2446) | .0195 (.2472) |
| Male | .5270*** (.1339) | .5251*** (.1344) | .5087*** (.1325) | .3991** (.1352) |
| Family SES | −.0162 (.0508) | −.0213 (.0512) | .0249 (.0519) | .0237 (.0510) |
| Two Biological Parents | −.1778 (.1515) | −.1720 (.1514) | −.1705 (.1504) | −.0768 (.1508) |
| Family Supervision | −.3102** (.0931) | −.3096** (.0929) | −.3187** (.0910) | −.2795** (.0888) |
| Family Attachment & Support | −.2866** (.0823) | −.2920** (.0815) | −.2956*** (.0801) | −.1197 (.0777) |
| Prior Problem Behavior | | | | .3273*** (.0630) |
| Wave 1 Exposure to Violence | | | | .3757*** (.0917) |
| *Neighborhood Level* | | | | |
| Active Streets | .3170 (.3431) | .5299 (.3896) | .6422 (.4919) | .6806 (.5361) |
| Active Streets$^2$ | −.0378** (.0126) | −.0390(.0123) | −.0375** (.0111) | −.0310** (.0113) |
| | * | ** | | * |
| Mixed Land Use | | −.5735 (.5573) | −.0292 (.5515) | .3155 (.5730) |
| Concentrated Disadvantage | | | .4154*** (.0849) | .2889** (.0928) |
| Residential Stability | | | −.0914 (.0770) | −.0893 (.0777) |
| Immigrant Concentration | | | .0015 (.0830) | .0061 (.0827) |
| Ln. Population Density | | | −.3835** (.1199) | −.3981** (.1295) |

| Independent Variables | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| 1991-93 Homicide Rate | | | | .1671 (.0852) |
| Intercept | −1.1940*** (.0907) | −1.1828*** (.0922) | −1.1342*** (.0917) | −1.1970*** (.0883) |

* p<.05

** p<.01

*** p<.001 (two-tailed significance tests).

[a] Log odds with robust standard errors in parentheses

## Table 3

Multivariate Models of 1995-97 Homicide and Violent Victimization on Active Streets and Neighborhood Controls (Neighborhood-Level N=176).

| | 1995 Homicide[a] | | | 1995 Victimization (PHDCN-CS)[b] | | |
|---|---|---|---|---|---|---|
| **Independent Variables** | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** | **Model 6** |
| Active Streets | .0538 (.1856) | −.4165 (.2624) | −.4513+ (.2332) | 1.4299*** (.3419) | .0329 (.5396) | .0037 (.5578) |
| Active Streets$^2$ | −.0226** (.0074) * | −.0185* (.0081) * | −.0151* (.0071) * | −.0422*** (.0112) *** | −.0326** (.0115) * | −.0307** (.0112) * |
| Business Presence | | .1258* (.0506) | .0911 (.0505) | | | |
| Mixed Land Use | | | | | .5746 (.3823) | .5742 (.3905) |
| Concentrated Disadvantage | | .3097*** (.0438) | .1848*** (.0462) | | .0768 (.0894) | −.0053 (.1001) |
| Residential Stability | | −.0217 (.0375) | −.0196 (.0364) | | −.1101 (.1041) | −.0978 (.1035) |
| Immigrant Concentration | | −.0152 (.0316) | −.0062 (.0311) | | .1387 (.0783) | .1347 (.0765) |
| Ln. Population Density | | −.0235 (.0586) | −.0191 (.0564) | | .2919 (.1537) | .2846 (.1556) |
| 1991-93 Homicide Rate | | | .2375*** (.0500) | | | .1667 (.0963) |
| Intercept | −1.2444*** (.0476) | −1.2583*** (.0415) | −1.2700*** (.0398) | −1.9205*** (.0836) | −2.0215*** (.0832) | −2.029*** 0.08357 |

* p<.05

** p<.01

*** p<.001 (two-tailed significance tests).

[a] OLS regressions (coefficients with robust standard errors in parentheses).

[b] Two-level hierarchical logit models (log odds and robust standard errors in parentheses; coefficients on individual-level controls not shown).

## Table 4

Multivariate Models of Exposure to Violence and 1995 Homicide: Interactive Effects of Active Streets and Social Organization.

| | Exposure to Violence[a] | | 1995 Homicide[b] | |
|---|---|---|---|---|
| **Independent Variables** | **Model 1** | **Model 2** | **Model 3** | **Model 4** |
| Active Streets | .6701 (.4779) | .7911 (.5280) | −.4643$^{+}$ (.2430) | −.4848$^{+}$ (.2713) |
| Active Streets$^2$ | −.0376$^{**}$ (.0108) | −.0298 (.0182) | −.0222$^{***}$ (.0065) | −.0151$^{+}$ (.0084) |
| Mixed Land Use | −.0028 (.5519) | .0284 (.5569) | | |
| Business Presence | | | .1401$^{**}$ (.0505) | .1017$^{*}$ (.0487) |
| Concentrated Disadvantage | .3531$^{**}$ (.0986) | .4185$^{***}$ (.0902) | .3022$^{***}$ (.0517) | .2556$^{***}$ (.0420) |
| Residential Stability | −.1561$^{+}$ (.0910) | −.1099 (.0857) | −.0253 (.0386) | .0230 (.0374) |
| Immigrant Concentration | −.0107 (.0821) | −.0014 (.0842) | −.0155 (.0307) | −.0345 (.0326) |
| Ln. Population Density | −.3668$^{**}$ (.1278) | −.3779$^{**}$ (.1257) | −.0365 (.0597) | −.0740 (.0591) |
| Anonymity | −.3561 (.3018) | | −.3023 (.1852) | |
| Anonymity*Street Activity | .0027 (.0141) | | .0073 (.0070) | |
| Anonymity*Street Activity$^2$ | −.0002 (.0004) | | .0006$^{*}$ (.0003) | |
| Collective Efficacy | | −.0212 (.3105) | | −.4254$^{+}$ (.2199) |
| Coll. Eff. *Street Activity | | .0088 (.0156) | | .0038 (.0077) |
| Coll. Eff. *Street Activity2 | | .0004 (.0005) | | −.0003 (.0003) |
| Intercept | −1.1378$^{***}$ (.0895) | −1.1409$^{***}$ (.0928) | −1.2589$^{***}$ (.0401) | −1.2595$^{***}$ (.0408) |
| Neighborhood-Level N | 157 | 157 | 176 | 176 |

$^{+}$p<.10

$^{*}$p<.05

$^{**}$<.01

$^{***}$p<.001 (two-tailed significance tests).

[a]Three-level Rasch models (log odds with robust standard errors in parentheses; coefficients on individual-level controls not shown).

[b]OLS regressions (coefficients with robust standard errors in parentheses).

[c]Two-level hierarchical logit models (log odds and robust standard errors in parentheses; coefficients on individual-level controls not shown).