Block, Tract, and Levels of Aggregation: Neighborhood Structure and Crime and Disorder as a Case in Point

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This article highlights the importance of considering the proper level of aggregation when estimating neighborhood effects. Using a unique nonrural subsample from a large national survey (the American Housing Survey) at three time points that allows placing respondents in blocks and census tracts, this study tests the appropriate level of aggregation of the structural characteristics hypothesized to affect block-level perceptions of crime and disorder. I find that structural characteristics differ in their effects based on the level of aggregation employed. While the effects of racial/ethnic heterogeneity are fairly robust to the geographical level of aggregation, the stronger effects, when measured at the level of the surrounding census tract, suggest more dispersed networks are important for perceived crime and disorder. In contrast, economic resources only show a localized effect when aggregating to the block-level and differ based on the outcome; higher average income reduces disorder but increases crime, most likely by increasing the number of attractive targets. Additionally, the presence of broken households has a localized effect for social disorder but a more diffuse effect for perceived crime. These findings suggest the need for neighborhood studies of crime rates, as well as the broader neighborhood effects literature, to consider the mechanisms involved when aggregating various structural characteristics.

Considerable social science research focuses on how structural characteristics affect various outcomes. One form of this research tests whether structural characteristics of neighborhoods affect various aggregate outcomes, such as crime, economic vibrancy, cohesion, or even death from heat waves (Browning et al. 2006). Another form of this research employs multilevel models to test whether the structural or cultural characteristics of neighborhoods affect various individual-level outcomes, such as educational achievement, psychological well-being, or residential satisfaction. Despite the variety of research paradigms focusing on the importance of neighborhoods, a commonality of many studies is that less attention is paid to the appropriate level of aggregation for such neighborhood effects. Consequently, whereas a shared knowledge suggests that the size of such neighborhood effects is relatively small compared to individual-level effects (Liska 1990), it is possible that misspecification of the proper level of aggregation for such effects might partially explain these smaller than expected contextual effects.

The importance of considering the level of aggregation is not new and is the basis of the modifiable areal unit problem (MAUP) (Openshaw and Taylor 1979, 1981). The MAUP occurs when aggregating processes that are not homogenous over the geographic area (Anselin

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1988). Particularly dramatic illustrations of the problem come from studies that aggregated measures to differing units of analysis and found considerably different results for spatial weights matrices (Openshaw and Taylor 1979, 1981). The Netherlands Institute for the Study of Crime and Law Enforcement held a conference in 2006 to specifically address the issue of proper spatial aggregation. Nonetheless, despite the cautions regarding the importance of considering the level of aggregation when testing for structural effects, most research on neighborhood effects does not seriously consider this issue.

While studies purport to test the effects of neighborhood structural characteristics on various outcomes, the definition of neighborhood frequently remains buried in the methodological details. The common strategy of measuring structural neighborhood effects by simply summing up the responses of households in a particular geographic unit—or using empirical Bayes estimates (Browning, Feinberg, and Dietz 2004; Bryk and Raudenbush 1992; Morenoff, Sampson, and Raudenbush 2001) to create such measures—rarely considers whether this particular geographic unit is actually appropriate for the outcome of interest or the structural predictors being used. Consequently, studies testing the effects of these structural characteristics have used such varying geographical units as blocks, block groups, tracts, two tracts, zip codes, and even 8 to 10 tracts as proxies for the neighborhood. But is the definition of neighborhood really so geographically flexible? Theorists positing such structural effects must ascertain the proper geographical aggregation for both the outcome measure employed and the structural predictors.

Recent scholarship considering why levels of crime and disorder vary by neighborhood is one subset of this more general interest in neighborhoods. Building on both the social disorganization model (Sampson and Groves 1989; Shaw and McKay 1942) and the routine activities perspective (Cohen and Felson 1979), studies commonly adopt the strategy of testing whether certain neighborhood structural characteristics lead to higher levels of crime, physical disorder (e.g., the presence of litter, housing deterioration, and broken windows), and social disorder (the presence of undesirable persons or persons engaging in undesirable activities). While these studies focus on which neighborhood structural characteristics foster higher levels of crime and disorder (Crutchfield 1989; Crutchfield, Glusker, and Bridges 1999; Gyimah-Brempong 2001; Krivo and Peterson 1996; McNulty and Holloway 2000; Peterson, Krivo, and Harris 2000; Roncek 1981; Roncek and Maier 1991), less consideration is given to the proper level of aggregation for these structural characteristics. Without considering these different levels of aggregation and how they might affect the posited theoretical relations, the conclusions drawn from studies testing such structural relationships are unclear.

This study seeks to determine the appropriate geographic level of aggregation. I use the relationship between neighborhood structural characteristics and neighborhood crime and disorder as a specific case to demonstrate this larger issue. Testing the effect of different measures of neighborhood would ideally entail data for all residents in the larger community, enabling the researcher to construct various concentric circles to empirically determine the ideal geographic measure of the structural construct of interest. Unfortunately, such data are difficult to obtain. Instead, given that blocks and census tracts are most frequently employed in studies on neighborhood crime and disorder, I constructed a unique data set in which I linked tract-level structural characteristics with a novel survey of all households on each of 663 blocks over three points in time. This study provides three key advantages over prior work: 1) the assumption that crime or disorder are homogeneously distributed in the tract is unnecessary because I use the block as the unit of analysis when determining the degree of subjective crime and disorder; 2) I am able to compare the effects of block-level and tract-level structural characteristics on this perceived crime and disorder separately and simultaneously; and 3) by using a unique nonrural national sample of 663 blocks in the United States over three time periods to test these effects, this study provides greater generalizability of the findings compared to studies restricted to a sample from a single city.

SOCIAL DISORGANIZATION AND ROUTINE ACTIVITIES THEORIES

Two dominant perspectives guide neighborhood studies of crime rates—the social disorganiza-

tion theory and the routine activities theory. The social disorganization model, from the pioneering work of Shaw and McKay (1942), argues that particular social structures of neighborhoods (poverty, racial/ethnic heterogeneity, residential instability) lead to a lack of cohesiveness that then diminishes guardianship capability, leading to higher levels of crime and disorder. The routine activities perspective (Cohen and Felson 1979; Felson 2002) focuses on the co-occurrence of attractive targets, motivated offenders, and a lack of capable guardians. In this model, crime events occur when all three of these characteristics co-occur. For instance, the presence of a motivated offender will not induce a crime event if there is no attractive target. Even if a motivated offender and an attractive target cross paths, a crime event will not occur if a capable guardian is present (Felson 2002; Osgood et al. 1996). This guardian can come in the form of someone in an official role (e.g., a police officer) or an unofficial role (e.g., a citizen observing the happenings on the street) (Jacobs 1961). The presence or absence of guardians in the neighborhood is a commonality of these two perspectives, and recent scholarship suggests the fruitfulness of combining these perspectives (Smith, Frazee, and Davison 2000; Wilcox, Land, and Hunt 2003).

In these theoretical models, the cohesiveness of the neighborhood allows residents to perform guardian activities that confront possible challenges to neighborhood civility when they occur, possibly leading to lower levels of crime and disorder. For instance, work by Sampson and colleagues (Sampson 1991; Sampson and Groves 1989; Sampson and Raudenbush 1999) tests the mechanisms linking such neighborhood social structures to crime and disorder using cross-sectional data with census tracts as the unit of analysis. While social disorganization theory has produced a large volume of work testing these proposed relationships between neighborhood structural characteristics and neighborhood crime and disorder (Hirschfield and Bowers 1997; Markowitz et al. 2001; Sampson and Groves 1989; Smith et al. 2000; Warner and Pierce 1993), and research has tested for a possible reciprocal effect from neighborhood crime and disorder to residential instability and racial/ethnic transformation (Bursik 1986a; Schuerman and Kobrin 1986), less attention has been paid to the appropriate geographic unit for measuring such contextual effects.

Measuring Physical Disorder, Social Disorder, and Crime

Physical disorder is frequently measured in one of three manners: by a single interviewer, by a team of researchers through systematic observation, or by resident assessments.

Regardless of the measurement technique, this construct is generally focused on such characteristics as housing deterioration and litter. Given that these characteristics of neighborhoods are relatively permanent—a house in poor condition is in that condition regardless of the time of day it is observed and will likely remain in that condition for weeks or months—physical disorder is relatively straightforward to measure.

On the other hand, measuring social disorder is much more difficult. Because of its relative impermanence and disproportionate appearance during certain times of the day, it is difficult to observe. This poses a challenge for studies that attempt to measure it by allowing an interviewer to assess the amount of social disorder, even if this assessment is based on systematic observation (Sampson and Raudenbush 1999; Taylor 1996).[1] In response to this difficulty, an alternative approach uses the residents of a neighborhood as "expert witnesses." Given that residents spend much of their time in their own neighborhoods, they have a reasonable assessment of the level of social disorder in them. Studies generally ask residents about the presence of undesirable persons living in or hanging out in the neighborhood. While asking any one individual to assess the amount of social disorder in a neighborhood would run the risk

[1]Another strategy is an ethnographic study, in which researchers immerse themselves in one or more neighborhoods for a long period of time. This allows observations of brief appearances of social disorder over a long period of time, providing a more accurate assessment of its general prevalence. A downside is that a researcher is usually only able to study a handful of neighborhoods, limiting the utility of this approach for studies of a large number of neighborhoods.

of also capturing individual-specific biases, asking several residents in the neighborhood provides a more accurate measure of this construct. Using this approach, studies have obtained relatively high reliability values. Additionally, by taking into account systematic biases on the part of respondents, the accuracy of these aggregated assessments is likely improved even more (Sampson and Raudenbush 1999; Sampson, Raudenbush, and Earls 1997).

While there is no ideal way to measure the actual amount of crime in a neighborhood, three common approaches have evolved for measuring this construct: victimization surveys, counts of incidents officially reported to the police, and reports of perceived crime by neighborhood residents. While victimization surveys are intuitively appealing—it seems reasonable to suppose that those who have experienced crime are most able to report on its prevalence—this approach is limited because the data are subject to recall response biases (Cohen and Land 1984; Gove, Hughes, and Geerken 1985). More importantly, we need to know *where* the crime occurred. Residents reporting victimizations that occurred in a different neighborhood, or even a different city or state, are not providing information about the neighborhood they reside in. If victims of crime in the neighborhoods of interest are not included in the sample, the actual level of crime in the neighborhood will be underestimated. Additionally, the relative rarity of experiencing crime events requires very large samples to obtain reasonable estimates of crime rates for small geographic areas such as blocks, block groups, or tracts. Without such blanket surveying, the estimates obtained in such analyses will have too much uncertainty to be useful for practical analysis. Because of the limitations of victimization surveys for estimating neighborhood crime rates, studies frequently use official statistics of incidents reported to the police given the relative ease of collecting such data. A well-known limitation, however, is that not all incidents are reported to the police. While nonreporting occurs for various reasons, if it is related to the constructs of interest in the model, estimates comparing neighborhoods will be biased. Given the limitations of the other two measures of neighborhood crime, some recent research asks residents to assess the amount of crime in their neighborhoods (Sampson et al. 1997).

Considering the Geographic Aggregation of the Outcome Measures of Crime and Disorder

The appropriate unit of analysis for crime, social disorder, and physical disorder is unclear. If the unit of analysis is too large, the researcher runs the risk of capturing a geographic unit that contains several neighborhoods within it. For instance, the outcomes of disorder and crime are aggregated constructs based on a summation of individual instances—that is, each undesirable person or group adds to the perceived social disorder, each dilapidated building or piece of trash adds to the physical disorder, and each additional crime event adds to the crime rate. So what size of geographic unit is appropriate for aggregating these instances when constructing a neighborhood measure of crime or disorder? Should it be the block? Two adjacent blocks? Four? The census tract? This question confronts all studies regardless of *how* they measure crime or disorder. If too great a level of aggregation is employed, the crime and disorder rates of different neighborhoods will be aggregated into a larger unit, possibly obscuring empirical relationships.

In part, the question of the appropriate aggregation depends on the spatial component of the processes being studied. For instance, it may be that physical and social disorders are more localized phenomena. Trash and litter on one block may not affect the physical disorder on adjacent blocks, and the presence of youth hanging out on a corner of one block will not affect the perceived social disorder on adjacent blocks. To the extent that social and physical disorders are particularly localized, a potential problem will arise when studies aggregate the responses of households living on different blocks in the same census tract or larger units. In contrast, given the mobility of offenders it is likely that crime is less geographically localized than are physical and social disorders. If offenders indeed commit crimes in a concentric circle around their residences with a distance decay (Smith 1976), or if they commit them in a concentric circle with a distance decay but also a buffer around their own personal residences (Rengert, Piquero, and Jones 1999), one implication is the same: this will induce adjacent blocks to have more similar amounts of crime than would be the case if offenders only engaged in activity on their own blocks or in a random geographic

fashion. For instance, one study found that offenders travel, on average, between 1 and 2.5 miles to the site of crimes (Pyle 1974). Nonetheless, strolling the streets of many cities shows that blocks with high crime levels neighbor blocks with much less crime. This raises the possibility of considerable heterogeneity in the amount of crime on blocks that are then aggregated into a measure of the amount of crime in the overall census tract.

If a researcher aggregates microneighborhoods within a tract that are truly heterogeneous in their levels of crime and disorder, the potential exists to obscure otherwise detectable effects. That is, aggregating to the census tract implicitly assumes that blocks within a tract do not differ appreciably in their levels of crime and disorder. If this assumption does not hold, aggregating crime and disorder to the local block is more appropriate than aggregating to the census tract. On the other hand, if crime and disorder are distributed relatively homogenously across the blocks within a tract then randomly selecting a single block within the tract for estimating the level of crime and disorder will yield unbiased results. The block will not differ in any systematic way from the other blocks in the tract. In such an instance, there will only be an efficiency loss if the sample size of households in the block is smaller than that used when aggregating to census tracts. These considerations suggest that aggregating crime and disorder to the block level is a safer approach than aggregating them to the census-tract level.

Beyond the importance of considering the geographic region of these potential outcome measures, it is particularly important to theoretically consider the appropriate geographic area of the neighborhood when aggregating the structural characteristics used to explain the amount of neighborhood crime. I turn to these considerations next.

Considering the Geographic Proximity of Key Contextual Predictors of Crime and Disorder

The social disorganization model focuses on how certain structural characteristics of neighborhoods lead to higher levels of crime and disorder. In this model, key neighborhood characteristics such as racial/ethnic heterogeneity, residential instability, poverty, and broken households diminish a neighborhood's ability to provide oversight that would reduce crime and disorder. Recent scholarship also questions the direction of causality, asking whether crime and disorder may affect residential stability and racial/ethnic composition (Bursik 1986a; Liska and Bellair 1995). Regardless of the theoretical formulation, whether these key neighborhood characteristics should be measured at the same geographic level is an open question. While careful consideration of the theoretical mechanisms involved can provide some clues as to the most appropriate level of aggregation, little research to date has seriously considered these aggregation issues.

Racial/ethnic heterogeneity. Social disorganization scholars have suggested that greater levels of racial/ethnic heterogeneity in a neighborhood will reduce the frequency of residential interactions (Sampson 1991). Reduced social interaction is important because the social disorganization model posits that social interaction enhances the ability of residents to band together to address problems when they emerge (Sampson and Groves 1989), fostering higher levels of neighborhood collective efficacy—the sense that others will intervene to confront problems when they arise (Sampson et al. 1997). Studies using census tracts as the unit of analysis have tested the effect of racial/ethnic heterogeneity for the creation of neighborhood ties (Connerly and Marans 1985; Rountree and Warner 1999; Sampson 1991; Warner and Rountree 1997).

It is not clear what size geographic area we should use when constructing a measure of racial/ethnic heterogeneity. There are two key questions to consider: 1) What geographic area defines the social interactions of residents? 2) What geographic dispersion of networks is important for fostering crime-fighting activities? Some research (Caplow and Forman 1950; Festinger, Schachter, and Back 1950) has suggested that social interaction is higher with fellow residents on the block, and that this probability drops considerably with residents living on surrounding blocks. A counter-argument is that even if the probability of social interaction with neighbors in surrounding blocks is lower, there will be more total ties given the larger population base (Butts forthcoming).

It is also important to consider the geographic area that social networks impact through crime fighting activities. If residents on the local block can act in concert to reduce crime, then local block networks will be most salient for explaining crime reduction. In this case, any additional ties with neighbors on surrounding blocks will be immaterial to the amount of crime on the local block. However, if crime reduction requires linkages with neighboring blocks in a coordinated strategy to combat crime, then these broader networks will play a crucial role in explaining crime reduction (Bellair 1997). This latter consideration suggests that measuring the racial/ethnic heterogeneity of the entire tract is important for understanding the amount of perceived crime and disorder on the local block.

The existing empirical evidence suggests that the effect of racial/ethnic heterogeneity on crime may be particularly robust over various geographical aggregations. For instance, studies using blocks as the unit of analysis have found a positive relationship between racial/ethnic heterogeneity and various violent crime types (Roncek and Maier 1991; Smith et al. 2000). Studies have also found a positive relationship between the level of racial/ethnic heterogeneity in a census tract and the rate of aggravated assault (Sampson and Groves 1989; Warner and Rountree 1997).

ECONOMIC CLASS. The second key component of the social disorganization model is the economic resources of the neighborhood. Economic resources are generally measured either as a continuous measure for households (as the average income in the neighborhood) or as a threshold measure for households (the percentage in poverty). The proper geographical unit of analysis for this construct is also uncertain. On one hand, the social disorganization model suggests that neighborhoods with more poverty will have more crime due to their inability to obtain resources from the larger community that might help in combating neighborhood problems when they emerge. This suggests that neighborhoods with higher levels of income will have less crime.

On the other hand, the routine activities perspective suggests that an important component of crime is the presence of attractive targets. Thus, the presence of several high-income households (living in high-value homes) on a street may provide attractive targets to offenders and lead to *increased* levels of crime. That is, as long as there are motivated offenders relatively nearby, and the lack of guardians is held constant, the routine activities theory hypothesizes that the relatively high-income units will be attractive targets and increase crime. This raises an interesting distinction: whereas these high-income households should provide attractive targets that increase crime, there is no reason to expect them to foster social or physical disorder. This also suggests a particularly localized effect in which the average income level of the local block has important implications for crime.

These theoretical considerations suggest that studies combining neighborhood income and poverty measures into a single construct of SES may result in uncertainty regarding the posited direction of the effect on neighborhood crime, as well as geographical uncertainty regarding the proper unit of analysis for measuring this construct. Supporting this conjecture, whereas one study found a negative relationship between average SES and robbery rates in neighborhoods essentially the size of two census tracts (Bellair 1997), another study found no relationship between average SES in census tracts and aggravated assault or robbery rates (Sampson and Groves 1989).

Studies measuring the relationship between economic resources and crime/disorder often use relatively large units as measures of neighborhoods. For instance, studies viewing disorder as the outcome frequently find a positive relationship between the percent in poverty and the disorder in tracts (Geis and Ross 1998; Kearns and Forrest 2003; Ross and Mirowsky 2001) and block groups (Sampson and Raudenbush 2004). Studies testing the effects of economic resources on crime often find mixed results. Whereas one study finds a positive relationship between the percent in poverty and the tract violent-crime rate (Krivo and Peterson 1996), other studies fail to find significant effects for tract-level poverty (Crutchfield 1989; Rountree and Warner 1999) or for per capita income (Gyimah-Brempong 2001). Again, it may be that using large units of analysis obscures the posited relationships.

RESIDENTIAL INSTABILITY. The third key component of the social disorganization model is the

residential (in)stability of the neighborhood. Analogous to the effect of racial/ethnic heterogeneity, studies have suggested that greater neighborhood residential stability increases familiarity between neighbors and fosters more social interactions among them (Adams 1992; Austin and Baba 1990; Bolan 1997; Campbell and Lee 1992; Kasarda and Janowitz 1974; Logan and Spitze 1994; Sampson 1988, 1991). This greater frequency of social interaction can ease the process of neighborhood residents engaging in guardianship activities to reduce the level of crime (Sampson and Groves 1989; Shaw and McKay 1942). This again raises the question of the geographic efficacy of networks. If block-level interlinkages are most important, then residential stability on the local block will have the strongest effect on block-level crime. But if social connections beyond the local block are key, then the level of residential stability in the larger census tract will affect the reported crime in the local block.

The empirical evidence for the effect of residential instability on crime rates is mixed. Studies using block groups as the unit of analysis have produced conflicting findings (Gorman et al. 2001; McNulty and Holloway 2000). The evidence is no more consistent among studies using census tracts as the unit of analysis, which find insignificant effects for the percentage of new households in the last five years (Ouimet 2000; Warner and Rountree 1997), a residential stability factor score (Nielsen and Martinez 2003; Sampson and Raudenbush 1999), and the average length of residence (Bellair 1997). While studies have created factor scores including the percent homeowners along with stability and found a negative relationship with violent crime at the block level (McNulty 2001), and with various types of violent crime at the tract level (Peterson, Krivo, and Harris 2000), these conflate the effect of homeownership with residential stability.

PRESENCE OF BROKEN FAMILIES. Finally, the focus of the social disorganization model on providing guardianship for the neighborhood suggests the importance of traditional households for monitoring the activities of youth. Given that unsupervised adolescents have the potential to create crime and disorder, the presence of more broken families limits oversight capability in the neighborhood and should increase crime and disorder. Since oversight provided by parents may imply a more geographically specific effect than the networks fostered by residential stability and racial/ethnic homogeneity, it is possible that the most appropriate geographic aggregation may differ for this measure compared to the measures of racial/ethnic heterogeneity and residential instability. Therefore, although the empirical evidence suggests a particularly robust relationship between the percent of broken families in a neighborhood and the amount of crime, regardless of the geographical unit of analysis employed (Crutchfield 1989; Krivo and Peterson 1996; Ouimet 2000; Roncek and Maier 1991; Rountree and Warner 1999; Sampson and Groves 1989; Smith et al. 2000), I directly compare the effects of broken families aggregated to either the block or the tract level when assessing their relationship to block-level perceived crime and disorder.

SUMMARY. Despite the voluminous social disorganization literature viewing the relationship between various neighborhood structural characteristics and neighborhood crime and disorder, less attention has been paid to the theoretical importance of the geographical aggregation employed. As highlighted above, given the differing causal mechanisms of structural characteristics, the most appropriate geographical aggregation for any given construct may differ from that for other constructs. I next test these effects at different levels of aggregation using my unique sample design.

DATA AND METHODOLOGY

DATA

The subsample of the American Housing Survey (AHS) I employ is uniquely suited to address these research questions. In this subsample, my unit of analysis is approximately 11 housing units sampled in each of 663 nonrural blocks across the United States in the years 1985, 1989, and 1993 (the samples were augmented in each of the two latter years with new blocks so that I have a total of 2,256 block time-points over the three waves). The AHS is a national sample of about 60,000 housing units conducted in odd-numbered years. For this special neighborhood subsample, the AHS initially randomly select-

ed 663 housing units in 1985 from the full AHS that were located in either urban or suburban locations. They then interviewed the 10 closest neighbors of the initial respondent.[2] I refer to these 11 households as a "block," even though this does not precisely match the census definition of a block. In addition, I take into account the surrounding area by placing these blocks into their respective census tracts using special access to data at the Triangle Census Research Data Center.[3] Importantly, none of these "blocks" straddle two census tracts. This unique data set has households nested within blocks as the units of analysis, with additional information on the tract in which these blocks reside, enabling comparisons of the effect of these structural characteristics measured either at the local block level or at the census tract level.

Outcome Measures

My key outcome measures are the constructs of perceived crime, physical disorder, and social disorder measured at the block level. To measure perceived crime, the AHS asks respondents a series of three questions: is crime a problem, is it so much of a problem that it's a bother, and is it such a bother that the respondent wishes to move. I combined these responses into a four-point response in which the respondent either replies "no" to all questions, "yes" to one, "yes" to two, or "yes" to all three. The physical disorder concept is a single yes/no question asking whether "litter or housing deterioration is bothersome." The social disorder concept is a single yes/no question asking whether "people in the neighborhood are bothersome." In all instances, the definition of "neighborhood" was left to the respondent. While continuous measures (rather than dichotomous ones) would be preferable for these constructs, using 11 respondents on each block improves the reliability of the measures. For instance, the reliability of the block-level physical disorder measure is .46, whereas the social disorder measure reliability is .50; in contrast, the four-category crime measure has a block-level reliability of .74. For each of these measures, I have approximately 11 respondents from each block at each time point reporting on these constructs.

Block- and Tract-level Predictors

The key predictors are the social disorganization constructs measured at both the block and the tract level. The block measures are constructed by summing the responses of the 11 adjacent AHS residents. The tract measures are summed responses to the U.S. Census.[4] I measure racial/ethnic heterogeneity (EH) in a neighborhood (block or tract) k by an identity based on a Herfindahl index (Gibbs and Martin 1962:670) of several racial/ethnic groupings,[5] which takes the following form:

$$\mathrm{EH}_k = 1 - \sum_{1}^{j=J} G_j^2 \qquad (1)$$

where G represents the proportion of the population of ethnic group j out of J ethnic groups. Subtracting from 1 makes this a measure of heterogeneity. I measure economic conditions by the average income in the block or tract[6]

[2] Sample units in the AHS were selected from the 1980 Census Sample Housing Unit Record File. A Housing Unit Coverage Study was performed to locate units missed by the 1980 census, and an additional sample was selected from the units located by this study (e.g., nonresidential to residential units and new mobile home parks). Building permits were also sampled to represent newly constructed housing since the 1980 census. For a more complete description of the AHS sampling design, see Hadden and Leger (1995).

[3] For the AHS waves in 1989 and 1993, I used the census-tract data for 1990 to create the structural measures. For the 1985 wave, I created an estimate by taking the mean of the census-tract measures in 1980 and 1990.

[4] The AHS is administered by the Census Bureau and has an equally high response rate as the U.S. Census. As a result, there is little reason to expect systematic differences introduced into how these block and tract structural measures are created.

[5] These groups are white, African American, Latino, and other races for blocks. When constructing this measure for tracts, I also include a fifth grouping: the percent Asian. Because of the small size of the blocks, including the percent Asian at this level is not statistically feasible. I therefore collapsed Asians into the other race category for the block-level measure.

[6] I also tested additional models, including a measure of the percent in poverty in the block or tract. This measure showed weaker effects than the continuous

and residential stability with the average length of residence in the block or tract. To measure the presence of broken households, I include measures of the percent married at the block level, the percent divorced at the tract level, and the percent of households with children of various ages at both the block and tract level (0 to 5, 6 to 12, and 13 to 18 at the block level; 0 to 5 and 6 to 18 at the tract level).

Other Measures of Social and Physical Characteristics of Neighborhoods

To minimize the possibility of spurious findings, I also take into account several other social and physical characteristics of the block and tract. I account for possible racial/ethnic composition effects beyond the effect of racial/ethnic heterogeneity with measures of the percent African American, Latino, and other race (with white as the reference category) at the block level. For the census tract measures I also include percent Asian. Finally, I include measures of the average education level of the block and the percentage in the tract with at least a bachelor's degree, measures of the percent homeowners in the block or tract, and measures of the percent vacant units in the block or tract.

Since past work suggests that the presence of youth hanging out on street corners fosters a sense of disorder, I include two measures to capture this effect. First, from the U.S. Census I include a measure of the percent of youth (ages 16 to 19) in the tract not in the labor force. Second, since quality local schools might keep youth off the streets, I construct a measure of the completion rate of students in the local school district. This information is taken from the Local Education Agency (School District) Universe Survey Longitudinal Data File: 1986–1997 (U.S. Department of Education 2001). To capture possible effects of the age of residents, I include measures of the average age of the household head in the block and the tract. I take the percent unemployed in the tract from the U.S. Census. Since crowding may increase crime and disorder, I include measures of the average number of persons per room in the block and the tract.

I account for physical characteristics of the tracts. Since certain types of retail outlets may affect crime and disorder rates, I include measures of the number of employees of bars and liquor stores per 10,000 population in the tract, taken from the U.S. economic census.[7] To maintain temporal precedence, I use data from the 1982 economic census for the 1985 AHS sample, data from the 1987 economic census for the 1989 AHS sample, and data from the 1992 economic census for the 1993 AHS sample.[8] I include a measure of the number of restaurant or recreation employees per 10,000 population in the tract. I also include measures of the presence of parks or broken windows on housing units within 300 feet as assessed by the AHS interviewer.

Finally, since this is a national sample of blocks, I also want to take into account the characteristics of the surrounding county to minimize the possibility of spurious effects. I thus include four measures aggregated to the county level using U.S. Census data: the percent

measure of average income. A model simultaneously including both poverty and average income showed the latter to have stronger effects. This suggests that the effect of income is not only salient for those at the lowest levels of income, but it has a more general effect captured by the continuous measure.

[7] I use the number of employees rather than the number of establishments, since this measure likely provides a more accurate depiction of the impact such businesses have on the neighborhood. That is, it is not the simple presence of these establishments that is posited to increase crime; it is the number of people they attract (both patrons and possible perpetrators). Since establishments with more patrons will generally have a greater number of employees, the number of employees better captures this effect than a simple count of the number of establishments. Nonetheless, I assessed this decision by also running models including the simple count measures of number of establishments. The substantive results of the reported models were unchanged.

[8] While this economic census data is reported for zip codes, I apportion this zip code data into its constituent 1980 census tracts based on the proportion of the zip code population contained within a given tract with the Master Area Reference File (Census 1980). I place the 1992 data into 1990 tracts using the MABLE/GEOCORR Web site at the University of Missouri (http://mcdc2.missouri.edu/websas/geocorr90.shtml) and additionally apportion the 1990 tracts into 1980 tracts (since the AHS respondents are placed into 1980 census tracts).

urban, the median income, the household inequality in the county (measured by the Gini coefficient), and the racial/ethnic heterogeneity (measured with the Herfindahl index as described above).[9]

Household and Individual Characteristics

Since the goal of the analyses is to obtain estimates of block-level perceived crime and disorder that are purged of individual-level biases, I include several individual- and household-level demographic measures. There may be gender differences in perceptions of the amount of crime and disorder, so I include a dichotomous measure coded 1 for females. I capture SES with measures of household income (logged) and years of education of the respondent. To account for racial/ethnic differences, I include dichotomous indicators for African Americans, Latinos, and other race (with whites as the reference category). To measure community investment, I include an indicator of whether the respondent owns the residence. To account for life course, I include a measure of the age of the respondent, dichotomous indicators for marital status (married and divorced, with single/widowed as the reference category), and indicators of whether the respondent has children under 5 years of age, between 6 and 12 years of age, and between 13 and 18 years of age at home. I include the length of time in the residence and a measure of the persons per room (both log transformed). Note that all these measures take into account the differences in individuals assessing the same block. Table 1 shows the summary statistics for the variables used in the analyses.

METHODOLOGY

I estimate the perceived crime model as a multilevel model and the two dichotomous social disorder models as logit models with standard errors corrected for clustering using the Huber/White sandwich estimator.[10] All models were estimated in SAS 9.1. In the individual-level equation of the multilevel perceived crime model, I test whether individuals with a particular characteristic view *the same* neighborhood more or less favorably than individuals without that characteristic. In this multilevel model, individual characteristics are at level one, while the block and tract measures are at level two. Thus, for the perceived crime model, I estimate a multilevel model with the following household-level equation:

$$y_{ik} = \eta_k + \Gamma X_{ik} + \varepsilon_{ik} \qquad (2)$$

where y_{ik} is the combined outcome in the AHS regarding the level of perceived crime in the block reported by the i-th respondent of I respondents in the k-th block, η_k is the random block-level component of crime in the block (and can be conceived as the block's common perception of crime), X_{ik} is a matrix of exoge-

[9] I calculated a measure of overall inequality in the county based on the Gini coefficient, defined as:

$$G = \frac{2}{\mu n^2}\sum_{i=1}^{n} i x_i - \frac{n+1}{n}$$

where x_i is the household's value of income, μ is the mean income value, the households are arranged in ascending values indexed by *i,* up to *n* households in the county. Since the data is binned (as income is coded into various ranges of values), I take this into account by using the Pareto-linear procedure (Aigner and Goldberger 1970; Kakwani and Podder 1976), which Nielsen and Alderson (1997) adapted from the U.S. Census Bureau strategy (for further details of this algorithm, see Nielsen and Alderson [1997]). To calculate these values, I use the prln04.exe program provided by Francois Nielsen at http://www.unc.edu/~nielsen/data/data.htm.

[10] I also estimated multilevel models using a logit link in SAS. The results were very similar: all of the estimates for the social structural constructs of interest were in the same direction with similar significance levels. While estimating multilevel models with a logit link in SAS currently requires using the penalized quasi-likelihood approach, which has known limitations (Agresti et al. 2000; Guo and Zhao 2000; Neuhaus and Segal 2001), software constraints at the Census Data Center required employing this particular software rather than HLM, which uses more desirable techniques for estimating multilevel logit models. Because of this, the fact that this population-average model requires fewer assumptions about the distribution of the random effects (Heagerty and Zeger 2000; Raudenbush and Bryk 2002:304), and given that the results of the two approaches were so similar, I present the logistic models with corrected standard errors here.

Table 1. Summary Statistics for Variables Used in Analyses

Outcome Measures	Mean	SD	Mean	SD
Average perception of crime	.588	.942		
Proportion perceiving social disorder	.166	.344		
Proportion perceiving physical disorder	.068	.223		
Demographic Measures	**Block**		**Tract**	
Average age	48.026	9.029	37.299	4.765
Proportion African American	.142	.276	.146	.250
Proportion Latino	.084	.173	.108	.169
Proportion other race	.029	.068	.010	.017
Proportion Asian			.037	.069
Ethnic heterogeneity	.227	.226	.279	.193
Education	12.796	1.738	22.805	16.201
Average income	3.458	2.163	4.606	2.621
Average length of residence	1.895	.613	10.450	3.133
Proportion married	.500	.242	.251	.145
Proportion with children, 0–18 years old	.677	.466	.469	.100
Proportion with children, 0–5 years old	.221	.202	.218	.069
Proportion with children, 6–12 years old	.248	.221		
Proportion with children, 13–18 years old	.208	.185	.371	.094
Proportion owners	.574	.357	.574	.225
Average persons per room	.494	.160	.396	.102
Proportion vacant units	.082	.151	.077	.066
Percent unemployed			7.0	4.8
Percent teens not in the labor force			7.6	7.1
County-Level Measures				
Percent urban	86.2	18.2		
Median income (in $10,000's)	3.6	1.0		
Inequality (Gini)	39.8	4.5		
Ethnic heterogeneity	38.5	20.3		
Physical Characteristics Measures				
Per capita bar employees in tract	2.414	1.104		
Per capita liquor store employees in tract	1.914	.874		
Per capita restaurant employees in tract	5.524	.840		
Per capita recreation employees in tract	3.389	1.193		
Graduation rate of local schools	.726	.175		
Presence of broken windows	.015	.068		
Presence of park nearby	.143	.286		

Note: N = 25,332 household time points; 2,256 block time points.

nous predictors with values for each individual *i* in block *k,* Γ shows the effect of these predictors on the subjective assessment, and ε_{ik} is a disturbance term. Note that the outcome measure is *each individual's assessment* of crime. The matrix X is constructed from responses to the AHS and includes the household measures described above.[11] Thus, this approach attempts to parse out possible biasing effects of these individual characteristics to get a more accurate measure of the block-level perceived crime and

[11] Note that the effect of these household measures on the outcome, the γ's, can be allowed to vary randomly over blocks. This is accomplished by adding an additional equation in which the γ is the outcome, and there is an intercept and a random term. I tested for randomness of the household-level measures over blocks and found significant variation for the following measures in the perceived crime equation: African American, Latino, years of education, number of children ages 0 to 18, persons per room, perceived social disorder, and perceived physical disorder. I thus allow these parameters to vary in the perceived crime models, though I do not attempt to explain this variance since it is outside the scope of this study.

disorder (Sampson and Raudenbush 2004; Sampson et al. 1997).

The equation of substantive interest to this study is the neighborhood-level equation. Adding neighborhood predictors results in this second equation:

$$\eta_k = BZ_k + \beta_{YR}YR + \varepsilon_k \quad (3)$$

where η_k represents the overall perceived crime in block *k,* Z represents a matrix of variables measured at the level of neighborhood *k* (either block- or tract-level measures), B shows the effect of these measures on overall perceived crime, YR are indicators of the year in which the neighborhood was observed (with the first wave as the reference category) with β_{YR} vector of effects on the outcome, and ε_k is a disturbance for block *k.*[12] This is the key equation for this analysis, as it shows the effect of these block and tract structural characteristics on the block-level measures of perceived crime and disorder after they have been purged of individual-level biases in Equation 2.

Since almost no tract contains multiple blocks, it is not feasible to treat the census tract as an additional level in the multilevel framework. While this precludes comparing the degree of variance existing at the block- and tract-level, it also alleviates concerns about improper estimation of standard errors, as the tracts do not constitute an additional level of nesting since they are nearly coterminous with blocks. Importantly, this sample design introduces no bias to the parameter estimates for block- or tract-level measures. That is, the design does not include tracts as a sampling cluster; instead, the tracts and blocks arise from the initial sampling selection of a household. There is essentially a one-to-one correspondence between blocks and tracts, and blocks were randomly selected within tracts, so no bias occurs in the coefficients (Angeles, Guilkey, and Mroz 2005).

I adopt the following methodological strategy: I control for the household-level characteristics and the physical characteristics of the tract in all models (but for brevity do not present these coefficients), and for each outcome measure I begin by estimating a model containing the block-level measures. I then estimate a model that replaces the block-level measures with the tract-level measures to compare the effect of these structural characteristics when measured at these two different geographical aggregations. I next estimate a model including the block- and tract-level measures simultaneously. Finally, I estimate a trimmed model including just the most appropriate geographic aggregation of the demographic measure (either block and/or tract). I present these models for each of the three key outcomes: social disorder, physical disorder, and crime.[13] While I only show the results for the variables of theoretical interest, the models control for the other neighborhood variables described above.

RESULTS

Effects of Racial/Ethnic Heterogeneity on Social Disorder

I begin by viewing the effects of racial/ethnic heterogeneity on block-level perceived social disorder. There is strong evidence in Models 1 and 2 of Table 2 that greater levels of racial/ethnic heterogeneity lead to a greater perception of block-level perceived social disorder. This occurs whether ethnic heterogeneity is measured at the block level (Model 1) or at the tract level

[12] While this model includes indicator variables to distinguish neighborhoods for the three waves of data, this assumes that the coefficients are equal over the three years. I tested this assumption by running models including interactions between these yearly indicator variables and the variables in the model. The results suggested that the coefficients do not differ substantively over the three waves. For instance, in the perception of crime model with the block measures, the value of the Akaike Information Criterion (AIC) worsened from 28,458 to 28,495 when adding this set of interactions (smaller values indicate a better fit). In the analogous perceived physical disorder models, the AIC worsened from 9,830 to 9,859, while the AIC worsened from 22,648 to 22,661 in the analogous perceived social disorder models.

[13] There was no evidence of estimation problems in these models, nor evidence of collinearity among these predictors, as all variance inflation factors were below 4—a commonly specified cutoff value. There was also no evidence of influential cases or outliers. I estimated parsimonious models including few of these control variables and found substantively similar results.

Table 2. Determinants of Perceived Social Disorder, Including Block-Level and Tract-Level Measures of Neighborhood Composition

	(1)	(2)	(3)		(4)	
Neighborhood Measures	Block	Tract	Block	Tract	Block	Tract
Ethnic heterogeneity	.597**	1.000**	.324*	.800**	.131	.900**
	(5.01)	(6.27)	(2.50)	(4.65)	(1.22)	(5.11)
Average income	–.093**	–.021	–.076**	–.012	–.099**	
	–(4.27)	–(1.21)	–(3.17)	–(.72)	–(4.76)	
Average length of residence	–.028	–.003	–.026	.007	.017	
	–(.43)	–(.21)	–(.35)	(.55)	(.26)	
Proportion married (block), proportion divorced (tract)	–.588**	.800*	–.578**	.500	–.596**	
	–(4.15)	(2.01)	–(3.64)	(1.21)	–(3.94)	
Proportion with children, 0–5 years old	.279*	.724	.223†	.413	.317*	
	(2.22)	(1.34)	(1.70)	(.73)	(2.40)	
Proportion with children, 6–12 years old	.350*		.325*		.376**	
	(2.17)		(2.11)		(2.60)	
Proportion with children, 13–18 years old	.152	–.656	.150	–.336	.270†	
	(1.08)	–(1.16)	(1.01)	–(.61)	(1.84)	

Source: American Housing Survey special neighborhood subsample, 1985, 1989, 1993.
Notes: T-values in parentheses. N = 25,332 household time points, 2,256 block time points. Logit models with standard errors corrected for block-level clustering. All models include household level measures of gender, age, race, household income, education, length of residence (logged), marital status, number of children ages 0 to 18, owner, and persons per room. They also include block and tract measures of racial/ethnic composition, education, homeowners, vacant units, average age, and average person per room; and tract measures of the unemployment rate, percent teens not in the labor force, per capita bar employees, per capita liquor store employees, per capita restaurant/recreation employees, and graduation rate of local schools. Models also include county measures of percent urban, median income, racial/ethnic heterogeneity, Gini for household income, and indicator of year.
* $p < .05$; ** $p < .01$ (two-tail tests). † $p < .05$ (one-tail tests).

(Model 2). For instance, a one standard deviation increase in ethnic heterogeneity at the block level increases the odds of perceiving social disorder 14.4 percent, while a one standard deviation increase at the tract level increases the odds 21.3 percent.[14] I next include the block and the tract structural measures *simultaneously* to assess their relative effect at these two levels of aggregation. Model 3 of Table 2 shows that whereas an increasing level of block-level ethnic heterogeneity increases perceived social disorder, an increasing level of ethnic heterogeneity in the surrounding tract has a reinforcing positive effect above and beyond this effect at the local block level. A one standard deviation increase in the level of racial/ethnic heterogeneity in the block and surrounding tract increases the likelihood of perceiving social disorder 25.5 percent. This is consistent with the hypothesis that racial/ethnic heterogeneity can reduce local network ties when it occurs on the block, as well as broader network ties when it occurs in the tract, resulting in greater perceived social disorder.

Effect of Racial/Ethnic Heterogeneity on Physical Disorder

Turning to the models predicting block-level perceived physical disorder, the effect of racial/ethnic heterogeneity, whether measured

[14] Since a standard deviation in racial/ethnic heterogeneity in the block is .226, this effect is calculated as exp(.226 × .597) = 1.144. Because a standard deviation in racial/ethnic heterogeneity in the tract is .193, this effect is calculated as exp(.193 × 1.0) = 1.213. An argument could be made to view these in terms of equal value changes rather than standard deviations. While such an approach is usually preferable, I argue in this instance that these differing standard deviations represent the fact that these measures likely will have differing ranges because of the differing aggregation levels. That is, tracts tend to have a smaller dispersion on these racial/ethnic heterogeneity measures since they are larger and more heterogeneous than the smaller unit of blocks. Indeed, this is empirically seen in this sample as the average degree of heterogeneity is higher in tracts (.279) than blocks (.227), but the standard deviation is smaller.

Table 3. Determinants of Perceived Physical Disorder, Including Block-Level and Tract-Level Measures of Neighborhood Composition

	(1)	(2)	(3)		(4)	
Neighborhood Measures	Block	Tract	Block	Tract	Block	Tract
Ethnic heterogeneity	.599**	.960**	.299	.820**	.202	.890**
	(2.79)	(4.20)	(1.31)	(3.22)	(1.09)	(3.54)
Average income	–.184**	–.026	–.172**	–.013	–.196**	
	–(5.79)	–(.76)	–(5.21)	–(.33)	–(6.75)	
Average length of residence	.110	.033*	.058	.036*		.032*
	(1.11)	(2.11)	(.51)	(2.11)		(2.34)
Proportion married (block), proportion divorced (tract)	–.324	1.030†	–.308	.760		.890
	–(1.34)	(1.65)	–(1.22)	(1.18)		(1.51)
Proportion with children, 0–5 years old	–.042	.102	–.114	–.539	–.144	
	–(.19)	(.13)	–(.52)	–(.67)	–(.67)	
Proportion with children, 6–12 years old	.429*		.386*		.418*	
	(2.55)		(2.18)		(2.42)	
Proportion with children, 13–18 years old	.216	.082	.151	.364	.216	
	(.92)	(.10)	(.63)	(.42)	(.95)	

Source: American Housing Survey special neighborhood subsample, 1985, 1989, 1993.
Notes: T-values in parentheses. N = 25,332 household time points, 2,256 block time points. Logit models with standard errors corrected for block-level clustering. All models include household level measures of gender, age, race, household income, education, length of residence (logged), marital status, number of children ages 0 to 18, owner, and persons per room. They also include block and tract measures of racial/ethnic composition, education, homeowners, vacant units, average age, and average person per room; and tract measures of the unemployment rate, percent teens not in the labor force, per capita bar employees, per capita liquor store employees, per capita restaurant/recreation employees, and graduation rate of local schools. Models also include county measures of percent urban, median income, racial/ethnic heterogeneity, Gini for household income, and indicator of year.
* $p < .05$; ** $p < .01$ (two-tail tests). † $p < .05$ (one-tail tests).

at the geographic level of the local block or the surrounding tract, remains robust, as seen in Models 1 and 2 of Table 3. A one standard deviation increase in racial/ethnic heterogeneity in the block increases the odds of perceived physical disorder 14.5 percent, whereas a similar increase at the tract level increases the odds 20.3 percent. This effect is stronger when aggregated to the broader tract, and in Model 3, which includes both the block- and tract-level measures simultaneously, the effect at the tract level remains significant while the effect of the block-level measure is halved.

Effect of Racial/Ethnic Heterogeneity on Crime

In the models predicting the common perception of crime, racial/ethnic heterogeneity behaves differently than in the models predicting social or physical disorder. While racial/ethnic heterogeneity measured at the tract level remains a strong positive predictor of perceived crime (Model 2 of Table 4), racial/ethnic heterogeneity measured at the block level is not related to perceived crime, controlling for the other block-level measures (Model 1 of Table 4).[15] This suggests that the effects of racial/ethnic heterogeneity are more geographically diffuse for perceptions of crime compared to perceptions of disorder.

[15] While one might plausibly assume that the effect of the neighborhood racial/ethnic composition might depend on the race/ethnicity of the respondent, no such effects are detected in this sample. I also estimated models that included an interaction between either the racial/ethnic heterogeneity of the block or tract and the race/ethnicity of the respondent, or an interaction between the racial/ethnic composition of the block or tract and the race/ethnicity of the respondent. No significant effects were found for the perception of crime or disorder, suggesting that these perceptions, given the racial/ethnic makeup of the neighborhood, do not differ based on the race/ethnicity of the respondent.

Table 4. Determinants of Perceived Crime, Including Block-Level and Tract-Level Measures of Neighborhood Composition

	(1) Block	(2) Tract	(3) Block	Tract	(4) Block	Tract
Neighborhood Measures						
Ethnic heterogeneity	.029	.080*	.033	.070		.080*
	(.97)	(2.18)	(.98)	(1.56)		(2.23)
Average income	.008*	.003	.008*	.001	.006†	
	(2.50)	(.82)	(2.19)	(.14)	(1.95)	
Average length of residence	–.025†	–.002	–.023†	–.001	–.029**	
	–(1.91)	–(1.05)	–(1.70)	–(.36)	–(3.15)	
Proportion married (block), proportion divorced (tract)	–.113**	.190*	–.074*	.160†	–.086**	.150†
	–(3.63)	(2.28)	–(2.45)	(1.90)	–(3.17)	(1.83)
Proportion with children, 0–18 years old	–.006	.120	–.001	.130	.006	
	–(.40)	(.80)	–(.03)	(.86)	(.48)	
Physical Characteristics						
Block perceived physical disorder	.274**	.223**	.239**		.236**	
	(5.02)	(4.18)	(4.47)		(4.44)	
Block perceived social disorder	.274**	.265**	.241**		.241**	
	(7.59)	(8.04)	(7.04)		(7.06)	
Variance Explained at Level 2	.88	.91	.91		.92	

Source: American Housing Survey special neighborhood subsample, 1985, 1989, 1993.
Notes: T-values in parentheses. N = 25,332 household time points, 2,256 block time points. Multilevel models using maximum likelihood estimation. All models include household level measures of gender, age, race, household income, education, length of residence (logged), marital status, number of children ages 0 to 18, owner, and persons per room. They also include block and tract measures of racial/ethnic composition, education, homeowners, vacant units, average age, and average person per room, and tract measures of the unemployment rate, percent teens not in the labor force, per capita bar employees, per capita liquor store employees, per capita restaurant/recreation employee, and graduation rate of local schools. Models also include county measures of percent urban, median income, racial/ethnic heterogeneity, Gini for household income, and indicator of year.
* $p < .05$; ** $p < .01$ (two-tail tests). † $p < .05$ (one-tail tests).

Effects of Other Structural Constructs on Disorder and Crime

Having seen that the racial/ethnic heterogeneity of the larger tract has a stronger effect on perceived crime and disorder than does the racial/ethnic heterogeneity of the local block, I now turn to the effects of the other structural characteristics in these models. Notably, average income has a very localized effect, though the direction of these effects differs dramatically depending on the outcome. While the average income of the *tract* has no effect in these models, higher levels of average income in the *block* *reduce* perceived physical and social disorder but *increase* perceived crime. For instance, a one standard deviation increase in the block average income reduces perceived social disorder about 18 percent and perceived physical disorder almost 40 percent. These findings are consistent with the routine activities perspective. While the presence of higher income households has the expected negative effect on disorder, they apparently provide attractive targets to motivated offenders.

On the other hand, residential stability shows very weak effects. There is no evidence that residential stability (whether measured at the block or the tract) reduces block-level perceived physical or social disorder, and there is only a modest negative effect (only significant for a one-tail test) on perceived crime when measuring residential stability at the block level. In fact, tracts with greater residential stability actually have higher levels of physical disorder when controlling for these other neighborhood characteristics. This is inconsistent with the social disorganization perspective that the stability of such neighborhoods enhances their ability to combat incivilities when they appear and hence results in lower levels of disorder. Since some

argue that stable, disadvantaged neighborhoods are particularly susceptible to crime and disorder (Warner and Pierce 1993; Warner and Rountree 1997), in ancillary analyses I also test for interactions between neighborhood stability and income measures and find no significant effects (results not shown).

Finally, there is strong evidence that the presence of broken households has consistent positive effects on social disorder and crime, though the geographical specificity of this effect differs depending on the outcome. For social disorder, the effects of broken households appear particularly localized. Whereas the proportion married in a block strongly reduces perceived social disorder (Model 1 of Table 2), the effect at the tract level is weaker (Model 2) and loses significance when these measures are included at both levels of aggregation simultaneously in Model 3. Thus, models aggregating this measure to the tract level, or even larger units of analysis, may run the risk of diluting this otherwise robust effect. This may explain the nonsignificant findings in some studies (Bellair 1997; Sampson and Groves 1989; Warner and Pierce 1993). Model 1 also shows that the presence of more unmarried households with children on the block strongly increases perceived social disorder; fewer married households and a greater number of young children (less than 12 years of age) in the block increase the amount of perceived social disorder. In this additive model, these combined results suggest that increasing the number of *married* households *with* children will have a similar effect on block-level perceived social disorder as increasing the number of *single* households *without* children (as this implies summing coefficients that are roughly of similar magnitude; a one standard deviation increase in the percent married decreases social disorder 13.3 percent, whereas a similar increase in the number of households with children ages 0 to 5 or 6 to 12 increases social disorder 5.8 percent and 8 percent). On the other hand, increasing the number of unmarried households with children has a particularly strong positive effect: a one standard deviation increase in unmarried households, households with children ages 0 to 5, and households with children ages 6 to 12 increases perceived social disorder 31.8 percent.

Although the effect of broken households on perceived social disorder appears particularly localized, their effect on perceived crime appears more diffuse. In Models 1 and 2 of Table 4, we see that marital status affects perceived crime, regardless of whether measured at the block or the tract level. Model 3 of Table 4 shows the additive effects from both the presence of divorced households in the surrounding tract and the local block when including them simultaneously. This again attests to the more geographically diffuse nature of crime compared to perceived social disorder. The presence of unsupervised youth likely increases residents' perception of crime, both on that block and neighboring blocks.

CONCLUSION

This article exploits a unique nonrural national sample of households nested within blocks, along with information on the census tract surrounding each block, to test the effect of both block- and tract-level aggregation of several structural characteristics posited to affect neighborhood crime and disorder. The findings suggest that for *all* studies of neighborhood effects, researchers should consider the appropriate level of aggregation. Carefully considering the causal mechanisms involved for these structural characteristics provides clues as to the proper geographic level of aggregation.

One important conclusion is that there is no single "appropriate" level of aggregation. Rather, it appears that the effects of these structural measures can work at different geographic levels. Additionally, some constructs work at different geographic levels depending on the outcome being studied. Such findings should not be particularly surprising or troublesome. Indeed, consideration of the theoretical mechanisms involved for these structural measures suggests that some of these differences are to be expected. Thus, whereas Land, McCall, and Cohen (1990) suggest that certain structural measures may obtain a degree of spatial invariance if measured correctly, it is reasonable to suppose that some measures do not have such invariance. As a result, the findings highlight the importance of measuring structural characteristics at appropriate geographic levels given the hypothesized theoretical mechanisms. The implications for researchers are clear: failing to measure constructs at the appropriate level of

aggregation can obscure structural effects that would otherwise be evident.

So what are the lessons regarding the geographical specificity of the key constructs of the social disorganization model? A notable finding is the particularly robust effect of racial/ethnic heterogeneity. This effect is particularly strong when measuring racial/ethnic heterogeneity at the wider tract level, suggesting that the broader networks affected by this heterogeneity may be more important for affecting crime and disorder than are local networks on the block. Racial/ethnic heterogeneity in the surrounding tract is positively related to block-level perceived crime, social disorder, and physical disorder, even controlling for the racial/ethnic composition of the block and tract and the racial/ethnic heterogeneity of the block.

In contrast, the effect of economic resources is particularly localized. Although there is no evidence that the average income of the larger tract affects the amount of perceived crime or disorder, the average income of the *local block* is important. However, whereas a higher average income on the block reduces perceived physical and social disorder, there is no evidence that such blocks are then able to reduce crime. Instead, the evidence is consistent with the routine activities theory that blocks with a higher average income provide a clustering of attractive targets for motivated offenders, as such blocks have *higher* levels of perceived crime when controlling for their lower levels of disorder. Studies employing larger geographic units of analysis are unable to detect these very localized effects. This effect of high-income households may be exacerbated when surrounded by lower income households, increasing the relative attractiveness of these targets, which is a possible avenue for future research. Given that these income effects are particularly localized, studies aggregating average income or outcome measures, such as crime or disorder, to larger units of analysis, such as census tracts, may be combining particularly heterogeneous blocks into a larger aggregation. Such a strategy has considerable potential to obscure otherwise detectable effects.

There is no evidence in these models that residential stability, whether measured at the level of the local block or the surrounding tract, decreases perceived social or physical disorder. Only when measuring average length of residence at the block level is there modest evidence that residential stability is associated with lower rates of block-level perceived crime. These findings are inconsistent with the social disorganization hypothesis that stability will reduce crime and disorder. It is possible that a different level of aggregation is needed to capture this effect. Perhaps a more intermediate unit, such as a block group, is appropriate. Nonetheless, this study highlights the importance of carefully considering and specifying these aggregate units when constructing theoretical models.

Finally, the aggregate broken households measure has differing effects for crime and social disorder. On one hand, the presence of broken households shows a particularly localized effect for fostering perceptions of social disorder. On the other hand, the presence of broken households on both local blocks and surrounding tracts simultaneously increases perceptions of crime. The fact that the lack of adult guardians, as measured by the presence of broken households, has a localized effect on social disorder but a more diffuse effect on perceived crime is unsurprising given the geographical mobility of such unsupervised youth and their ability (or even desire) to commit crimes outside their own block. Whereas the constant presence of a group of unsupervised youth hanging out on a block may create a localized perception of social disorder for the residents of the block, these youth likely impact the amount of crime on adjacent blocks.

While this study provides key insight into the appropriate level of aggregation when considering the effects of neighborhood structural characteristics on perceived crime and disorder, some limitations should be acknowledged. First, a more ideal approach would flexibly aggregate the structural characteristics to varying geographic sized areas, rather than just the block and the tract. For instance, Grannis (1998) suggests that a unit of analysis approximating block groups appeared to function as something proxying a neighborhood when viewing San Francisco and Los Angeles. Future studies should test the effects of this midsized geographic unit between blocks and tracts. Second, it is possible that a unit of analysis even larger than the tract may be appropriate in some instances. Indeed, studies have used units of analysis that combine two tracts (Logan and Stults 1999; Morenoff et al. 2001; Sampson et

al. 1997) or even nine or 10 tracts together (Almgren et al. 1998; Bursik 1986b; Heitgerd and Bursik 1987). Future studies should test for such possible effects, though given the heterogeneity over blocks within a tract for some of these measures it seems unlikely that such high levels of aggregation would be appropriate for many structural measures and theoretical questions. It should also be noted that I used a single question about the presence of bothersome people in the neighborhood to measure social disorder. While this is similar in spirit to social disorder measures constructed by others (Sampson and Raudenbush 2004), future research might test these spatial effects with a more complete scale.

This study measures crime and disorder based on the perceptions of these constructs as reported by block residents. Such a strategy is not uncommon in the social disorganization literature (Sampson and Raudenbush 2004; Sampson et al. 1997). Indeed, as highlighted above, it is not at all clear how we should measure the "true" level of crime or disorder in a neighborhood. Assessing the validity of measures of crime and disorder poses a particularly thorny issue since it raises the question of what can be considered a gold standard when measuring these constructs. Given the limitations of the three most frequently used measures of neighborhood crime—official reports to the police, victimization surveys, and perceptions of residents—it is unclear which is *truly* measuring the amount of crime. And given the somewhat ephemeral nature of social disorder, what is the "true" measure of this construct? Is it up to the ethnographer? Does the survey interviewer have a better understanding of neighborhood social disorder than do the residents? And even though physical disorder appears more straightforward to measure given its relative permanence, it still raises the question of why we might expect a trained observer viewing a neighborhood at one point in time to provide a more accurate assessment than would the residents living in the neighborhood. While physical disorder is relatively more permanent than social disorder or crime, it can ebb and flow as well—a window broken for three weeks can be fixed. Properly measuring physical disorder would require observations over a long period of time and somehow weighting the proportion of time that such physical disorder exists. Again, it seems likely that residents of a neighborhood are better able to do this than are trained observers viewing the neighborhood at one point in time.

Despite the lack of a gold standard for measuring crime, physical disorder, and social disorder, it is reassuring to note that there appears to be a considerable degree of correlation between the different measures of these constructs. For instance, a study in Chicago found a .56 correlation at the tract level between the researchers' coding of social disorder based on systematic observation and that reported by 3,864 respondents to a survey in 1994 to 1995 (Sampson and Raudenbush 1999). This same study found a correlation of .55 for the analogous measures of physical disorder. A second study found a correlation of .69 between the common perception of crime and official violent crime rates in tracts over several time points (Hipp 2007). Another study used three different measures of crime as outcomes—official crime statistics, victimization reports, and perception of crime by residents—and found that all three had similar relationships with the structural characteristics in the model (Sampson et al. 1997). A study of 50 blocks in Baltimore found adequate correlation between resident perceptions aggregated to the street block level and content analysis of crime- and disorder-related newspaper articles aggregated to the neighborhood level (Perkins and Taylor 1996).

Asking the residents of a neighborhood to assess the level of crime and disorder is thus not an unreasonable approach. While studies asking a single resident of a neighborhood to assess the characteristics of the neighborhood are clearly capturing something closer to a *perception* of crime and disorder (Austin, Furr, and Spine 2002; Geis and Ross 1998; Ross and Mirowsky 2001), combining the reports of several respondents on a block likely provides a relatively accurate portrayal. By taking into account certain demographic characteristics of residents that might influence their perceptions of neighborhood crime and disorder, the block-level estimates of crime, social disorder, and physical disorder are arguably quite good estimates of the true conditions in the neighborhood. Of course, it is possible that all residents on a block are equally uninformed regarding the true conditions of the neighborhood. While an intriguing possibility, I know of no studies pointing out measurable instances of such an effect.

Importantly, regardless of how crime or disorder are measured, the question of the appropriate level of aggregation will still be present. Given this, a fruitful direction for future research would employ different measures of crime and disorder when comparing the effect of different aggregations to assess the robustness of this study's findings.

As an aside, it is interesting to note that whereas this study uses resident reports of the neighborhood to measure disorder at the block level, this may not be possible when using systematic observation. For instance, whereas a study using systematic observation obtained high reliability estimates of social and physical disorder at the census tract level, this methodology in the same study broke down for observing street *blocks,* with a reliability estimate of just .37 for physical disorder and .00 for social disorder (Sampson and Raudenbush 1999:646). Such an approach is clearly not viable if there is considerable heterogeneity in the amount of disorder over blocks within the same tract. On the other hand, studies surveying residents in neighborhoods have shown more consistent reliability values for different levels of aggregation. One study obtained a reliability for social disorder of .67 at the block group level (Sampson and Raudenbush 2004), whereas another found a similarly high interrater reliability measure of .77 for residents in blocks (Perkins and Taylor 1996).

My findings highlight the importance of taking into account the appropriate geographic unit when measuring a *neighborhood.* Studies viewing the structural effects of neighborhoods on crime and disorder must consider the proper geographic unit both to aggregate the outcome measure of crime or disorder and to aggregate the structural characteristics used to explain this crime and disorder. For the outcome measures, a key consideration is that the researcher is not aggregating to units that contain a considerable amount of heterogeneity among the smaller units comprising them. This points out a clear need for future research to determine just how much heterogeneity exists across the microneighborhoods within a tract for crime and disorder. For the social structural constructs predicting crime and disorder, this article emphasizes that theoretical considerations can help in determining the appropriate unit of analysis. Researchers will need to consider this issue when measuring other neighborhood characteristics such as cohesion or collective efficacy. Simply measuring the reliability of such measures is not enough, as this article highlights that aggregating to an excessively large unit will potentially obscure relationships.

These findings also have implications for the more general neighborhood effects literature: while a common approach employs a multilevel model in which the individual-level outcome is in part explained by some neighborhood effects, carefully considering the appropriate level of aggregation is important. Failing to measure the aggregate effects at the proper unit of analysis given the hypothesized theoretical mechanisms may in part explain why some contextual effects appear to be small (Liska 1990). To the extent that the goal of research is disconfirmation of theories, such geographical aggregation issues are crucial. Failure to properly consider the appropriate level of aggregation leaves open the possibility that nonsignificant findings occur because of inappropriate measure of the aggregated construct, rather than a failing of the theory. Measuring these aggregate effects at more appropriate levels of aggregation may lead to estimates of contextual effects that are more precise and thus stronger.

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