FURTHERING THE INTEGRATION OF ROUTINE ACTIVITY AND SOCIAL DISORGANIZATION THEORIES: SMALL UNITS OF ANALYSIS AND THE STUDY OF STREET ROBBERY AS A DIFFUSION PROCESS

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Attempts to integrate the two predominant spatial theories of crime, social disorganization and routine activity theories, may benefit from examining empirical relationships at units of analysis smaller than the relatively large units characteristic of most ecological research (cities, SMSAs, census tracts, multiple city blocks). Small units of analysis, specifically, face blocks (both sides of a city block between two intersections) are analyzed in a study of street robbery within a medium-size southeastern U.S. city. Models of street robbery and street-robbery “potential” suggest a crime diffusion process. Several interaction effects between variables of social disorganization and routine activity theory are found, which may form the basis in future research for successful theoretical integration.

Most criminological research on the causes of crime and delinquency focus on individual-level explanations. Individuals are prone to crime or delinquency because of such factors as economic deprivation, inadequate socialization in the family, or exposure to social networks that provide normative support for learning techniques, motives, and rationalizations for criminal or delinquent behaviors (roughly, social control, strain, and social learning approaches, respectively). A subset of theories deemed “spatial” stresses the importance of geographic location in accounting for many of these same social processes. Specifically, neighborhood characteristics provide the context in which delinquent and criminal behaviors emerge that would not otherwise be observed. Spatial factors, such as distance and convenience, affect the chances that criminal careers will initiate, escalate, and desist. Because crime occurs in specific spatial contexts, spatial models of those contexts should enhance the explanation of crime.

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In recent years, interest has grown regarding two types of spatial theories of crime: social disorganization and routine activity theory. In the classical formulation of social disorganization theory, crime occurs in neighborhoods characterized by low income, ethnic heterogeneity, and residential instability. As revitalized in numerous recent works (e.g., Bursik, 1988; Bursik and Grasmick, 1993; Farrington et al., 1993; Sampson and Groves, 1989), the emphasis of the social disorganization approach has been placed on the social control processes at multiple levels: private (primary relational networks), parochial (secondary relational networks), and public (governmental).

Research support for routine activity theory (Cohen and Felson, 1979) and its intellectual cousin, rational choice theory, has also accumulated (Beavon et al., 1994; Clarke, 1994a, 1994b, 1996; Cohen, 1981; Felson, 1986, 1994). Within this now well-known framework crime occurs in specific locations where motivated offenders come together with suitable crime targets in the absence of capable guardianship. These concepts have been operationally defined and related to crime in numerous works (Clarke, 1983, 1994a, 1994b, 1996).

In addition to research narrowly construed as providing support for either of these two spatial theories, numerous researchers have suggested that the state of knowledge can be improved by integrating social disorganization and routine activity theory (Kennedy and Forde, 1990; Miethe and McDowall, 1993; Miethe and Meier, 1990, 1994; Miethe et al., 1987; Rountree et al., 1994; Sampson and Lauritsen, 1990; Sampson and Wooljdredge, 1987; Simcha-Fagan and Schwartz, 1986; Smith and Jarjoura, 1989). These researchers argue that propositions about criminality (criminal motivation) can be linked to those of context (criminal opportunity), improving knowledge of how individual predisposition interacts with context such that decisions to commit crime are made. Yet, as almost all of these authors point out, the empirical support for integration is not strong, and the results are only suggestive as to how the theories may be fully integrated (Miethe and Meier, 1994:177–179). In what follows, an assessment is provided of one type of theoretical integration of social disorganization and routine activity theory, one based on empirical interaction effects between variables across the two theories.

THEORETICAL INTEGRATION

Theoretical integration has often been touted as a goal for science (Messner et al., 1989; Thornberry, 1989; Tittle, 1995); yet, achieving it may be elusive (Gottfredson and Hirschi, 1987; Hirschi, 1979; Kornhauser, 1978). For theoretical integration to exist, of course, it is not sufficient to
simply include variables from each theory in the same regression equations. This is easily accomplished, and several studies have demonstrated that both routine activity variables and social disorganization variables contribute independently to the explanation of victimization rates (Gottfredson et al., 1991; Sampson and Wooldredge, 1987; Simcha-Fagan and Schwartz, 1986). For an integration of the two theories to exist, a set of empirically supported propositions involving the interrelations of each theory's concepts must exist (Miethe and McDowall, 1993; Rountree et al., 1994).

Several ways exist to go about developing propositions for theoretical integration, such as specifying some concepts of one theory as endogenous to the concepts of another (Elliott et al., 1985), or examining the improvement in prediction of a combined model that extends the scope of the constituent theories. One important way to integrate theories, as discussed by Miethe and Meier (1994:62), and others, is to interrelate the concepts of two theories as conditional (interaction effects): Relationships among variables derived from one theory are contingent on values of the variables of another theory.¹ Work by Miethe and McDowall, for example, posits interaction effects between use of security precautions and social disorganization. They report that security precautions (not leaving the home unoccupied, not participating in dangerous activities away from home, not carrying expensive goods, etc.) are ineffective in socially disorganized neighborhoods, but they are effective in other neighborhoods (1993). The fundamental hypothesis is that the effects of individual characteristics change as a function of neighborhood characteristics. Specifically, within socially disorganized neighborhoods, a "leveling" of the effects of individual components of risk may occur, presumably for reasons such as the prevalence of motivated offenders, short distances from crime target to perpetrator's home, and citizen disregard for alarms (Miethe and McDowall, 1993; Rountree et al., 1994).

Successful integration of social disorganization and routine activity theories can be built on an empirical basis of interaction effects between individual risk factors (as specified by routine activity theory) and type of neighborhood (as specified in social disorganization theory). For example, in models with individual victimization as the dependent variable, a proposition from the integration of social disorganization and routine activity theory would be as follows. The effect of security precautions on victimization varies as a function of the degree of the social disorganization of a

¹ Although theoretical integration might be based on other empirical relationships, such as specifying exogenous and endogenous relationships among the variables of each theory, or specifying different relations across different types of crime, the literature of integrating social disorganization and routine activity theory has focused on interaction effects.
neighborhood: The greater the disorganization, the less the effect. Relevant causal mechanisms lessening the protective effect of security precautions could be greater anonymity, offender convenience (proximity of place of victimization and safe escape, such as the offender’s home), familiarity (knowledge of the thoroughfares and alleys for escape), perceived risk of arrest by police (disorganized neighborhoods may be perceived by offenders as less “policed”), and offenders thinking they appear less suspicious (compared with a minority offender in an all-white neighborhood, for example). Stated at a more general level, “bad neighborhoods” have a leveling effect on individual differences of crime targets and locations.

Despite the promise of theoretical integration built on a foundation of interaction effects, researchers have shown only a few instances of them. The most notable interaction effect found has been the one between the social disorganization of a neighborhood and the use of security precautions. Both Miethe and McDowall (1993) and Rountree et al. (1994) have shown with Seattle data that the benefits of security precautions are attenuated in socially disorganized neighborhoods (as mentioned above, Miethe and McDowall claim they are nullified, 1993:756). More interesting, however, is the fact that neither Miethe and McDowall nor Rountree et al. find widespread statistically significant interaction effects between individual- and neighborhood-level variables. In fact, Miethe and McDowall report that none of the 27 interaction effects tested in models of violence is statistically significant (1993:753). As for their burglary models, in addition to the above-mentioned interaction effect between security precautions and social disorganization, only two additional interaction effects involve individual characteristics across neighborhood contexts: The beneficial effects of security precautions declines as the number of “busy places” (number of public places nearby) increases, and the risk of burglary as a result of living alone declines as the number of busy places increases. Thus, in “mixed-land use” areas (mix of residential and public places), the effects of security precautions and living alone are reduced. Yet, these are only three significant cross-level interaction effects of the 21 tested on burglary models (or 3 out of 42 tests for cross-level interactions for violence and burglary models combined).

Rountree et al. (1994), using the same Seattle data and measures as Miethe and McDowall (but employing hierarchical linear models), arrive at the same disappointing conclusion for theoretical integration based on interaction effects: only one statistically significant interaction effect in the models of violence out of six potential cross-level interaction effects (nonwhites are more likely to be victimized in racially homogeneous neighborhoods, 1994:404). As for the model of burglary, only the previously mentioned negative interaction effect between safety precautions
and the number of incivilities in a neighborhood is statistically significant (1994:408).

WHY SO FEW INTERACTION EFFECTS?

Why has the research been so disappointing for cross-level interaction effects? One possibility is measurement error. Testing for interaction effects in an Ordinary Least-Squares (OLS) regression equation involves computing a product term and entering it into the regression equation, along with the variables used to create the product term. Measurement error of product terms is compounded relative to that of individual variables, lessening the likelihood of finding a statistically significant effect (Cohen and Cohen, 1983). Also, multicollinearity in regression equations with product terms is commonplace, such that the models may not have adequate statistical power to reveal interaction effects (type I errors). Finding statistically significant product terms in regression models is made difficult by these liabilities.

Another possibility is heterogeneity within the units of analysis typically studied. Heterogeneity is a confusing term, if only because social disorganization theory posits that heterogeneity itself (ethnic and racial) is a cause of crime. To clarify, spatial heterogeneity within a unit of analysis must be differentiated from conceptual or theoretical heterogeneity (Janson, 1993). For example, a variable measuring racial mix can be operationalized by multiplying the proportion African American by the proportion white (with .5 x .5, or .25 representing the maximum mix of the two groups). If all of the African Americans in a census tract live on one side of a tract and all of the whites on the other, however, within-unit spatial heterogeneity exists (two entirely homogeneous spatial subareas), and arguably, no racial heterogeneity exists in residential patterns. Compared with other census tracts with a real mix of race by residence, the same .25 value would be misleading. The segregated census tract would be classified as mixed when most observers would say it is highly segregated.2 Similarly, if an aggregate measure consists of counts of land uses, such as number of stores, those stores may be concentrated in a small fraction of the unit of analysis (e.g., a corner of a census tract), possibly having little bearing on the activities in the rest of the area. If areas are large and boundaries arbitrarily drawn, the unit of analysis is likely to suffer from

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2. Aggregate-level independent variables are described as having a compositional or an emergent property interpretation. A positive correlation between percent African American and crime, for example, is explained as a compositional effect if, at the individual level, African Americans are committing the crimes, and as an emergent property effect if everyone (black or white) is more likely to commit a crime in an area with a higher percentage of African Americans.
within-unit spatial heterogeneity, possibly resulting in attenuation of effects and complexities in the interpretation of the variables in the model.

Spatial heterogeneity, as defined here, within large units of analysis, such as census tracts, has been long recognized as a problem by researchers (Janson, 1993; Robinson, 1950; Sampson, 1987). Even in the Seattle data, however, with relatively small units of analysis, spatial heterogeneity is possible. Survey respondents in Seattle were asked to report on neighborhood characteristics within three or four blocks of each resident's household. Within-unit spatial heterogeneity can characterize such multiple-block areas. Teenagers hanging out, or the presence of commercial land uses within three or four blocks of one's residence, may be irrelevant to the household victimization risk if motivated offenders do not traverse the street in front of the respondent's home, and thus the home is not part of the "awareness space" of motivated offenders (Brantingham and Brantingham, 1984). Even ethnic heterogeneity at the block level (as measured in the Seattle data) can include within-unit spatial heterogeneity if African Americans live on one side of a standard four-sided city block and whites on the other.

Because of such spatial heterogeneity, it is argued here that a preferable unit of analysis for the purpose of achieving a more spatially homogenous measure of neighborhood context is the face block, by which it is meant more precisely "opposing face blocks" (both sides of the street between two intersections or between one intersection and a dead end; called "street blocks" by Taylor, 1997; Taylor et al., 1995). Land uses and the presence of neighborhood incivilities on the face block might be a more accurate index of the characteristics of the neighborhood in which one lives than are such measures at larger units of analysis. With a more spatially homogeneous unit of analysis, such as face blocks, empirical results may be more sensitive to interaction effects with individual-level characteristics. In fact, spatial heterogeneity within a face block may be immaterial to the risk of household victimization because presumably all of the residences and other buildings may be visible to someone visiting that face block. Motivated offenders visiting any address in the face block are more

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3. The terms conceptual and spatial heterogeneity and homogeneity are confusing because spatial heterogeneity implies pockets of homogeneous grouping within units of analysis: that is, a heterogeneous distribution of the characteristic measured for the unit of analysis. If a census tract is 50% African American, this does not imply that every African American has a white for a next-door neighbor.

4. Specifically, respondents were asked to report on the number of busy places within three blocks and number of neighborhood incivilities within four blocks.

5. As defined by the Census Bureau, a "block" is often larger than a standard "city block," as occurs 46% of the time in the Seattle data (Miethe and McDowall, 1993:756).
likely to have a location (residence or other building) in their awareness space than a location on a face block only a block away that they rarely or never traverse (Beavon et al., 1994; Brantingham and Brantingham, 1984).

Taylor (1997) has thoroughly discussed the ecological validity of the face block. He points out in his discussion of the systemic model developed by Bursik and Grasmick (1993) and Hunter (1985) that the face block (or street block in Taylor’s terminology) is “a key mediating social and spatial construct” in which parochial informal social control occurs. Residential face blocks, according to Taylor, are “physically bounded” by the fronts of houses, providing behavioral settings where residents know one another, participate in role obligations associated with neighborliness, and to varying degrees share norms about acceptable or unacceptable behavior. From a routine activity perspective, face blocks have “recurring rhythms of activity” in which people leave for work and play at regular times (Taylor, 1997:120). For these reasons, the face block represents a geographically and ecologically validated unit of analysis and, thus, lessens concern for spatial heterogeneity within the face block.

Although the face block unit of analysis may adequately address concerns of within-area spatial heterogeneity, other reasons explain why empirical studies have yielded so few interaction effects. Miethe and McDowall speculate that crime heterogeneity may be responsible. They suggest that a specification of crimes (robbery, assault, etc.) within the violence category, for example, might result in more cross-level interaction effects (1993:756).

It is argued here that regression models that include product terms for identifying interaction effects may be more likely to find statistically significant interaction effects using the face block as a unit of analysis, because it has more within-unit spatial homogeneity than larger units of analysis. Also, in the current analysis, far more observations are available than in the Seattle data, making multicollinearity problems less likely (Cohen and Cohen, 1983:112). Furthermore, focus is given to one crime type, street robbery, to minimize the impact of heterogeneity in crime types. For these reasons, the present data analysis may be more likely to yield statistically significant interaction effects, and avoid type I errors, than previous research.

DIFFUSION

It was suggested above that motivated offenders living on a given face block may be unaware of land uses on the other side of the block, and thus, they will not consider committing crimes on the other side of the block: It is not part of their awareness space. Empirically, of course, some
offenders will be aware of such targets. Within a routine activity framework, awareness space will be limited by would-be offenders' routine activities (among residence, work, and play—Brantingham and Brantingham, 1984). Motivated offenders presumably "diffuse" from where they live to commit street robbery in an area where their routine activities take them (Costanzo et al., 1986). Social disorganization theory also assumes that offenders diffuse from where they live into the surrounding community. Classically, the socially disorganized communities are located in a band of residential areas located between the downtown commercial and working-class neighborhoods. Crime rates are high throughout socially disorganized communities because community controls are weak, and thus, offenders are relatively free to commit crimes "anywhere" within such neighborhoods. Thus, both disorganization and routine activity theory make assumptions about diffusion of crimes relative to where offenders live, work, and play.

In the absence of detailed data on offenders' physical movements and their awareness space, however, the role that diffusion plays may be difficult to ascertain. Yet, as argued below, one can crudely take into account such diffusion processes with available data at the face-block level using a two-stage regression strategy (as detailed below) as an alternative to OLS regression. For the latter, using geographic units often violates the assumption of independent errors. One reason for such violations is that the value of the dependent variable (e.g., street robbery count) in one geographic unit is influenced by the value in another geographically proximate unit. Why would they be related? According to routine activity theory, proximate face blocks are likely to have similar robbery rates because they are part of the same awareness space of motivated robbers, because robbers' pattern of movement (work, play, home) is systematic rather than random (Felson, 1994). Alternatively, within a social disorganization conceptualization, proximate face blocks are more likely to be part of the same socially disorganized neighborhood in which the robbers spend their time. Thus, within the conceptualization of either theory, motivated offenders diffuse in a systematic way, with implications for regression models. Below, two-stage least-squares modeling is described to account for such spatial diffusion. Within this approach, it is meaningful to talk of the "robbery potential" of a face block (the prevalence of robbery in proximate face blocks) because of the geographic diffusion of robbers. If robberies are occurring in proximate face blocks, robbery in a given face block is more likely, all else equal. By modeling street robbery potential, as done in the analysis below, insights can be made into the causal processes of the diffusion of street robbery. Implications for integration of social disorganization and routine activity theories are discussed.
UNIT OF ANALYSIS

As discussed above, the unit of analysis in the present study is the face block, defined as opposing sides of a street located between two intersections, or between one intersection and a dead end. Although face blocks are rarely used as units of analysis (Taylor, 1997; Taylor et al., 1995, call them "street blocks"), they approximate what residents often think of when they refer to "my neighborhood" (Hunter and Suttles, 1972; Slovak, 1986). Although an ideal unit of analysis may not exist for all research purposes, using the face blocks as the unit of analysis may provide a more accurate view of the role that variables play in affecting the likelihood and frequency of street robbery.

DATA

Data for this project consist of tax data, 1990 Census Bureau data, and 1993 police department crime-incident data for a midsized southeastern U.S. city. The tax address data and police crime data were aggregated to the face block level, a process that was made relatively easy by the fact that the software program (Atlas GIS, Strategic Mapping, Inc., Santa Clara, Calif.) uses this unit of analysis for locating street addresses. Locations of bars, restaurants, taverns, convenience stores, and cocktail lounges were geocoded in the tax assessor database and matched using phone directory and Yellow Pages information. Face-block address information was taken from files associated with an Arc-Info map originally designed for the county school system.

Although street robbery can occur anywhere, it is most often an urban crime. The city chosen for the study had a 1993 population of approximately 230,000, 69% of which were white, 27% African American, and the remaining 4% other races. The reported 1990 unemployment rate was 4%, and 7.7% of families were living below the poverty line, with a median household income of $32,451. Minorities were much more likely to be living in poverty than whites. Educational levels were relatively high. For residents over the age of 25, 86.6% had at least a high school diploma and 40.6% had a bachelor's degree or higher. Fifty-two percent of residents between the ages of 18 and 24 were enrolled in college in 1990 (Bureau of the Census, 1992). Overall, the city's population was well educated and financially prosperous when compared with other urban areas in the southeast. Nevertheless, within the city, large areas would be classified as socially disadvantaged.

VARIABLES

The number of street robbery incidents per face block reported to the
police is the dependent variable analyzed in this study. Excluded are commercial robberies or robberies of banks. Descriptive statistics for the dependent and independent variables are shown in Table 1. Street robbery varies considerably across face blocks, with 92% of face blocks experiencing no robberies. A few face blocks, however, had several street robberies.

Table 1. Description of Variables

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>S.D.</th>
<th>Maximum</th>
<th>IQR*</th>
<th>Valid N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Street Robberies 1993</td>
<td>.082</td>
<td>.488</td>
<td>12.000</td>
<td>.000</td>
<td>12,081</td>
</tr>
<tr>
<td>Total Population</td>
<td>44.950</td>
<td>92.736</td>
<td>1,127.00</td>
<td>37.000</td>
<td>12,066</td>
</tr>
<tr>
<td>Number of Places per Face Block</td>
<td>11.929</td>
<td>21.290</td>
<td>496.00</td>
<td>9.000</td>
<td>8,789</td>
</tr>
<tr>
<td>Number of African Americans</td>
<td>8.969</td>
<td>19.340</td>
<td>238.50</td>
<td>9.500</td>
<td>12,066</td>
</tr>
<tr>
<td>Racial Heterogeneity</td>
<td>.068</td>
<td>.074</td>
<td>.250</td>
<td>.118</td>
<td>10,709</td>
</tr>
<tr>
<td>Number Single-Parent Households</td>
<td>1.293</td>
<td>2.726</td>
<td>27.000</td>
<td>1.167</td>
<td>12,067</td>
</tr>
<tr>
<td>% Building Values &lt; 25th Percentile</td>
<td>25.479</td>
<td>36.020</td>
<td>100.000</td>
<td>50.000</td>
<td>8,789</td>
</tr>
<tr>
<td>Av. Value of Apartments-Offices (units of $10,000)</td>
<td>6.679</td>
<td>25.268</td>
<td>1,039.999</td>
<td>2.762</td>
<td>8,789</td>
</tr>
<tr>
<td>Distance from Center of City (in miles)</td>
<td>4.510</td>
<td>2.464</td>
<td>10.131</td>
<td>4.100</td>
<td>12,080</td>
</tr>
<tr>
<td>Number Motels/Hotels</td>
<td>.008</td>
<td>.144</td>
<td>9.000</td>
<td>.000</td>
<td>8,789</td>
</tr>
<tr>
<td>Number Stores</td>
<td>.098</td>
<td>1.800</td>
<td>108.000</td>
<td>.000</td>
<td>8,789</td>
</tr>
<tr>
<td>Number Vacant Lots</td>
<td>.455</td>
<td>1.249</td>
<td>32.000</td>
<td>.000</td>
<td>8,789</td>
</tr>
<tr>
<td>Number Multifamily Residential Units</td>
<td>1.387</td>
<td>5.453</td>
<td>220.000</td>
<td>.000</td>
<td>8,789</td>
</tr>
<tr>
<td>Number Youth-Related Places</td>
<td>.028</td>
<td>.262</td>
<td>8.000</td>
<td>.000</td>
<td>12,081</td>
</tr>
<tr>
<td>Number Bars, Restaurants, and Gas Stations</td>
<td>.081</td>
<td>.600</td>
<td>20.000</td>
<td>.000</td>
<td>8,716</td>
</tr>
<tr>
<td>Number Business Off., Indust., and Warehouses</td>
<td>.488</td>
<td>1.983</td>
<td>48.000</td>
<td>.000</td>
<td>8,789</td>
</tr>
<tr>
<td>Number Owner-Occupied Places</td>
<td>4.903</td>
<td>6.466</td>
<td>120.000</td>
<td>7.000</td>
<td>8,789</td>
</tr>
</tbody>
</table>

* IQR = Interquartile Range; variables highly skewed have IQRs of zero.

Incidents of street robbery were obtained from police crime incident data. Using police data to measure crime has well-known limitations. However, previous research has shown that using official records usually produces results consistent with victimization data (Bastian, 1993; Blumstein et al., 1991; Byrne and Sampson, 1986; McDowall and Loftin, 1992). Although the amount of bias in our results because of the use of official data is unknown, most robberies are reported to the police (based on national victimization data, about two-thirds), lessening the bias relative to some less serious crime types.

In the regression analyses, count data are used instead of rates. Thus, it is necessary to control for population size, because, all else being equal, face blocks with many people may have more potential robbery victims than do face blocks with few people. The total population count is thus entered as an independent variable in all of the regression models. In addition, in the present study, it is possible to have multiple apartments, or
even multiple buildings at a given address. These multiple units are referred to as "places," and it is necessary to control for the number of them under the assumption that, all else being equal, the more places, the more likely a robbery victimization will occur on a face block. The number of places (houses, apartments, businesses) is aggregated to the face block level. The population size and number of places represent control variables that lessen bias caused by comparing more populated face blocks and those with many "places" with those with fewer. somewhat surprisingly, as will be shown below, the population control variable is found to be negatively associated with the number of street robberies, suggesting that robbers tend to target victims where fewer people reside, and perhaps where fewer witnesses are likely.

Social disorganization variables include measures of racial composition (number of African Americans and racial heterogeneity, as measured by multiplying the proportion African American by proportion white—following Mieth and McDowall, 1993), family structure (as measured by number of single-parent households), economic composition (as measured by the building values of the properties on a face block, as well as by the average tax-assessed value of each apartment, house, or office on a face block). In addition, a general measure of social disorganization exists, distance from the geographic center of the city [as in the classic Shaw and McKay work (1942)].

Routine activity would be ideally tested by direct measures of the extent of suitable street robbery targets on each face block. Lacking such data, however, researchers have relied on using land use variables and making interpretive assumptions about the victims and motivated offenders drawn to (or living on) a face block. Many land uses exist in a tax-assessor data base, and certain types of land uses are often found in combination. Because of empirical redundancy among the measures, factor analysis was used to guide the formation of a smaller number of land use variables, resulting in four indices (the metric is counts). The first index, multifamily residences, consists of an index of the number of garden apartments, duplexes, and dwellings designed for three or more families. The second index, youth-related places, measures the effect of the presence of places that attract large numbers of young people to a face block, such as movie theaters, video arcades, swimming pools, as well as middle and high schools. The third index, bars, restaurants, and gas stations, identifies face blocks that might be particularly attractive for potential offenders because of easy accessibility and the presence of people carrying cash, often under

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6. This definition of place corresponds to the city's police department's definition of a place, which is less than ideal for research purposes. A more detailed address, such as an apartment number, would have been preferred.
the influence of alcohol. The presence of restaurants and bars approximates "hot spots" of robbery (Ronck and Maier, 1991; Sherman et al., 1989; Stark, 1987). The last index is the sum of the number of commercial places, such as business offices, industrial buildings, and warehouse facilities on a face block.

Finally, the number of owner-occupied households, it is argued, can be seen as an indicator of the concept of guardianship in routine activity theory, as well as of the social control concept of parochial control (Bursik and Grasmick, 1993): Resident homeowners are more likely to take actions to "guard" against deviant behaviors in their neighborhood (Rohe and Stegman, 1994). Thus, both social disorganization and routine activity theorists could lay conceptual claim to the number of owner-occupied households.

The census variables (population counts, number of African Americans, racial heterogeneity, and single-parent households) present a special problem: how to average the characteristics of one block with that of another so that a reasonable estimate of the characteristics of a face block could be made. When each side of a face block is in a different census block, each block count was divided by four and summed for each face block. If three census blocks were adjoining a face block, the value was estimated to be one-sixth of the total (2 of 12 "sides" of the census blocks). For those few with four adjoining census blocks, one-eighth (2 of 16) of the total was used. Numerous individual face blocks were examined on the digitized street maps, and the estimates were deemed reasonable. Nevertheless, some error is introduced by such estimation procedures. Also, it should be noted that this estimation procedure is used only for the four variables mentioned. All other variables are derived from data sources with addresses that were geocoded precisely to their face block. Finally, it should be noted that two variables often associated with social disorganization theory, social class and residential mobility, are not available in census block data, and thus they cannot be included in the analysis. To the extent that social disorganization variables included in the model correlate with these unavailable variables, the consequences for our conclusions may be minor.

Finally, it should be noted that because the dependent variable is highly skewed, potentially causing problems of heteroscedasticity, in the analysis below the natural log of street robbery is used (Cohen and Cohen,

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7. The number of owner-occupied homes also may be seen as a socioeconomic indicator. However, in regression models that control statistically for building value, single-parent households, and number of African Americans, it is argued that the number of owner-occupied households can be reasonably interpreted as a measure of guardianship or parochial control.
FURTHER METHODOLOGICAL ISSUES

Doreian (1981) and others have pointed out that regression analysis with data that have geographic units of analysis may violate the regression model's assumption of independent errors. Errors are likely to be correlated across locations because of a systematic ordering across spatial units, attributable to the effect of some unmeasured variable. In addition, as discussed above, the value of the dependent variable for one spatial unit may be systematically related to values in adjacent units; e.g., the robbery count in one face block is related to the counts in nearby face blocks. Based on Ord's work (1975), Doreian describes maximum-likelihood estimation procedures for a regression model in the first instance as the "spatial disturbances model" and in the second instance as the "spatial effects model." It is plausible that robbers set out to commit robbery in an area of the city, rather than on a specific face block. Because whatever attracts would-be robbers to a specific face block may result in a robbery on a nearby block, it would seem that the spatial effects model is the most appropriate for face block robbery counts.

The spatial effects model, following the notation of Land et al. (1991:239), is as follows:

$$Y = pWY + XB + e,$$

where $Y$ is a column vector of $N$ observations of the number of street robberies, $X$ is an $N$ by $k$ matrix of observations on the $k$ independent variables, $B$ is a $k$-row column vector of slopes (and intercept), $e$ is an $N$-row column vector of unobserved random errors with expected values of zero and variance $\sigma^2$, and $W$ is an $N$ by $N$ matrix of weights with elements $w_{ij}$ that describe the "proximity" of sample units $i$ and $j$ (assuming zeros on the principal diagonal, the distance of a unit to itself). The parameter $p$ is especially interesting because it indicates the relationship of the values of $Y$ in a face block to the values of $Y$ in other areas. If $p$ is statistically significant, it can be interpreted to mean that a diffusion process is occurring (Doreian, 1980:34). Ord (1975) and Doreian (1981) show how maximum-likelihood estimators of $p$, $B$, and $\sigma^2$, and their standard errors can be estimated. Heitgerd and Bursik essentially follow this approach in their analysis of 74 Chicago neighborhoods (1987). One problem with this approach, as discussed by Roncek and Montgomery (1984,) is that a $N \times N$ matrix needs to be inverted (the $W$ matrix of weights). For large samples, such as the approximate 8,000 cases used in the analysis here, this process is not possible with available software. Roncek and Montgomery (1984)
proposed that the product of the weight matrix and the dependent variable vector be computed to yield a new variable, $Y^* = WY$. This new variable can be used in the estimation of the model above in a regression equation in which the elements of the weight matrix are defined as inverses of the geographical distances between sample units. The $Y^*$ values could be interpreted to mean the "street robbery potential" similar to the population potential discussed in Duncan et al. (1961), the crime potential of Roncek and Robinson (1984), and, more recently, the population change potential of Chicago neighborhoods used by Morenoff and Sampson (1997). Thus, the street robbery potential of a given face block is measured by the street robberies in other face blocks, weighted by their distance from the face block (e.g., the inverse of the distance). Land et al. (1991) argue convincingly that the spatial diffusion model should be determined simultaneously with that of the dependent variable (here, the street robbery count for a face block). Land and Deane (1990) point out that a nonzero correlation exists between the potential variable $Y^*$ and the error term, $e$, in the approach of Roncek and Montgomery. Land and Deane (1990) suggest a simultaneous-equation, two-stage least-squares approach to the problem of estimating the spatial effects in the above model with $Y^*$ and $Y$ treated as simultaneously determined variables. They demonstrate that the resulting estimator is consistent and has asymptotic variance equal to that of Ord's maximum-likelihood estimator.

In the present analysis, the large number of units of aggregation (roughly, 8,000) makes cumbersome the computation of the distance between each face block and every other. Moreover, it is of little substantive interest as a spatial diffusion process. Specifically, the street robberies on a face block are not likely to be related to the majority of a city's face blocks, most of which are located too far away to plausibly have an effect. Thus, in the current analysis, "potential" is defined as the weighted average of a sample of 20 proximate face blocks within a mile of each face block, rather than the weighted average of all geographic units in the sample (as in Land et al., 1991). Although 20 is arbitrary, models based on 10 were examined, with similar results. "Proximate" does not imply the most proximate face blocks, (i.e., those with geographic centroids closest to the centroid of the face block in question), but rather a sample of 20 face blocks, each further away from a given face block. That is, 10 segments on either side of a face block are sampled, where "side" is defined as a face block east/west or north/south of a given segment. Up to 10 face blocks are counted, moving 1 through 10 face blocks away from a given face block, in each of two directions (four directions might be preferred but was not feasible because of the large number of cases and the organization of the file). These 10 proximate face blocks on each side of a segment are approximately, on average, .11, .22, .33, through .99 miles from the face
block. The weighted average of the street robberies on these proximate face blocks are computed weighting those further away less. Thus, the street robbery potential of a face block is the weighted average of two sets of 10 face blocks (one set for each direction), with each segment 1 block further away than the last, and less weight assigned to the face blocks further away.

The street robbery potential variable is central to understanding crime as a spatial diffusion process. As argued above, both social disorganization and routine activity theory conceptualize criminal activities as a diffusion process. According to social disorganization theory, crime occurs in neighborhoods where low levels of social control occur. Offenders commit crimes in socially disorganized areas—not necessarily on the face block where they live, but on any face block within a socially disorganized area. That is, the motivated offenders “diffuse” throughout the socially disorganized area and into nearby areas (not equally, to be sure). According to routine activity theory, offenders commit crimes in their “awareness space,” which could be defined as the face blocks near land uses that attract motivated offenders (busy streets, bars, stores, etc.). Motivated offenders, like everyone, tend to move between residence, place of work, and of play. They tend to commit crimes as they go about their routine activities. Thus, according to both theories, crime emanates from a spatial area, presumably their residential area, and moves along proximate and frequently used streets. Offenders have been shown to seldom wander more than a couple of blocks from main thoroughfares, or their routine routes, in selecting targets for burglary (Beavon et al., 1994; Brantingham and Brantingham, 1984, 1993). Lenz reports with Milwaukee data between 1965 and 1975 (1986:113) that commercial robberies tend to occur 44% to 48% of the time in the same zone where the robbers live (where a zone would be described as a large sector of the city). If a similar pattern exists for street robbery in other cities, the occurrence of a street robbery on a face block may be accounted for by its nearness to streets that attract would-be robbers.

It should be noted that an alternative analytic strategy to two-stage, least-squares, generalized negative binomial regression, is also used, and the results discussed below. Because street robbery events on a face block in a given year are rare, it could be useful to use an analytic model from a family of models associated with Poisson regression, generalized negative binomial regression. In essence, the advantage of such models is that they remove concern for heteroscedasticity associated with linear OLS regression models. Generalized negative binomial regression models of street robbery are discussed below, and the results are similar to those obtained
in the two-stage least-squares regression analysis presented here.\(^8\)

As stated, two-stage least-squares regression models are presented in which variables are entered simultaneously in two different equations. In the instrumental equation, all variables hypothesized to affect street robbery potential are entered (including several interaction terms), and in the substantive equation, a subset of variables is used, based on the following screening principle: If a theoretically hypothesized variable (including product terms of two variables hypothesized to have an interaction effect) has a statistically significant zero-order correlation with the dependent variable (logged number of street robberies in a face block), the variable is included in the initial substantive equation.

It should be noted that regression models have a reduced sample size of 8,704 for street robbery because of missing data from the tax database. Missing data are deleted listwise. Use of mean substitution results in substantively similar results. In the Appendix, the representativeness of analysis sample is compared with that of all cases.

As mentioned above, the dependent variable is logged, correcting for extreme skewness of the dependent variables and reflecting the likelihood that the independent variables are proportionately related, rather than linearly, to the dependent variables (Cohen and Cohen, 1983:260; Gujarati, 1988). That is, a one-unit change in the independent variable results in a proportionate change (not additive) in the dependent variable. Logging also lessens problems associated with heteroscedasticity (Cohen and Cohen, 1983:125).

**CORRELATIONS**

Variable correlations are shown in Table 2. Although most variables are not highly correlated, several correlations are notable. The strongest bivariate relationship (.76) among the independent variables is that of the number of African Americans with the number of single-parent households. The literature on single-parent African-American households is extensive (see Parnell et al., 1994), and it shows that African-American women are more likely to give birth outside of marriage or before it and

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\(^8\) Generalized negative binomial regression involves a two-stage modeling procedure in which the shape of distribution of the events studied, alpha, is modeled (specifically, the log of alpha), as well as the events themselves. Poisson models represent the case in which the alpha value is zero. When greater variation occurs in the distribution of events than Poisson (so called “extra-Poisson” variation, in which the standard deviation is greater than the mean), negative binomial regression models are used. Researchers may assume that the alpha parameter is a constant across the sample (negative binomial regression), or use generalized negative binomial regression, in which variables are used to model the log of alpha. The latter option is employed in the robustness analysis discussed in the main text.
Table 2. Correlation Coefficients of Variables (Listwise Deletion of Missing Data) \( N = 8,704 \)

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Key
1. Number of Street Robberies
2. Total Population
3. Number of Places per Face Block
4. Number of African Americans
5. Racial Heterogeneity
6. Number Single-Parent Households
7. Percent of Building Values below the 25th Percentile
8. Apartment/Office Value
9. Distance from Center of the city
10. Number Motels and Hotels
11. Number Stores
12. Number Vacant Lot
13. Number Multi Family Residences
14. Number Youth-Related Places
15. Number Bars, Restaurants, and Gas Stations
16. Number Businesses, Industries, and Warehouses
17. Number Owner Occupied Places

* \( p < 0.05 \).
more likely to have their marriages terminated by divorce than are white women. A strong positive relationship also exists between total population and the number of single-parent households (.69), indicating that as total population on a face block increases so does the number of single-parent households (and presumably the number of children). A more moderate positive (.44) relationship exists between total population and the number of African Americans. These relationships are not surprising. Single-parent households and African Americans tend to be relatively poor and more likely to live on face blocks that have more residents. The findings from the bivariate analysis are generally concurrent with the literature.

**HYPOTHESIZING INTERACTION EFFECTS**

Before discussing the empirical results of the regression models, hypotheses relevant to the integration of social disorganization and routine activity need be discussed. In the present study, data are measured at only one level, the face block, and thus hypotheses are formulated at that level. (Unlike the Seattle data, too few observations exist within many face blocks at the individual level to conduct a multilevel analysis.) In general, it is hypothesized that the effects of the social disorganization variables will vary with the characteristics measured by the land use variables. As will be seen below, because of multicollinearity constraints, the hypothesized interactions are limited to two of the social disorganization variables: number of single parent heads of household and distance from the center of the city. The basic hypothesis is that proximity to motivated offenders, as measured by the number of single-parent heads of household and distance to the downtown area (where would-be robbers presumably visit and near where many also live), interacts with the land use variables, which measure the availability of attractive targets and what draws motivated offenders to a face block. It is hypothesized that where more single-parent households exist in the presence of land uses that attract victims as well as would-be robbers, street robbery is more likely. As distance from the center of the city increases, the criminogenic effect of various land uses is hypothesized to decline.

**RESULTS**

Results of the analysis are shown in Table 3. In the first model, a traditional OLS regression equation with two control variables (population and places), six social disorganization variables, and six land use variables (routine activity variables), along with the number of owner-occupied households (as a measure of guardianship/parochial control) are included in the model. Because the dependent variable is logged, the coefficients
can be interpreted as representing a proportional change in the dependent variable per unit change in the independent variable.\footnote{9}

The purpose for including the population variable is to provide a statistical control because the dependent variable is a count and not a rate. The more people residing on a face block, the less robberies that occur: Ten residents decrease the number of robberies by approximately one-tenth of a percent (\(-.0001\)).\footnote{10} This negative relationship is somewhat surprising, because it is often found that increasing density is associated with more crime. If all face blocks were the same size (area), the count of people would effectively be a density measure. However, the presence of residents on a street implies potentially more “eyes on the street,” making street robbery less likely. In effect, no statistical control for population size is necessary.

The number of places per face block is positively associated with street robbery, as hypothesized in the discussion of this variable as a statistical control for areal size: Every 10 places results in a 1% increase in street robberies. Because the number of places at an address may be high when several apartment buildings or office buildings are at a site, the variable partly controls for the areal size of the face block and partly for the type of land uses likely to be found there, particularly the number of multifamily units.

Of the six social disorganization variables, four are statistically significant: the number of single-parent households, distance from the center of the city, racial heterogeneity, and average value of buildings. Two of the social disorganization variables (number of African Americans and percent of buildings in the lowest quartile of value) are not statistically significant. Distance from the center of the city results in a reduction in the number of street robberies by about 2% per mile, whereas each single-parent household increases the number of robberies by about 1%. As for the land use variables, the number of motels/hotels is most strongly related to street robbery (a 9% increase with the presence of each added motel/}

\footnote{9}{A model in which the dependent variable is logged, and the independent variables are not logged, is sometimes called a log-lin model (Gujarati, 1988). The slope coefficient in log-lin models measures the proportional or relative change in the dependent variable given an absolute change of one unit of the independent variable. Multiplying the coefficient (the relative change in the dependent variable) by 100 yields the percentage change in the dependent variable for an absolute change of one unit of the independent variable.}

\footnote{10}{As stated earlier, the effect of a continuous independent variable on a logged dependent variable can be represented as a proportionate or percentage effect in which the coefficient can simply be multiplied by 100. Thus, each person reduces the number of robberies by .01%, net all the other variables in the model. Each mile from the center of the city results in a 1.8% net decrease in street robberies.}
Table 3. Regression Models of Street Robbery, 1993  
\(N = 7,931\) Metric Coefficients

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<th>OLS Model 1</th>
<th>OLS Model 2</th>
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</tr>
<tr>
<td>Distance from Center of City (\times) Bars, Rest., and Gas</td>
<td>—</td>
<td>—</td>
<td>-.0257***</td>
</tr>
<tr>
<td>Distance from Center of City (\times) Vacant or Park Lots</td>
<td>—</td>
<td>—</td>
<td>-.0044***</td>
</tr>
<tr>
<td>Constant</td>
<td>.0537***</td>
<td>-.0013</td>
<td>.0070***</td>
</tr>
</tbody>
</table>

\(R^2\) | .150*** | .167*** | .209*** |
Adjusted \(R^2\) | .149*** | .165*** | .207*** |

**NOTES:** All independent variables have been centered at the mean.  
* \(p < .05; **p < .01; ***p < .001.\)

hotel). Each bar, restaurant, or gas station also has a substantial criminogenic effect (5%). Other land uses have smaller effects of about a 1 to 2% increase: the number of stores, vacant/parking lots, and commercial establishments. An increase in one multifamily residential unit results in less than a 1% increase in street robberies, net of all other variables in the model. All land use variables have statistically significant effects. Finally, each owner-occupied household has a reductive effect of approximately 0.2% on street robberies.
In Model 2, diffusion is controlled by including the street robbery potential variable as an instrumental variable in a two-stage least-squares equation. A one-unit change in street robbery potential results in a 32% increase in the number of street robberies. Proximity to street robberies is influential to the chances of street robbery occurring. Motivated street robbers may target proximate face blocks because they are aware of them, due to their proximity to the offender's routine activities. Most of the coefficients in Model 2 (trimmed model) are similar to those in Model 1, with one notable exception: Two social disorganization variables are found not to be statistically significant in Model 2 and are dropped (racial heterogeneity and mean building value).

In Model 3, interaction terms (product terms) are introduced. A trimmed model is presented. Two social disorganization variables with strong effects in Model 1 (the number of single-parent households and distance from center city) are hypothesized to interact with all six land-use variables. The direction of the observed effects are as expected: positive between number of single parents and land uses, and negative between distance from the center of the city and land uses. Five of the 12 interaction terms tested in a forward-entry regression procedure are statistically significant. The results indicate that the proximity of residences of likely motivated offenders (as measured by prevalence of single parents) with motels, hotels, or bars, restaurants, and gas stations results in a nonadditive (conditional) effect on street robbery. Indeed, when an average number of single-parent households exists, the effect of the number of motels/hotels is negative (−.08). On face blocks with a motel/hotel, each additional single-parent household has an approximate 24% increase in the number of street robberies (sum of .32.004−.08). Where bars, restaurants, and gas stations are found on the same face block with single-parent households, street robbery is more likely [however, the “main effect” of bars, restaurants, and gas stations (.142) is considerably stronger than the interaction with single-parent households, .01].

As hypothesized, distance from center city reduces the criminogenic effect of multifamily residences, bars, restaurants, gas stations, and vacant/

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11. In the present analysis, whether an F test for increment to variance explained or the statistical significance of the regression coefficient is used, the same product terms are statistically significant. It should be noted that 1 of the 12 product terms is excluded from the reduced model because of multicollinearity concerns and not because of a failure to reach statistical significance: distance from center of the city × number of commercial places. The variance inflation factor was 5.18, with a tolerance of .193, and the coefficient for number of commercial places tripled in size, relative to a model without the coefficient. Because of these results, it was decided to drop this product term as a conservative data analytic decision. Other researchers might include this product term in the reduced equation, in which case 6 of the 12 product terms would be judged statistically significant.
parking lots. Interestingly, the "main effect" of distance has a positive sign (.0095), indicating that at the mean of the land use variables (zero, as all these variables are centered), each mile from the center of the city increases the risk of street robbery, net of all other variables in the model, which could be interpreted as a lack of guardianship effect: Street population densities (only poorly measured with the population count variable) may decline with distance, facilitating street robbery. As distance to the city center declines from zero (the mean), however, each of the mentioned land uses has a criminogenic effect. It should also be noted that at the average distance from the center of the city, each of the land uses has a relatively large main effect (compared with the interaction effects) of between 1 and 14%.

Comparisons of the five product terms retained in the reduced model with the seven omitted ones are suggestive of possible causal mechanisms for the interaction effects. The interaction of single-parent households with the number of motel/hotels and with the number of bars, restaurants, and gas stations is suggestive of the possible importance of night activities in the proximity of motivated offenders where parental guardianship is relatively low (where single-parent households are prevalent). Other land uses, such as those measured by number of stores, vacant or parking lots, multifamily residences, and commercial places, may be more indicative of the prevalence of day-time or early evening activities—times when street robbery is less attractive. As for the product terms involving distance from the center of the city, which is interpreted to indicate proximity to motivated offenders, the presence of land uses, such as bars, restaurants, and gas stations, vacant or parking lots, as well as multifamily residential units, may measure the prevalence of night activities and physical environment/design features conducive to street robbery. Closer to downtown, motivated offenders may be brought together with suitable targets moving through space from parking place to restaurant late at night when few "eyes on the street" exist. The proximity of motivated offenders to parking lots, or parking areas somewhat removed from the residence (characteristic of parking facilities of multifamily apartment complexes), may be conducive to street robbery. Motels/hotels, stores, and commercial places, however, may not involve all of these factors simultaneously. These latter land uses may attract would-be targets, but during daylight hours, when risk of detection for street robbery would be higher.

MODELS OF STREET ROBBERY POTENTIAL

Before discussing the implications of the above models of street robbery, it is also useful to discuss the first-stage model of the two-stage least-squares regression, the model of street robbery potential. Because of space limitations, empirical results are not presented here in tabular form.
The independent variables in the instrumental equation of the two-stage least-squares approach above are used in an OLS regression of street robbery potential ($R^2$ is .29). The unique variance explained attributable to social disorganization variables, routine activity variables, and interaction effects is .082, .001, and .029, respectively. (Unique variance explained is defined here as that variance explained by a given set of variables while controlling for the other two sets of variables.) Thus, social disorganization variables are most strongly related to street robbery potential. Note that the analysis of street robbery potential as a dependent variable involves the use of a weighted average of the street robberies in the 20 blocks proximate to a given face block, and not the street robberies of a face block itself. As such, this equation represents the impact of characteristics of a face block associated with the nearby face blocks and is suggestive of the spatial diffusion of street robbery from a given face block to neighboring ones.12

As to specific social disorganization variables, street robbery potential is well predicted by the number of African Americans, single-parent head of households, proportion of households of low-assessed value, distance from the center of the city, and number of owner-occupied households. Street robbery potential is also predicted by routine activity variables (land use variables), such as the number of vacant/parking lots. Two interaction effects with distance from downtown are notable: the number of vacant/parking lots (which are more criminogenic closer to downtown) and the number of owner-occupied households (which has more of a deterrent/prevention effect closer to downtown). Thus, as one moves further from the center of the city, vacant/parking lots and the number of owner-occupied households have less of an impact on street robbery potential. This latter effect is surprising as owner-occupied households were anticipated to have less of a preventive effect closer to downtown, following the research of Rountree et al. (1994) and Miethe and McDowall (1993), who find that safety procedures are less effective in socially disorganized multiblock areas. Apparently, the effect of the presence of owner-occupied

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12. Alternative interpretations are possible, however. It may be that the variables that predict street robbery potential would also be found to predict other characteristics of the nearby face blocks. For example, the number of owner-occupied households may be found to be predictive of "owner-occupied potential." Thus, the strength of the negative relationship between owner-occupied households and street robbery potential may be because of a spatial diffusion involving owner-occupied homes: Home owners may tend to live in their homes in areas of the city where they perceive other homeowners living. The latter is a plausible mechanism to account for the relationship between the number of owner-occupied households and the street robbery potential. It is beyond the scope of this paper to address these interpretive complexities; yet, it should be recognized that spatial diffusion is probably not limited to street robbery.
households may be different than the effects of security devices. The present results suggest that the effects are opposite. The presence of owner-occupied households in neighborhoods closer to the downtown area actually has stronger preventive effects than they do further from downtown. Such a finding offers support for those individuals having advocated home ownership as a means for neighborhood improvement and to fight crime (Rohe and Stegman, 1994).

Vacant lots interact with distance from downtown in a reverse direction. The closer to downtown, the more criminogenic are vacant/parking lots, resulting in greater street robbery potential. Presumably, the causal mechanism here is that parking lots are providing would-be robbers with attractive robbery targets or places conducive to robbery.\textsuperscript{13}

UNIQUE VARIANCE EXPLAINED

The primary findings of the OLS regression of street robbery potential support an interpretation that considerable intercorrelation exists among both social disorganization and routine activity variables. Only 11% of the variance can be uniquely attributable to one or the other of the three sets of variables (of a total of 29%), implying that 18% of the total variance explained is shared by the three blocks of variables. Social disorganization variables are more strongly associated with street robbery potential than are routine activity variables. It could be concluded that social disorganization attributes have more of an impact on street robbery in the surrounding area than do the land use variables associated with routine activity theory, which makes sense in that land use characteristics on a face block have limited contagious effects on surrounding face blocks. Social disorganization characteristics, however, have a stronger impact on surrounding face blocks, as motivated offenders diffuse into the surrounding streets of the neighborhoods in which they live. Thus, robbery potential is largely a product of social disorganization factors.\textsuperscript{14}

In the models in Table 3 for street robbery (not potential), only two of the social disorganization variables are statistically significant. Land use

\textsuperscript{13} It should also be noted that street robbery potential is influenced by the number of African Americans. Following Blau and Blau (1982), it is interpreted to mean that both structural and cultural correlates of race (poverty, subculture of violence) are operative. That is, socioeconomic inequalities create latent animosities that foster criminal violence, but also, race may be indicating certain normative orientations among African Americans that are in some sense less prohibitive of acts of robbery. Similarly, it should be remembered that race is a variable with a strong social class aspect to it (not measured directly in the present study).

\textsuperscript{14} It should be noted that we included the number of owner-occupied households among the social disorganization variables for this equation.
variables have relatively strong effects in the street robbery models compared with the street robbery potential models. The unique variance explained of the (logged) count of street robbery suggests a different pattern than what was found for street robbery potential. The instrumental variable from the equation predicting street robbery potential uniquely explains .068 of the variance in logged robbery counts. Land use variables were second with .038, whereas social disorganization variables uniquely explained only .004 of the variance. Thus, land uses seem more important than social disorganization variables in explaining street robbery. However, because street robbery potential is determined by social disorganization variables, one can assume that both social disorganization and routine activity variables are affecting street robbery—the former primarily through diffusion effects. In summary, these results can be interpreted to mean that robbery in a relatively large, multiblock area (robbery potential) is more determined by social disorganization factors than by land use factors (routine activity variables). Land use factors have greater effects on the robbery count on face blocks than do social disorganization attributes of the face block.

ROBUSTNESS

The robustness of the two-stage least-squares model (Model 3) is addressed by examining a Poisson regression model of the count of street robberies. The model was found to be extra-Poisson (Land et al., 1996; Nagin and Land, 1993). A general binomial regression equation model, consisting of the same variables used in the instrumental equations of Models 2 and 3 in Table 3, was evaluated. The results of that model are substantively similar to those presented in Model 3, with some exceptions: The effect of number of multifamily units is not found to be conditional on the distance from the center of the city, and the number of multifamily units' "main effect" is positive instead of negative. In addition, the main effect of vacant/parking lots was not statistically significant, and the interaction effect of distance with vacant/parking lots was positive (rather than the negative effect observed in Model 3). Yet, all other interaction effects were statistically significant and in the same direction as the two-stage results. (In the extra-Poisson model, the shape of the distribution varied with three variables: street robbery potential, number of commercial establishments, and number of bars, restaurants, and gas stations.)

15. That is, the predicted value from the OLS model of street robbery potential is included as one of the predictor variables in the negative binomial regression model. Thus, we approximate the two-stage least-squares approach used in Table 3 in implementing the negative binomial regression model. In essence, street robbery potential is controlled for in the negative binomial regression models tested. These results are available from the first author on request.
CONCLUSIONS

Several hypothesized interaction effects between social disorganization and routine activity variables have been found using units of analysis smaller than those used by most previous researchers. Whereas previous research has found only a few cases of interaction effects across these two theories, the present research has found 5 out of an hypothesized 12 relationships. All of the effects are in the hypothesized direction, with criminogenic social disorganization attributes interacting with criminogenic land use variables to produce more street robberies than would be the case if only an additive linear model fit the data. Whether the success here in finding cross-theory interaction effects is because of the small unit of analysis is not known. The success of the present search in finding interaction effects may be because of the fact that the unit of analysis is either spatially homogeneous (e.g., single-parent households are spread evenly across the face block) or that the spatial heterogeneity is irrelevant. The latter seems a more likely explanation, assuming that, if a land use on a face block is part of the awareness space of a would-be robber, potentially any place on that face block may be the scene of a street robbery. Previous research using larger units of analysis suffers from spatial heterogeneity, and the paucity of interaction effects may be a consequence.

In addition, the research here shows that street robbery involves diffusion processes. Street robberies near a face block are important influences of street robbery on a face block. In itself, this finding may not seem remarkable. However, what mainly predicts street robbery potential are social disorganization variables. Thus, not only is strong support found for social disorganization theory, but support is also found for a strong diffusion interpretation of the theory. Offenders choose to commit street robberies in the general area where they live or where their routine activities take them. A face block's proximity to other face blocks where street robberies occur is a strong determinant of street robbery occurring on that face block. At the same time, some land uses are also found to determine street robbery potential, but to a lesser extent.

Both social disorganization and routine activity variables are determining street robbery. Street robbers commit their crimes in socially disorganized neighborhoods proximate to where they live or are routinely active. Thus, support is found for a diffusion interpretation of street robbery in which robbers commit crimes on face blocks with which they are familiar—in their “awareness space” near where they live and traverse in their routine activities. In brief, street robbery potential is caused more by social disorganization than by routine activity factors, whereas street robbery is the result of combination of both social disorganization and routine activity factors. If the social disorganization variables are measuring the
neighborhoods where motivated offenders live and local controls are weak, proximity to these face blocks entail risk of street robbery. Social disorganization alone, however, does not account for street robbery on a face block. Specific land uses in interaction with social characteristics, such as the number of single-parent households or the distance from the center of the city, are important in determining the risk of street robbery. Face blocks are not chosen randomly for street robbery, but they are in accordance with the routine activities that take place on those face blocks. However, it is generally not the land uses alone that account for the presence of street robbers. The location of land uses (e.g., proximate to downtown) also determines whether crime will occur.

It should also be noted that, independent of street robbery potential, however, are important effects of both social disorganization and land use variables of the face block where the street robbery occurred. Street robbery is a local phenomenon, not just the result of a diffusion process. Robberies can occur on a face block because of the land uses on those face blocks, and not the face blocks nearby.

The results of the study are limited by the type of data available. Finding variables that adequately operationalize all of the theoretically relevant concepts is difficult, and the omission of some here may be having an effect in the models above (Kiecolt and Nathan, 1985). In future research, it would be useful to look at mobility, a factor that was not measured in this analysis. Highly mobile communities tend to have high crime rates, regardless of the socioeconomic status of the residents (Bursik and Webb, 1982). Also, future research using small units of analysis should test the generalizability of the findings to other cities.

The findings here are also relevant to the classic work of Shaw and McKay (1942), who demonstrated how with each mile from the center of Chicago, delinquency rates declined. Here, it is shown that the relationship between social conditions and crime is more complex. The criminogenic effects associated with land uses are themselves changed with distance from downtown. Nevertheless, the findings here would best be interpreted as providing strong support for the pattern of findings associated with the classic Chicago School: Distance from downtown is a key variable in the prediction of street robberies. Also, support is found for a social control interpretation of social disorganization theory. Where family structures are weaker (as in the presence of single-parent households), street robberies are more likely, especially in the context of mixed land uses (i.e., face blocks where motels/hotels, bars, restaurants, and gas stations are located).

The idea of integrating social disorganization and routine activity theories through the study of interaction effects would seem more promising than previous research suggests (Miethe and McDowall, 1992; Rountree et
al., 1994). Social disorganization attributes of a face block combine with
land use factors to affect the probability that street robbery will occur. In
brief, if social disorganization factors measure the presence of motivated
offenders, and land uses indicate the presence of suitable targets, street
robbery is more likely than if only linear additive effects are operating
(i.e., no interaction effects).

As Tittle states, "No causal process works exactly the same way and to
the same degree in all circumstances" (1995:281). According to him,
attempts at theoretical integration should take into account relationships
that are contingent on one another, which has been clearly demonstrated
in the analysis above in that social disorganization and routine activity
variables have effects contingent on one another. Stated more generally,
the specific contexts in which individuals find themselves are important to
behavior. Spatial theories and research involving spatial measurements
provide clear insights into the conventional sociological wisdom of the
importance of context (Abbott, 1997).

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APPENDIX

One limitation of the data used for this research is that of missing data. Approximately one-third of cases are missing, primarily because of missing tax information data in the original data set. The primary reason for missing data is that the data set made available to researchers excludes data from areas for which basic data checks and cleaning were being implemented. For the preceding analysis, missing data are deleted listwise, although equations using mean substitution give substantively similar results for all of the models presented here. However, to address the issue of possible bias resulting from missing data, Table A1 presents the differences in mean values for variables obtained from census block data. They allow for comparisons of the cases with missing data to those without missing data (included in the analysis), as well as to the overall mean for all cases. Census variables are examined because they are the most complete source of data in the data set.

Table A1. Mean Comparison of Missing and Nonmissing Face Block Data with Overall Census Variable Data (N of cases)

<table>
<thead>
<tr>
<th>Census Variables</th>
<th>Nonmissing</th>
<th>Missing</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Population</td>
<td>50.81 (7,944)</td>
<td>33.65 (4,122)</td>
<td>44.95 (12,066)</td>
</tr>
<tr>
<td>Number of African Americans</td>
<td>10.21 (7,944)</td>
<td>6.57 (4,122)</td>
<td>8.97 (12,066)</td>
</tr>
<tr>
<td>Number of Single-Parent HHs</td>
<td>1.48 (7,944)</td>
<td>.93 (4,123)</td>
<td>1.29 (12,067)</td>
</tr>
<tr>
<td>Racial Heterogeneity</td>
<td>.07 (7,944)</td>
<td>.07 (2,765)</td>
<td>.07 (10,079)</td>
</tr>
<tr>
<td>Distance from Center of City (in miles)</td>
<td>4.16 (7,944)</td>
<td>5.17 (4,136)</td>
<td>4.51 (12,080)</td>
</tr>
</tbody>
</table>

From the table above, some differences are apparent between the missing and nonmissing data. The actual mean for total population per face block is 44.95. However, population is greater for the nonmissing data (50.81 vs. 33.65), which may be in part because much of the missing data are from face blocks containing government buildings, which also tend to be nonresidential face blocks. Racial heterogeneity is the same in missing and nonmissing groups. However, face blocks included in the analysis (nonmissing) are considerably more likely to have greater numbers of African Americans (10.21 nonmissing vs. 6.57 missing vs. 8.97 overall) and single-parent households (1.48 nonmissing vs. .93 missing vs. 1.29 overall). Data included in the analysis also average approximately one mile closer to the center of the city than do nonincluded data, and about one-third of a mile closer than the actual mean distance from the center of the city.

In summary, face blocks included in our analysis contain a greater number of African Americans and single-parent households, have a
greater total population, and are closer to the center of the city than are the face blocks not included in the analysis. Although the exact effect of these differences on the results is unknown, it is likely that some bias is present.