THE BUILT ENVIRONMENT AND COMMUNITY CRIME RISK INTERPRETATION

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In this article, the authors examine whether subjective perceptions of community safety are informed by the built environment. They posit that the built environment serves as a heuristic device, providing cues about likely levels of neighborhood crime, independent of the effects of neighborhood crime itself. Using data on 4,456 individuals nested within 100 census tracts, the authors estimate hierarchical logistic models of perceived community crime risk. They focus on the role of the neighborhood built environment in the form of aggregated perceptions of nonresidential land use, while controlling for individual-level criminal opportunity, community-level social structural antecedents, and community-level objective crime. The findings indicate that the neighborhood-level presence of businesses and parks and playgrounds increases individual perceptions of community danger, but these effects disappear once neighborhood crime rates are controlled. The presence of schools has no effect on subjective interpretations of community crime, regardless of whether actual area crime is considered.

Keywords: community; risk; fear

If a healthy community is in part defined as one in which residents feel safe from crime, regardless of objective crime risk, then understanding the complex nexus of factors involved in subjective risk perception is an important task. Although previous studies have addressed this complex nexus of factors in micro-, macro-, and multilevel studies, an interesting omission from previous investigations is an examination of the contextual effects of the physical, built environment. Yet the physical environment seems particularly

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susceptible to shaping subjective perceptions of crime. Because the built environment is externally “obvious” to residents—especially in comparison to social structure, typically the focus of contextual studies—it would stand to reason that it serves as a strong heuristic tool in shaping public opinion about community crime risk (Schneider et al. 1999).

The present study addressed this possibility by estimating multilevel models of perceived community crime risk, incorporating both individual-level predictors as well as environmental ones, including characteristics related to the social structure and the physical structure. More specifically, using data on 4,456 individuals nested within 100 Seattle, Washington, neighborhoods, we estimated hierarchical logistic regression models of individual perceptions of community crime risk, focusing on the effects of citizen-reported public land use while controlling for individual-level victimization risk factors, community social structure, and community “objective” crime. Through this analysis, we aimed to delineate the extent to which aspects of the physical environment—public land uses, in particular—serve as a heuristic tool in shaping individual residents’ perceptions of crime risk, net of individual-level differences, social structural conditions, and in particular actual crime.

PERCEPTIONS OF CRIME RISK: PREVIOUS STUDIES

Studies of perceived crime risk—conceptualized as a cognitively based assessment of safety and risk (Ferraro and LaGrange 1987)—have revealed relatively consistent findings for both micro and macro predictors.1 Important micro-level effects include sociodemographic characteristics: Being female, elderly, poor, or non-White tends to heighten perceived risk (Baumer 1979; Chiricos, Hogan, and Gertz 1997; Ferraro 1995; Garofalo 1979; LaGrange and Ferraro 1989; Lewis and Salem 1986; Liska, Sanchirico, and Reed 1988; Wilcox Rountree and Land 1996a, 1996b), though such effects can be conditional on neighborhood crime (Maxfield 1984).2 Other individual-level factors that appear important are routine activities or lifestyle characterizations, including involvement in “dangerous” public activities, leaving the home unoccupied, carrying valuables or money in public, and engaging in safety precautions (Wilcox Rountree and Land 1996a, 1996b). The evidence is more mixed regarding the effect of individual-level victimization experiences on risk perception, but several studies have found that respondents’ victimization experiences increase concern about area crime or perceptions of area safety (Ferraro 1995; Garofalo 1979; Lee and Ulmer 2000; Liska et al. 1988; Skogan 1987; Taub, Taylor, and Dunham 1981). Important macro-
level effects on perceived risk merging from the extant literature include pop-
ulation density (Lee and Ulmer 2000; Liska, Lawrence, and Sanchirico
1982); poverty (Skogan 1990; Wilcox Rountree and Land 1996a, 1996b); the
proportion of the population that is non-White (Chiricos et al. 1997;
Covington and Taylor 1991; Liska et al. 1982; Taylor and Covington 1993);³
social cohesion (Lewis and Salem 1986; Wilcox Rountree and Land 1996a,
1996b); community crime (Lewis and Salem 1986; Liska et al. 1982; Wilcox
Rountree and Land 1996a, 1996b);² local homicide media coverage (Liska
and Baccaglini 1990); and social and physical disorder (Ferraro 1995;
LaGrange, Ferraro, and Supancic 1992; Lewis and Maxfield 1980; Lewis and
Salem 1986; Skogan 1990; Skogan and Maxfield 1981; Taub et al. 1981;
Wilcox Rountree and Land 1996a, 1996b), including, more specifically, the
presence of teenage groups (Taylor and Covington 1993).

Recent multilevel theorizing on subjective crime-related reactions,
including cognitively based risk perception and emotionally based fear or
anxiety, have suggested that the micro and macro factors above are both
important in formulating such reactions because they represent criminal
opportunity (Ferraro 1995; Wilcox Rountree 1998). Drawing on Ferraro

An individual’s assessment of risk involves interpretation of one’s exposure to
the chance of injury or loss. Estimation of risk thus entails defining a poten-
tially problematic situation. One can never be certain of the risks of victimiza-
tion. One can only gather the information related to the risk and make a judg-
ment about it. (P. 1176)

The fact that this “information related to the risk” comes simultaneously
from multiple levels of analysis is important. Lee and Ulmer stressed this in
saying, “The risk interpretation model is an individual- and community-level
theory. To leave out either individual experiences and perceptions or com-

unity-level characteristics is to have an impoverished and incomplete explana-
tion” (p. 1177). Although many individual- and community-level aspects of
this risk interpretation have been addressed in previous studies (see above), a
particularly neglected community-level risk factor is community physical
structure.

Most extant studies that have addressed the role of the physical environ-
ment in understanding risk perception are those typically community-level
studies that have examined the effects of physical incivilities (see, e.g., Taylor
1987, 2001; Taylor, Schumaker, and Gottfredson 1985; Wilson and Kelling
1982). Taylor and Covington (1993) described clearly the role of physical
incivilities such as litter, broken windows, and graffiti within macro models
of “fear” or risk:
Community structure affects the ability of residents to informally control their streets and to fend off crime and fear. Fear of crime models incorporating incivilities elaborate this core proposition by pointing to specific physical and social cues which inform residents about safety and informal control on the street. Residents infer attenuated informal controls from more extensive incivilities. (Pp. 390-91)

Physical incivilities are particularly visible environmental cues signaling criminal opportunity or risk to an individual within that context. And as already indicated, there is substantial empirical evidence that physical incivilities do indeed heighten subjective perceptions. But aside from incivilities, other aspects of the built physical environment seem important in assessing cognitive risk perception. Merry (1981:413) addressed this issue in her study of the Dover Square housing project:

Each resident has a mental topography of the relative safety and danger of the various locations in the project which he develops through his own experience, information from friends and relatives, and his response to the visual characteristics of the buildings and their layouts. (P. 413)

She compared these cognitive maps of “perceived dangerous locations” to actual robbery locations. Merry clearly discerned discrepancies between the perception of danger and the actual danger presented by certain physical locations. She noted that

[the] discrepancies suggest that places appear dangerous not simply because of the frequency of crime but also because of their design, their familiarity, residents’ anticipation that someone will intervene to help them, and the behavior and reputations of their habitual users. (P. 413)

Subsequent site-specific work has supported Merry’s findings, suggesting that features of the built environment such as poor building design (e.g., those with alcoves, niches, blind spots), poor lighting, and overgrown landscaping—all allowing for refuge while disallowing prospect and escape— increase perceptions of crime risk (Brantingham and Brantingham 1994; Fisher and Nasar 1992, 1995; Kirk 1988; Warr 1990). Physical environment–perceived risk linkages most relevant to the present study’s focus on nonresidential land use at the neighborhood level have also been found. Taub et al.’s (1981) study of eight Chicago neighborhoods, for instance, revealed that land uses affected risk perception. More specifically, renters living in close proximity to parks or playgrounds, alleys, or other open spaces experienced heightened victimization risk perception. However, Taub et al. did not estimate these effects within the context of a multilevel model, and thus their estimates of con-
textual effects might be inefficient. In fact, no study to date that we are aware of has examined the possible direct effects of land use on risk perception within a multilevel model.

Building on the above-cited work, we assumed that the effects of public land use on risk perception are direct and net of actual crime. We posited that public land use can provide to residents risk-related cues in terms of the reputation of users and the likelihood of supervision and intervention. We suspected that the information conveyed by such cues might be at odds with actual community crime risk as indicated by objective crime rates, and thus the effects of public land use would be net of actual community crime.

**DATA AND METHODS**

In examining these potential direct effects of public land use, we have extended previous work invoking multilevel risk interpretation models (Ferraro 1995; Lee and Ulmer 2000). We estimated this conceptual model using a hierarchical modeling approach and the MLWin software specifically (Goldstein et al. 1998; see also Kreft and deLeeuw 1998). This modeling strategy accounts appropriately for the inherently nested data structure, with individuals distributed nonrandomly within neighborhoods. In short, the multilevel models estimated here, unlike ordinary least squares models, appropriately account for the dependence of observations within groups because it is likely that individuals within the same neighborhood are more similar to one another than individuals from different neighborhoods. Each of the levels in the structure of the data—individuals and neighborhoods—is represented with a submodel. These submodels, along with nested error terms, account for variation in crime risk perception at each of the levels (see, e.g., Bryk and Raudenbush 1992; Kreft and DeLeeuw 1998). The general level 1 model estimated for each individual \(i\) in neighborhood \(j\) is of the following form:

\[
\text{Logit (Risk Perception)}_{ij} = \beta_{0j} + \beta_{1j}X_{1ij} + \beta_{2j}X_{2ij} + \ldots + \beta_{kj}X_{kij} + e_{ij},
\]

where \(X_1, X_2, \ldots, X_k\) represent individual-level variables, the \(\beta_{kj}\) terms are logistic regression coefficients (or intercepts, as in the case of \(\beta_{0j}\)), and \(e_{ij}\) is a level 1 error term assumed to be distributed binomially. The level 2, or neighborhood-level, model is a normal-errors regression model of the following general form:

\[
\beta_{ij} = \Theta_{k0} + \Theta_{k1}W_{1j} + \Theta_{k2}W_{2j} + \ldots + \Theta_{kj}W_{kj} + u_{ij},
\]
where $W_1, W_2, \ldots, W_q$ represent neighborhood-level variables, the $\Theta_{eq}$ terms are regression coefficients (or intercepts) to be estimated, and $u_{kj}$ is a normally distributed error term.

Data for our multilevel study of subjective crime risk came from a 1990 survey of 5,302 Seattle residents (Miethe 1992). Respondents were selected for study on the basis of a multistage sampling design. First, 100 of Seattle’s 121 “stable” census tracts were randomly chosen. Three neighborhoods—or pairs of blocks—were then selected from within each of the 100 tracts, leaving 300 sampled block pairs. Because the original study was partially motivated by the study of crime displacement across contiguous blocks, a criterion for selection was that one of the blocks in each selected pair had experienced at least one reported burglary within the previous year, while the other block adjoined. On average, 18 individuals were surveyed within each selected block pair, using a reverse telephone directory, creating a total sample of 5,302 Seattle residents. We focused on respondents nested within census tracts here. In the present study, the census tract was used instead of the block-pair unit because census data were readily matched to these units, and they are commonly used as neighborhood approximations in community-level research (Bellair 2000; Warner and Wilcox Rountree 1997). The listwise deletion of cases with missing values left 4,456 individuals within 100 census tracts for the analyses presented herein.

Measures of Variables

The dependent variable for this study was community crime risk perception. Perceived community crime risk was measured as a dichotomous variable (1 = yes, 0 = no), indicating whether or not the respondent felt that his or her neighborhood was unsafe from crime at the time of the survey. This dichotomous measure was attained by recoding a four-category, ordinal-level response set. Those respondents indicating that they felt very or somewhat unsafe were combined (and coded as 1 = unsafe), whereas those feeling somewhat or very safe were coded as 0. As the descriptive statistics in Table 1 suggest, 24 percent of the respondents perceived their neighborhoods to be unsafe.

Individual-level explanatory variables were largely derived from criminal opportunity theory, with the assumption being that opportunity (indicated by exposure, target attractiveness, and guardianship) shapes risk interpretation. In particular, exposure to crime was operationalized with two separate measures. First, we measured exposure as the number of nights per week a respondent left his or her home unoccupied. We also measured exposure as the number of dangerous public activities in which a respondent was recently involved, including whether or not the respondent had visited bars or
### TABLE 1: Descriptive Statistics for Study Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Metric</th>
<th>M</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
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<tr>
<td><strong>Dependent variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crime risk perception (1 = unsafe, 0 = safe)</td>
<td></td>
<td>.24</td>
<td>.43</td>
<td>.00</td>
<td>1.00</td>
</tr>
<tr>
<td><strong>Individual-level explanatory variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (1 = 10-19 years to 7 = 70 years and older)</td>
<td></td>
<td>4.26</td>
<td>1.68</td>
<td>1.00</td>
<td>7.00</td>
</tr>
<tr>
<td>Sex (1 = male, 0 = female)</td>
<td></td>
<td>.51</td>
<td>.50</td>
<td>.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Race (1 = non-White, 0 = White)</td>
<td></td>
<td>.14</td>
<td>.34</td>
<td>.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Family income (1 = &lt; $10,000 to 7 = &gt; $100,000)</td>
<td></td>
<td>3.41</td>
<td>1.36</td>
<td>1.00</td>
<td>7.00</td>
</tr>
<tr>
<td>Home unoccupied (number of nights per week)</td>
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<td>1.87</td>
<td>1.98</td>
<td>.00</td>
<td>7.00</td>
</tr>
<tr>
<td>Dangerous activities (number of activities)</td>
<td></td>
<td>.90</td>
<td>.82</td>
<td>.00</td>
<td>3.00</td>
</tr>
<tr>
<td>Household goods (number of items owned)</td>
<td></td>
<td>2.60</td>
<td>1.40</td>
<td>.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Carried valuables (number of times per month)</td>
<td></td>
<td>3.22</td>
<td>2.61</td>
<td>.00</td>
<td>8.00</td>
</tr>
<tr>
<td>Safety precautions (number of precautions)</td>
<td></td>
<td>4.21</td>
<td>1.47</td>
<td>.00</td>
<td>9.00</td>
</tr>
<tr>
<td>Live alone (1 = yes, 0 = no)</td>
<td></td>
<td>.25</td>
<td>.44</td>
<td>.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Burglary victimization (1 = yes, 0 = no)</td>
<td></td>
<td>.18</td>
<td>.38</td>
<td>.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Violent victimization (1 = yes, 0 = no)</td>
<td></td>
<td>.03</td>
<td>.17</td>
<td>.00</td>
<td>1.00</td>
</tr>
<tr>
<td><strong>Neighborhood-level explanatory variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty (residents below poverty/total tract population)</td>
<td></td>
<td>.12</td>
<td>.10</td>
<td>.02</td>
<td>0.57</td>
</tr>
<tr>
<td>Proportion non-White (non-White residents/total tract population)</td>
<td></td>
<td>.23</td>
<td>.22</td>
<td>.04</td>
<td>.87</td>
</tr>
<tr>
<td>Residential stability (residents of five or more years/tract population)</td>
<td></td>
<td>.44</td>
<td>.12</td>
<td>.15</td>
<td>.66</td>
</tr>
<tr>
<td>Business places (number of total reported business places within three blocks/total survey respondents)</td>
<td></td>
<td>2.73</td>
<td>1.06</td>
<td>.88</td>
<td>5.46</td>
</tr>
<tr>
<td>Schools (number of residents living within three blocks of a school/total survey respondents)</td>
<td></td>
<td>.17</td>
<td>.20</td>
<td>.00</td>
<td>.79</td>
</tr>
<tr>
<td>Playgrounds (number of residents living within three blocks of a playground/total survey respondents)</td>
<td></td>
<td>.57</td>
<td>.23</td>
<td>.01</td>
<td>.98</td>
</tr>
<tr>
<td>Burglary rate (number of burglaries per 100 tract households)</td>
<td></td>
<td>7.40</td>
<td>3.84</td>
<td>1.81</td>
<td>18.52</td>
</tr>
<tr>
<td>Violence rate (number UCR Part I violent crimes per 100 persons)</td>
<td></td>
<td>2.78</td>
<td>3.43</td>
<td>.10</td>
<td>14.91</td>
</tr>
</tbody>
</table>

**NOTE:** UCR = Uniform Crime Reports. Descriptive statistics are based on 4,456 individuals within 100 neighborhoods (census tracts).
nightclubs during the previous week, whether or not the respondent had visited places where teens hang out during the previous week, and whether or not the respondent had used public transportation.

Target suitability was measured with several variables. We measured this construct first as the number of times in the month preceding the survey that a respondent indicated having carried valuables (more than $50 in cash or more than $100 in jewelry). Target suitability was also measured as the number of portable, expensive household goods owned, including color TVs, VCRs, 35-mm cameras, home computers, and bicycles or motorcycles.

A nonsocial dimension of individual-level guardianship was measured by summing individual responses to nine dichotomous (1 = yes, 0 = no) survey items asking respondents whether or not they engaged in safety precautions, including locking doors, installing extra locks, leaving lights on (or using light timer devices), owning dogs, belonging to neighborhood watch associations, having neighbors watch their homes, owning weapons, carrying weapons, and owning burglar alarms. The resulting safety precautions index had possible responses ranging from 0 to 9. A social dimension of guardianship was tapped with a dichotomous variable measuring whether or not a respondent lived alone (1 = yes, 0 = no).

Because previous victimization is likely to affect risk perception, we controlled for (1) whether or not (1 = yes, 0 = no) a respondent was a victim of stranger violence (assault or robbery) within four blocks of his or her home and within the two years preceding the survey and (2) whether or not (1 = yes, 0 = no) the respondent’s current home had been burglarized (including attempts) in the two years preceding the survey. In addition, because sociodemographic characteristics are often presumed proxy measures for exposure, target attractiveness, and guardianship (e.g., see Cohen et al. 1981), these were controlled in our analyses. Age was measured as an ordinal variable with a seven-item response scale, with 1 = 10 to 19 years of age and 7 = 70 years of age or older. Sex and race were both dichotomous measures, with 1 = male and 1 = non-White, respectively. Finally, family income was measured by way of a seven-item ordinal scale, with a score of 1 representing respondents with annual family incomes of less than $10,000 and a value of 7 characterizing respondents with family incomes of greater than $100,000.

The neighborhood-level explanatory variables of interest in this study included poverty, minority concentration, stability, the presence of business places, the presence of schools, the presence of playgrounds, area burglary rates, and area violent crime rates. The social structural variables all came from 1990 U.S. census tract data. Poverty was measured as the proportion of total tract residents living below the official poverty line. Minority concentration was measured as the tract-level proportion of non-White residents.
Residential stability was measured as the proportion of total tract residents (aged five years or over) who had lived in the same house for at least five years.

To tap neighborhood-level public land use, we examined nine dichotomous (1 = yes, 0 = no) survey items asking respondents about the presence of various public land uses within three blocks of their homes. The results of a factor analysis of these items are depicted in the Appendix. The items loaded onto two factors—the first seemingly representing the perceived presence of commercial or business places and the second representing the perceived presence of nonbusiness, resident-centered public land use. Item 9—a bus stop within three blocks—loaded poorly on both factors and was thus dropped from further analysis. The six items loading onto the first factor were summed, creating a measure of the total perceived number of business-oriented establishments within three blocks of each respondent’s home (α = .72). These scores were then aggregated within each tract, creating neighborhood-level scores representing the average number of businesses within three blocks of respondents’ homes, thus tapping the general presence of commercial land use within the community. The two items loading onto the second factor—living within three blocks of a school and living within three blocks of a playground—were not combined because of an unacceptably low reliability coefficient (α = .26). Instead, they were examined in the analysis presented herein as separate, single-item measures. Each of these items was aggregated within neighborhoods, creating, respectively, the proportion of respondents reporting that they lived within three blocks of a school (tapping the general presence of or proximity to schools) and the proportion of respondents reporting that they lived within three blocks of a park or playground (tapping the general presence of or proximity to parks or playgrounds).

We measured area burglary and violent crime rates using 1989 and 1990 tract-level data from the Seattle Police Department. The burglary rate represents the two-year average tract-specific rate of reported burglaries per 100 tract households. The violent crime rate represents the two-year average tract-specific rate of reported Uniform Crime Reports Part I violent crimes (homicides, rapes, aggravated assaults, and robberies) per 100 tract persons.

RESULTS

Individual-Level Effects

Given the data and measures described above, an initial random-coefficient regression model for crime risk perception was first specified. Initial examination of the cross-tract variation in all $\beta_{ij}$ revealed that only $\beta_0$ and $\beta_3$...
were significantly variable across contexts. As a result, all other coefficients were specified as fixed at level 2 in the model shown here. This “reduced” random-coefficient model for crime risk perception was specified as follows for the level 1 model:

\[
\text{Logit (crime risk perception)}_{ij} = \beta_{0j} + \beta_{1j} \text{Age}_{ij} + \beta_{2j} \text{Sex}_{ij} + \beta_{3j} \text{Race}_{ij} + \beta_{4j} \text{Family Income}_{ij} + \beta_{5j} \text{Home Unoccupied}_{ij} + \beta_{6j} \text{Dangerous Activities}_{ij} + \beta_{7j} \text{Household Goods}_{ij} + \beta_{8j} \text{Carried Valuables}_{ij} + \beta_{9j} \text{Safety Precautions}_{ij} + \beta_{10j} \text{Live Alone}_{ij} + \beta_{11j} \text{Burglary Victimization}_{ij} + \beta_{12j} \text{Violent Victimization}_{ij} + e_{ij}
\]

The model was specified as follows for the level 2 model:

\[
\begin{align*}
\beta_{0j} &= \theta_{00} + u_{0j} \\
\beta_{1j} &= \theta_{10} + u_{1j} \\
\beta_{kj} &= \theta_{kj} + u_{kj}, \quad \text{for } k = 1, 2, 4 \text{ to } 12
\end{align*}
\]

Table 2 presents the results of this model specification. As can be seen, the level 2 variance component for mean crime risk perception—shown in the random-effects portion of the table—was significant. We can thus infer that mean crime risk perception did vary significantly across Seattle neighborhoods. This suggests that contextual effects, net of individual-level factors, are important in understanding crime risk perception. Also, the effect of race on risk perception varied across neighborhoods, implying that neighborhood-level factors interact with race in predicting perceived risk.

Although the model presented in Table 2 shows that cross-neighborhood variation did exist for mean risk perception and the effects of race thereon, the focus of the model was on the individual-level effects on crime risk perception. As can be seen in the fixed-effects panel of Table 2, 7 of the 12 individual-level predictors included in the model had significant effects on crime risk perception. For example, age was negatively related to crime risk perception. The exponentiated coefficient shows that for every one-unit increase on the ordinal age scale, the odds of assessing the community as unsafe decreased by 5 percent. Similarly, Table 2 demonstrates that men, as opposed to women, were less likely to perceive their communities as unsafe. For example, the odds of unsafe perceptions were nearly 22 percent lower for men than for women. Another individual-level characteristic that significantly affected one’s community crime risk perception was race. The odds of assessing the community as unsafe were 34 percent lower for non-Whites than for Whites. Table 2 shows that family income also had a significant negative impact on crime risk perception. The exponentiated coefficient demonstrates that as family income increased by one unit on the ordinal scale, the odds of assessing one’s community as unsafe decreased by nearly 7 percent.
In addition to the sociodemographic variables of age, sex, race, and income, there were other individual-level factors that influenced one’s perception of community crime risk. For instance, the number of safety precautions an individual took was positively related to how unsafe he or she perceived the local community to be. Table 2 shows that for every additional safety precaution in which an individual engaged, the odds that he or she saw the local community as unsafe increased by 11 percent. Although this finding may seem counterintuitive at first glance, it makes sense in that individuals are likely to take safety precautions in response to risk perception. Yet engaging in the precautions does not necessarily alleviate the assessment of crime risk. This is especially plausible given that the measure of individual-level risk assessment examined here was “global” (e.g., assessing the generalized risk of community) rather than “specific” (e.g., assessing the individual likelihood of experiencing victimization, personally). Finally, as might be expected, those who had been the victims of violent crime or burglary were more likely to perceive their communities as unsafe than those who had not experienced these types of victimization. Table 2 demonstrates that the odds

<table>
<thead>
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<th>Fixed Effect</th>
<th>Coefficient</th>
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<tr>
<td>Mean census tract crime risk perception</td>
<td>–1.144 (—)</td>
<td>.097</td>
</tr>
<tr>
<td>Age</td>
<td>–.051* (.950)</td>
<td>.023</td>
</tr>
<tr>
<td>Sex (male)</td>
<td>–.245* (.783)</td>
<td>.066</td>
</tr>
<tr>
<td>Race (non-White)</td>
<td>–.416* (.660)</td>
<td>.142</td>
</tr>
<tr>
<td>Family income</td>
<td>–.070* (.932)</td>
<td>.029</td>
</tr>
<tr>
<td>Home unoccupied</td>
<td>.008 (1.008)</td>
<td>.018</td>
</tr>
<tr>
<td>Dangerous activities</td>
<td>.023 (1.023)</td>
<td>.043</td>
</tr>
<tr>
<td>Household goods</td>
<td>.026 (1.026)</td>
<td>.027</td>
</tr>
<tr>
<td>Carried valuables</td>
<td>.013 (1.013)</td>
<td>.013</td>
</tr>
<tr>
<td>Safety precautions</td>
<td>.103* (1.108)</td>
<td>.025</td>
</tr>
<tr>
<td>Live alone</td>
<td>.085 (1.089)</td>
<td>.084</td>
</tr>
<tr>
<td>Burglary victimization</td>
<td>.516* (1.675)</td>
<td>.081</td>
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<tr>
<td>Violent victimization</td>
<td>.948* (2.581)</td>
<td>.177</td>
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<table>
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<tr>
<th>Random Effect</th>
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<th>SE</th>
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<td>.132</td>
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<tr>
<td>Race (non-White), ( u_{ij} )</td>
<td>.565</td>
<td>.249</td>
</tr>
<tr>
<td>Level 1 extra binomial error, ( e_i )</td>
<td>.828</td>
<td>.018</td>
</tr>
</tbody>
</table>

NOTE: N = 4,456 individuals, 100 census tracts. 
*p < .05.
of assessing one’s community as unsafe were nearly 68 percent higher for those who had been the victims of burglary. Moreover, the odds of an unsafe assessment were nearly 158 percent higher for those who had been the victims of violent crimes. These findings indicate that past community-based victimization has a significant positive impact on one’s current perceptions of community crime risk.

**Neighborhood-Level Effects**

We next estimated four contextual models in which census tract–level indicators of resident-reported land use, social structural characteristics, and violent and burglary crime rates were added to the model in an attempt to account for level 2 variability in mean crime risk perception. Thus, we adjusted the level 2 model as such (the level 1 model stayed the same), noting, however, that violent and burglary crime rates were entered in a stepwise fashion throughout a series of four contextual models. For the level 2 model,

\[
\beta_{0j} = \theta_{00} + \theta_{01} \text{ Poverty}_j + \theta_{02} \text{ Proportion Non-white}_j + \theta_{03} \text{ Residential Stability}_j + \theta_{04} \text{ Business Places}_j + \theta_{05} \text{ Schools}_j + \theta_{06} \text{ Playgrounds}_j + \theta_{07} \text{ Violent Victimization Rate}_j + \theta_{08} \text{ Burglary Victimization Rate}_j + u_{0j}
\]

Table 3 presents the results of these four contextual models. The introduction of neighborhood-level variables generally decreased the cross-community variation in crime risk perception. Compared to the variance component in Table 2, the variance components displayed in the contextual models represent declines ranging from 68 to 76 percent. Despite these declines, crime risk perception continued to remain significantly variable across census tracts in all contextual models, suggesting that the contextual models were only moderately successful overall in accounting for neighborhood-level variation in subjective crime risk.

Model A in Table 3 includes the land-use and social structural level 2 variables, excluding the variables controlling for neighborhood violent and burglary crime rates. Model A shows that poverty, proportion of the population that is non-White, the aggregate perception of business places, and the aggregate perception of playgrounds were all significantly and positively related to community crime risk perception. Model A also shows that residential stability was significantly and negatively related to crime risk perception. In model B, the tract-level violent crime rate was controlled. When this variable was added to the model specification, it, along with poverty, was significant and
positively related to crime risk perception. In addition, residential stability continued to be negatively related to crime risk perception. However, proportion of the population that is non-White and the previously significant land-use variables, the aggregate perception of business places and the aggregate perception of playgrounds, were no longer significant. Thus, most importantly for the purposes of this article, the effects on risk of the built environment in the form of aggregate perceived public land uses do not appear to be net of objective levels of violent crime.

In model C, neighborhood-level violent crime rate was removed, and the neighborhood-level burglary rate was incorporated instead. As model C demonstrates, official neighborhood burglary was significantly and positively related to crime risk perception. Similar to model B, poverty was also positively related to risk perception. In addition, residential stability continued to have a significant, negative impact on crime risk perception. However, in contrast to the results reported in model B, proportion of the population that is non-White, the aggregate perception of business places, and the aggregate perception of playgrounds became significant once again, suggesting that these effects were net of objective community burglary risk.

Finally, model D in Table 3 included both the violent and burglary crime rates. As in model B, the effects on crime risk of proportion of the population that is non-White, the aggregate perception of playgrounds, and the aggregate perception of business places disappeared (compared to results shown in model A). In model D, poverty continued to have a significant positive effect on crime risk perception, controlling for both official rates of violent crime and official rates of burglary. In addition, residential stability continued to have a significant negative impact on crime risk perception. Further, both violent crime and burglary had significant positive effects.

Overall, the addition of neighborhood contextual variables to the models did not appear to affect the individual-level variables. For models A through D in Table 3, age, sex, race, family income, safety precautions, burglary victimization, and violent victimization were all significant; these findings remained unchanged from those discussed for Table 2.

DISCUSSION AND CONCLUSIONS

The results suggest that there are several individual-level predictors of crime risk perception. Older, male, and non-White respondents had lower perceptions of community crime risk, as did more wealthy individuals. In addition, those who took more safety precautions and who had been victims of either burglaries or violent crimes perceived more crime risk in their local communities. Although these individual-level predictors of community
### TABLE 3: Random-Coefficient Logistic Regression Models of Census Tract–Based Crime Risk Perception with Contextual Main and Mediating Effects (exponentiated coefficients in parentheses)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Model A</th>
<th></th>
<th></th>
<th></th>
<th>Model B</th>
<th></th>
<th></th>
<th></th>
<th>Model C</th>
<th></th>
<th></th>
<th>Model D</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean risk perception</td>
<td>−1.313</td>
<td>.065</td>
<td>−1.301</td>
<td>.062</td>
<td>−1.313</td>
<td>.063</td>
<td>−1.302</td>
<td>.060</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>*Poverty</td>
<td>3.453*</td>
<td>(31.595)</td>
<td>1.014</td>
<td>.387</td>
<td>2.664*</td>
<td>(14.354)</td>
<td>.985</td>
<td>2.881*</td>
<td>(17.832)</td>
<td>1.005</td>
<td>2.172*</td>
<td>(8.776)</td>
<td>1.004</td>
<td></td>
</tr>
<tr>
<td>*Proportion non-White</td>
<td>1.421*</td>
<td>(4.141)</td>
<td>.781</td>
<td>(2.184)</td>
<td>.409</td>
<td>.943*</td>
<td>(2.568)</td>
<td>.434</td>
<td>.522</td>
<td>(1.685)</td>
<td>.446</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>*Residential stability</td>
<td>−1.826*</td>
<td>(.161)</td>
<td>.844</td>
<td>−1.919*</td>
<td>(.147)</td>
<td>.799</td>
<td>−1.649*</td>
<td>(.192)</td>
<td>.828</td>
<td>−1.802*</td>
<td>(.165)</td>
<td>.803</td>
<td></td>
<td></td>
</tr>
<tr>
<td>*Businesses</td>
<td>.191*</td>
<td>(1.210)</td>
<td>.084</td>
<td>.048</td>
<td>(1.049)</td>
<td>.088</td>
<td>.201*</td>
<td>(1.223)</td>
<td>.081</td>
<td>.072</td>
<td>(1.075)</td>
<td>.087</td>
<td></td>
<td></td>
</tr>
<tr>
<td>*Schools</td>
<td>.158</td>
<td>(1.171)</td>
<td>.331</td>
<td>.142</td>
<td>(1.153)</td>
<td>.314</td>
<td>.164</td>
<td>(1.178)</td>
<td>.321</td>
<td>.158</td>
<td>(1.171)</td>
<td>.311</td>
<td></td>
<td></td>
</tr>
<tr>
<td>*Playgrounds</td>
<td>.717*</td>
<td>(2.048)</td>
<td>.288</td>
<td>.463</td>
<td>(1.589)</td>
<td>.280</td>
<td>.564*</td>
<td>(1.758)</td>
<td>.283</td>
<td>.384</td>
<td>(1.468)</td>
<td>.278</td>
<td></td>
<td></td>
</tr>
<tr>
<td>*Violence rate</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>.091*</td>
<td>(1.095)</td>
<td>.025</td>
<td>—</td>
<td>—</td>
<td>.081*</td>
<td>(1.084)</td>
<td>.026</td>
<td></td>
<td></td>
</tr>
<tr>
<td>*Burglary rate</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>.058*</td>
<td>(1.060)</td>
<td>.021</td>
<td>.046*</td>
<td>(1.047)</td>
<td>.021</td>
<td></td>
<td></td>
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<tr>
<td>Age</td>
<td>−.057*</td>
<td>(.945)</td>
<td>.026</td>
<td>−.062*</td>
<td>(.940)</td>
<td>.026</td>
<td>−.056*</td>
<td>(.946)</td>
<td>.026</td>
<td>−.061*</td>
<td>(1.063)</td>
<td>.026</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex (male)</td>
<td>−.269*</td>
<td>(1.764)</td>
<td>.076</td>
<td>−.271*</td>
<td>(1.763)</td>
<td>.077</td>
<td>−.270*</td>
<td>(1.763)</td>
<td>.076</td>
<td>−.272*</td>
<td>(1.762)</td>
<td>.077</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race (non-White)</td>
<td>−.576*</td>
<td>(1.562)</td>
<td>.134</td>
<td>−.591*</td>
<td>(1.554)</td>
<td>.136</td>
<td>−.577*</td>
<td>(1.562)</td>
<td>.136</td>
<td>−.593*</td>
<td>(1.553)</td>
<td>.139</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Family income</td>
<td>−.676*</td>
<td>(1.935)</td>
<td>.033</td>
<td>−.070*</td>
<td>(1.932)</td>
<td>.033</td>
<td>−.067*</td>
<td>(1.935)</td>
<td>.033</td>
<td>−.069*</td>
<td>(1.933)</td>
<td>.033</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Home unoccupied</td>
<td>.012</td>
<td>(1.012)</td>
<td>.020</td>
<td>.012</td>
<td>(1.012)</td>
<td>.021</td>
<td>.012</td>
<td>(1.012)</td>
<td>.020</td>
<td>.012</td>
<td>(1.012)</td>
<td>.021</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dangerous activities</td>
<td>.004</td>
<td>(1.004)</td>
<td>.049</td>
<td>.030</td>
<td>(1.003)</td>
<td>.050</td>
<td>.006</td>
<td>(1.006)</td>
<td>.049</td>
<td>.005</td>
<td>(1.005)</td>
<td>.050</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household goods</td>
<td>.027</td>
<td>(1.027)</td>
<td>.030</td>
<td>.027</td>
<td>(1.027)</td>
<td>.031</td>
<td>.025</td>
<td>(1.025)</td>
<td>.031</td>
<td>.026</td>
<td>(1.026)</td>
<td>.031</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Carried valuables</td>
<td>.013</td>
<td>(1.013)</td>
<td>.015</td>
<td>.012</td>
<td>(1.012)</td>
<td>.015</td>
<td>.014</td>
<td>(1.014)</td>
<td>.015</td>
<td>.013</td>
<td>(1.013)</td>
<td>.015</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Safety precautions</td>
<td>.127*</td>
<td>(1.135)</td>
<td>.028</td>
<td>.131*</td>
<td>(1.14)</td>
<td>.028</td>
<td>.122*</td>
<td>(1.130)</td>
<td>.028</td>
<td>.126*</td>
<td>(1.134)</td>
<td>.029</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Live alone</td>
<td>.092</td>
<td>(1.096)</td>
<td>.095</td>
<td>.083</td>
<td>(1.087)</td>
<td>.096</td>
<td>.098</td>
<td>(1.103)</td>
<td>.095</td>
<td>.087</td>
<td>(1.091)</td>
<td>.096</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burglary victimization</td>
<td>.542*</td>
<td>(1.719)</td>
<td>.091</td>
<td>.552*</td>
<td>(1.737)</td>
<td>.092</td>
<td>.543*</td>
<td>(1.721)</td>
<td>.091</td>
<td>.552*</td>
<td>(1.737)</td>
<td>.092</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Violent victimization</td>
<td>1.121*</td>
<td>(3.068)</td>
<td>.203</td>
<td>1.115*</td>
<td>(3.050)</td>
<td>.207</td>
<td>1.140*</td>
<td>(3.127)</td>
<td>.204</td>
<td>1.131*</td>
<td>(3.099)</td>
<td>.207</td>
<td></td>
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</tr>
</tbody>
</table>
### TABLE 3 (continued)

<table>
<thead>
<tr>
<th>Random Effect</th>
<th>Variance Component</th>
<th>SE</th>
<th>Variance Component</th>
<th>SE</th>
<th>Variance Component</th>
<th>SE</th>
<th>Variance Component</th>
<th>SE</th>
<th>Variance Component</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean crime risk perception, $u_{0j}$</td>
<td>.260</td>
<td>.057</td>
<td>.216</td>
<td>.051</td>
<td>.224</td>
<td>.053</td>
<td>.194</td>
<td>.049</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race (non-White), $u_{3j}$</td>
<td>.198</td>
<td>.165</td>
<td>.215</td>
<td>.171</td>
<td>.226</td>
<td>.175</td>
<td>.252</td>
<td>.185</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 1 extra binomial error, $e_{ij}$</td>
<td>.950</td>
<td>.020</td>
<td>.955</td>
<td>.021</td>
<td>.953</td>
<td>.021</td>
<td>.956</td>
<td>.021</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**NOTE:** $N = 4,456$ individuals, 100 census tracts.

$p < .05$. 
crime risk perception are important, many of such findings have been revealed previously elsewhere (see the above review). Our focus here was on neighborhood-level factors that affect crime risk perception, particularly those related to understudied public land use.

Our multilevel analyses indicate that crime risk perception indeed varied significantly across neighborhoods. We examined both social structural and land-use variables to account for this variation. Consistent with previous work, social structural characteristics, including poverty, proportion of the population that is non-White, and residential stability, had significant effects on risk perception. But we also found in initial contextual models that community-level perceptions of land uses involving businesses and playgrounds had significant effects on crime risk perception. The community-level perceived presence of schools, however, did not have an effect on crime risk perception. Although there was some reduction in mean crime risk perception across neighborhoods when these social structural and land-use variables were included in the models, there continued to be significant variation in risk perceptions across neighborhoods in the contextual models. This suggests that social structural and land-use variables are only moderately successful in explaining the variation across neighborhoods.

Most pertinent to our research was whether land-use variables exerted their effects on subjective perceptions of neighborhood safety net of actual or objective neighborhood crime. On the basis of previous research, we felt that neighborhood-level characteristics pertaining to the built environment might serve a heuristic function, providing cues about community crime net of the actual levels of crime. Our findings are only partially supportive of such a net effect. Community-level citizen-reported public land uses such as businesses and playgrounds do appear to have positive effects on community crime risk interpretation net of actual community rates of burglary. However, these effects are not net of community rates of violence. In the end, then, we conclude that the general presence of public land use does not serve as a heuristic device to inform residents about the dangers of crime net of actual rates of violent crime.

So what role, if any, does land use play in community crime risk interpretation? Although a complete answer to this question is beyond the scope of this article, we can speculate. First, our findings suggest that violent crime might mediate the effects of some public land uses, including businesses and playgrounds. Building on the early “defensible space” literature (Angel 1968; Jacobs 1961, 1968; Newman 1972/1973, 1996; Wood 1961), numerous studies have been conducted in an attempt to verify a relationship between land use and crime (for reviews, see Taylor and Gottfredson 1986; Taylor and Harrell 1996). Although the results of this research are still somewhat inconclusive, there is evidence that increased crime can result from...
proximity to nonresidential land uses such as secondary schools (Roncak and Faggiani 1985; Roncak and LoBosco 1983), bars or taverns and alcohol outlets (Roncak and Maier 1991; Roncak and Pravatiner 1989; Speer et al. 1998), fast-food restaurants (Brantingham and Brantingham 1982), “other” businesses (Kurtz, Koons, and Taylor 1998), and institutional land (Ley and Cybriwsky 1974). As such, the effects of land use on risk perception may simply be indirect, through community violent crime: Public land uses increase violence, and the actual rates of violence affect perceptions of community safety. In comparing the effects of public land uses with and without violence controlled, it appears as if in many cases, the cues people receive from public land uses regarding their danger are accurate. An exception to this trend in our analysis involves schools. Although schools have been shown to increase rates of violence (Roncak and Faggiani 1985; Roncak and LoBosco 1983), it is interesting in our study that the general presence of schools did not have effects on subjective community risk perception, with or without violence controlled. So the presence of businesses and the presence of playgrounds are perceived as threatening, seemingly because they are likely threatening objectively. In contrast, the presence of schools is unrelated to perceptions of threat, despite the fact that schools do probably pose an objective threat. Overall, however, our findings provide optimism in that characteristics of the built environment do not appear to be “scaring” people unnecessarily. Instead, public land uses appear, for the most part, to project cues or reflect conditions related to actual, objective levels of crime.

Our findings have several implications both for future research and for practical applications. Our analyses add to a growing yet still small body of literature indicating that characteristics of both individuals and neighborhoods affect perceptions of community crime risk. Future research addressing crime risk perception should continue to examine both of these sets of factors. Policymakers would be well advised to do the same. That is, any policy geared toward alleviating individuals’ perceptions of crime risk needs to address both the individuals and the neighborhood. To ignore one in favor of the other would be remiss, and such single-level or unidimensional approaches are likely to fail in uncovering and reducing the source of crime risk perception. Although we found that crime risk perception did vary across neighborhoods, and the social structural and land-use factors measured here assisted us in explaining why crime risk perception varied, our contextual models did not account for all of the level 2 variance. Therefore, future research should examine additional contextual factors to ascertain more comprehensively why crime risk perception varies across neighborhoods.

Regarding the contextual effect of public land uses specifically, although public land uses (based on aggregated citizen reports) do not affect risk net of
violent crime, they appear to possibly play an indirect role by affecting actual community violence, which in turn affects risk perception. As such, policy efforts aimed at decreasing violent crime in public-use areas might simultaneously decrease the perception of risk among community members. We examined several different types of public land use, but there may be important other types worthy of exploration in future work. Whether a “cue” provided by public land use is suggestive of low crime risk or high crime risk may depend on the specific land use in question. Although our various measures of public land use clearly represent at least two “types” of use, it is interesting that both are associated with adolescents and/or strangers—groups appearing “risky” to many observers. Public land uses associated with adolescents and/or strangers (all of those explored here) may appear particularly risky, whereas public land uses associated with older users and/or known residents of the community may seem safer. Also, public land use is only one aspect of the built environment. Other aspects, such as street layout or building design, may indeed have effects on community risk perceptions net of objective community crime and should thus be examined in future work to more fully understand the role of the built environment in individuals’ community risk assessments.

Finally, future work can elaborate on the findings revealed here by examining how effects of land use on community crime risk perception might be conditional. It is plausible that the effects of neighborhood land use on risk perception might be conditional on other neighborhood-level factors, such as neighborhood crime. As such, neighborhood crime may not only mediate the effects of land use, it might also moderate such effects. For instance, the presence of schools might serve to enhance risk perception in high-crime neighborhoods but not in low-crime neighborhoods. If such moderation occurs, then the null effects of the presence of schools found here might be better understood. The effects of neighborhood land use might also be conditional on the broader spatial context of the neighborhood (e.g., the characteristics of contiguous neighborhoods). For example, the effect of the neighborhood-level presence of businesses on risk perception might be exacerbated in communities surrounded by “disadvantaged” or high-crime neighborhoods, regardless of their own levels of disadvantage or crime. These possible conditional effects capture the notion of spatial autocorrelation. Although we note the importance of such “spillover” effects, and we recognize the presence of rather sophisticated strategies for handling these effects (see, e.g., Morenoff, Sampson, and Raudenbush 2001), we only speculate about such possible effects rather than actually testing them here, because we felt that the important first step in incorporating land use into a multilevel risk interpretation model was the estimation of main effects. However, given the findings
unearthed here, we encourage future researchers to make conditional effects—in terms of both intra-community-level moderating effects and spillover effects due to spatial autocorrelation—the focus of theory and models of risk perception.

### APPENDIX

Factor Loadings for Survey-Based Land-Use Items

<table>
<thead>
<tr>
<th>Survey Item</th>
<th>Factor 1</th>
<th>Factor 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. School within three blocks</td>
<td>-.018</td>
<td>.721</td>
</tr>
<tr>
<td>2. Store/gas station within three blocks</td>
<td>.632</td>
<td>.249</td>
</tr>
<tr>
<td>3. Bar/nightclub within three blocks</td>
<td>.703</td>
<td>.023</td>
</tr>
<tr>
<td>4. Fast food within three blocks</td>
<td>.710</td>
<td>.120</td>
</tr>
<tr>
<td>5. Bank/office within three blocks</td>
<td>.738</td>
<td>.090</td>
</tr>
<tr>
<td>6. Park/playground within three blocks</td>
<td>-.023</td>
<td>.705</td>
</tr>
<tr>
<td>7. Shopping center/mall within three blocks</td>
<td>.512</td>
<td>.041</td>
</tr>
<tr>
<td>8. Hotel/motel within three blocks</td>
<td>.502</td>
<td>-.101</td>
</tr>
<tr>
<td>9. Bus stop within three blocks</td>
<td>.241</td>
<td>.359</td>
</tr>
</tbody>
</table>

### NOTES

1. It should be noted that most of these studies referred to what is termed risk perception here as a fear of crime. However, Ferraro and LaGrange (1987) distinguished cognitive risk perception—operationalized through survey questions such as “How safe is your neighborhood from crime?” and “How safe do feel to walk alone in your neighborhood at night (during the daytime)?”—as distinct from an emotionally and physiologically based fear of crime. According to Ferraro and LaGrange’s typology, although traditionally viewed as measures of the fear of crime, they are better conceptualized instead as measures of the perception of risk. As such, studies using these measures are referenced in our review of the risk perception literature. Although Ferraro and LaGrange were also critical of the item “Is there any area right around here—that is, within a mile—where you would be afraid to walk alone at night?” as a measure of fear because of its nonspecificity, they did suggest that it does touch more on fear as opposed to judgments of personal risk. As a result, studies of the fear of crime using this operationalization (see, e.g., Braungart, Braungart, and Hoyer 1980; Clemente and Kleiman 1977) are not reviewed here. Studies using other measures or scales that clearly tap emotionally based fear reactions (see e.g., Perkins and Taylor 1996; Taylor and Hale 1986) are also not reviewed here.

2. As evidence that these effects may also be conditional on race and ethnicity, Lee and Ulmer’s (2000) examination of perceived incivilities, perceived risk, and the fear of crime among a Chicago sample of Korean Americans found that women experienced lower risk, and age and income were nonsignificant.

3. Chiricos et al. (1997) found that the proportion of the population that is non-White was significant for Whites only; the effect was nonsignificant for non-Whites in their sample.
4. Liska et al. (1982) found that official property crime rates affected risk perception for Whites only. This study also revealed that the proportion of crime that is interracial affected area-level risk perception for Whites but not for non-Whites.

5. Also, in a recent series of school crime and risk studies, researchers have shown that students perceive certain physical locations within schools to be dangerous, including hallways, bathrooms, parking lots, and cafeterias—all areas where a clear sense of ownership is lacking and surveillance is low (see, e.g., Astor and Meyer 1999; Astor, Meyer, and Behre 1999).

6. Stable census tracts were defined as those that had not changed their boundaries since 1960.

7. We note that ordinal logit is possible with hierarchical regression modeling software. However, we opted to use more traditional logistic regression procedures using a collapsed, dichotomous measure for several reasons. Most importantly, we ultimately were not interested in discerning the effects of “feeling very unsafe,” “feeling somewhat unsafe,” and “feeling somewhat safe” from “feeling very safe.” In line with previous work in this tradition using the same data set (e.g., Wilcox Rountree and Land 1996a, 1996b), our interest was in understanding “feelings of being unsafe” compared to “feelings of being safe.” Further, employing ordinal logit imposes a proportional odds assumption in estimating the likelihood of experiencing one level of safety perception vis-à-vis the other levels. This proportional odds assumption may in fact be inappropriate.

8. The number of factors was not forced.

9. We want to be clear that our measures of community land uses were limited in important ways. Because they were based on perceptions, it is possible that validity problems may have arisen if respondents were not aware of or sensitive to particular land uses. Also, validity problems could have ensued from differential interpretations of “three blocks” across the survey respondents. Despite the possible limitations, when these perceptions are averaged across the approximately 50 respondents per tract, we think that they represent reasonable measures of the “general presence” of various land uses within the 100 neighborhoods.

10. Caution should be used in interpreting the estimates for age and income. We recognize that because these variables were measured with ordinal scales, the most technically sound way to estimate their effects would have been to dichotomize the categories (with one reference category). However, this strategy would have more than doubled our number of explanatory variables, greatly increasing the complexity of already cumbersome multilevel models. Because age and income were essentially control variables in our analysis, presenting such complexity here would seemingly detract unnecessarily from our focus—the effects of community-level land use. As such, we elected to follow precedent for analyses using the Seattle data (see, e.g., Miethe and McDowall 1993; Wilcox Rountree and Land 1996a, 1996b) and report models that treated age and income as continuous variables. However, we do note that in models (not shown here) using dummy variables for each category, age did appear to exhibit some nonlinearity. For instance, although respondents in the younger and middle age categories largely felt more risk in comparison to those in the oldest age category (and the difference lessened to nonsignificance as the age category increased), the effects of the youngest age category dummy variable represented an exception to this trend. Those in the youngest age category were not significantly different from those in the oldest age category in terms of risk perception.

11. It should be noted that the level 2 model for $\beta_3j$ did not change from the previous specification, though $u_{3j}$ was significant. Given that the focus of this article is to unearth direct effects of land use on risk net of actual crime, we did not estimate micro-macro interactions in attempting to understand the variation in the effect of race on risk perception across neighborhoods.
REFERENCES


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