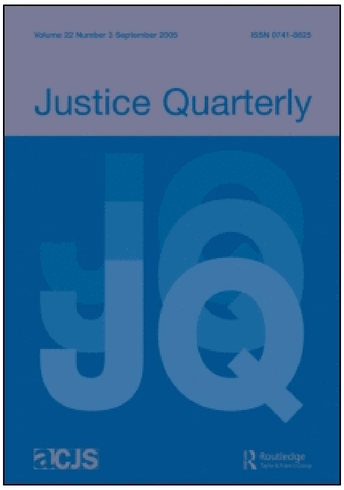

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On the Origins of the Violent Neighborhood: A Study of the Nature and Predictors of Crime-Type Differentiation across Chicago Neighborhoods

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Little of the literature on crime at the neighborhood level examines whether and why some crime types predominate in a given neighborhood over other types. Many macro-level theories do make predictions about the sort of crimes that occur in some neighborhoods, although they remain largely untested. This study focuses on one of these theories, differential opportunity, and its predictions about the making of violent neighborhoods. Drawing on various data sources, this inquiry determines whether crime profiles differ across Chicago neighborhoods—that is, whether there is significant variation across neighborhoods on ratio of violent crimes to other crime types. Next, it also investigates whether the structural factors implicated in the differential opportunity perspective distinguish these neighborhoods or only predict the incidence of crime. The results reveal significant differences in the distribution of crimes across neighborhoods, as well as show that certain factors identify neighborhoods that favor violence over other crimes.

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Introduction

The study of crime at the macro-level has generally focused on establishing why some neighborhoods have higher rates of crime than others. The social disorganization tradition is perhaps the most well-known and developed piece of this research. Beginning with the pioneering work of Shaw and McKay (1942), an extensive literature has linked weakened neighborhood structures with more crime. Shaw and McKay concluded that variation in delinquency across geographic areas was a function of the variations in social disorganization, defined as the breakdown in social institutions such as families, schools, and churches. In *Juvenile Delinquency and Urban Areas*, they also observed that a variety of social problems clustered in space along with delinquency, including truancy, infant mortality, tuberculosis, and mental disorder. They subsequently concluded that delinquency is not an isolated problem, but rather that the physical, social, and economic conditions of neighborhoods impact many social ills (see also Faris & Dunham, 1939; Silver, Mulvey, & Swanson, 2002). Thus, the social disorganization tradition leads researchers to expect a generality, or variety, of behaviors and social outcomes in socially disorganized neighborhoods.

Yet macro-theories of crime occasionally speak to variation in crime *types* within a geographically delimited unit, not just differences in the crime rate. Consider, for example, that the hypothetical distribution of offenses for all areas is approximately 40% violent and 60% nonviolent crime. Those areas featuring 70% violent and 30% nonviolent crime would represent a substantial departure from the prevailing pattern. The literature examining the factors responsible for the balance of violent to nonviolent crime within neighborhoods is quite scant, however, especially compared to what is known about the antecedents of overall neighborhood crime rates. Research has linked the key concepts of a number of macro-level theories, including differential opportunity (Cloward & Ohlin, 1960), with greater violence, yet this literature leaves open the possibility that the constructs theorized as facilitating higher rates of violent crime in fact lead to higher levels of crime across the entire spectrum of offense types, with no particular tendency toward violence (i.e., the count of violent crime is higher, but so too is property crime). An analysis that is specifically designed to study the contrast in violent and nonviolent crime rates across neighborhoods could clarify this issue and offer insight about the unique conditions that give rise to violent neighborhoods, thereby commenting on the need for theories to articulate violence-specific mechanisms. Should the factors purportedly fueling greater neighborhood violence in fact promote myriad outcomes, then violence-specific theories would have to be expanded to account for them. But the greater the differences between relatively violent high-crime neighborhoods and relatively nonviolent high-crime neighborhoods, then the greater justification there is for theories that disaggregate the mechanisms underlying various crime types in neighborhoods. Put another way, the answer to the question of whether neighborhoods significantly vary in the extent to which violence is responsible for their crime rates can have a profound effect on the evolution of macro-level theories of crime.

The current study attempts to fill this empirical void by investigating the extent to which neighborhoods in Chicago demonstrate a relative proclivity for violence over other crime types. Thus, this inquiry will comment on whether systematic variations in crime exist across neighborhoods, not just with regard to crime incidence, but also crime type. It also determines whether particular factors traditionally implicated as producing high levels of violence in neighborhoods (e.g., social disorganization) predict a differential tendency for violence as opposed to universally high crime rates across all types of crime. In order to do so, the current study uses data from the 1995 Project on Human Development in Chicago Neighborhoods (PHDCN) Community Survey, the 1990 Census, and officially reported crime data from the Chicago Police Department (CPD). It also relies on an extension of a recently developed analytic technique that detects both the extent and form of differential crime profiles (Osgood & Schreck, 2007). These data and this method afford the opportunity to investigate the theoretical expectations of the differential opportunity thesis with respect to the types of crimes which cluster in space.

Theory and Research on Differentiating Violent versus Nonviolent Neighborhoods

Whereas there is extensive literature on crime rates at the neighborhood level, little of it directly bears on the extent to which some neighborhoods favor particular crime types over others. The void of research explicitly addressing differential crime profiles at the neighborhood level, with regard to crime type rather than rate, is somewhat surprising since empirical work suggests that such patterns may exist. Early cartographic work that, in part, served as the foundation for the development of neighborhood-based theories demonstrated such patterns. For example, Balbi and Guerry mapped official crimes across France during the early part of the nineteenth century, noting that property and violent crimes tended to concentrate in different regions (see Weisburd & McEwan, 1998). More recently, research on crime at micro-level places (i.e., hot spots) also demonstrates that crime not only clusters at places, but that this concentration can be of particular crime types (Sherman, Gartin, & Buerger, 1989). The premise underlying hot spots draws heavily from environmental criminology (e.g., Cornish & Clarke, 1986) and routine activity theory (Cohen & Felson, 1979), suggesting that opportunities for crime vary across locations, whether because they provide differential access to crime targets, concentrations of motivated offenders or gaps in supervision/guardianship. In some cases, the opportunities for crime are ubiquitous, supporting a concentration of high crime rates that cut across all crime types. In other cases, however, hot spots reflect specific opportunities and crimes (e.g., Braga, Weisburd, Waring, & Mazerolle, 1999; Weisburd & Green, 1995). Because opportunities for crime are not solely dependent on the physical environment, but are also socially structured (Cloward, 1959), one may expect to see a similar pattern emerge at a slightly higher level of aggregation from hot spots: neighborhoods.

In addition to these empirical patterns, some core theoretical treatises on neighborhoods and crime discuss, explicitly or implicitly, how different social structures facilitate different crime patterns. These viewpoints arguably include subculture of violence perspectives, strain theories, and opportunity theories that focus on how the proximate environment affects the nature of crime. Perhaps the most explicit theory on this score is Cloward and Ohlin's (1960; see also Cloward, 1959) differential opportunity theory—indeed, a core contribution of this theory is its assertion that neighborhood characteristics mediate and shape the expression of crime. In an attempt to bring together the contemporary dominant theoretical traditions—anomie and differential association—into a single explanation, they proposed that crime arises because of frustration associated with unequal access to legitimate means to achieve success. For this reason, there is systematic variation in crime rates across places and populations, with neighborhood disadvantage being a key indicator of where high crime rates tend to cluster. Scholars often rely on this part of their proposition to label Cloward and Ohlin strain theorists, but the unique contribution of their argument is in their clear statement that "the pressures that lead to deviant patterns do not necessarily determine the particular pattern that results" (Cloward & Ohlin, 1960, p. 40; Cullen, 1988). They argue that, just as legitimate means are not equally distributed, nor are illegitimate means; opportunities to learn and engage in various types of crime are differentially distributed across neighborhoods. Thus, Cloward and Ohlin (1960) suggested that in disadvantaged neighborhoods, strain provides the motivation for crime and generally leads to higher crime rates. But a neighborhood's social structure channels this motivation so that the higher crime rates manifest in differential crime-type profiles (i.e., they anticipate both fluctuation in the incidence and distribution of crime proportions across neighborhoods). In particular, "criminal" subcultures situated around property crimes form in neighborhoods characterized by dense, though unconventional, social ties and cohesion while "conflict" subcultures situated around violence form in areas lacking integrated social relations and networks.

Just as differential opportunity theory implicated the role of social ties in the production of crime, so too does social disorganization theory, though with contrasting predictions. In socially disorganized areas, characterized at the macro-level by factors such as residential mobility and economic disadvantage, social networks are sparse or weak and formal and informal social controls are constrained (Bursik, 1986, 1988; Sampson & Groves, 1989). Under the social disorganization perspective, the void of stable and cohesive social networks in a neighborhood leads to a generalized increase in crime, of which violence is part. From this standpoint, structural factors should affect the incidence of crime but not necessarily the differential distribution of its form; factors indicative of social disorganization should not be implicated in shaping crime patterns that favor one type (e.g., violence) in any systematic way. To be sure, the original data with which Shaw and McKay (1942) illustrated their premise focused on a variety of delinquent offenses, not particular crime types (see also the complementary work of Thrasher, 1927).

In contrast, Cloward and Ohlin's (1960) differential opportunity perspective proposes that social disorganization leads to the emergence of a conflict subculture, not to generalized and universally high crime rates. As per their argument, in socially disorganized areas, there is a void of both legitimate and illegitimate means to deal with strain, and violence becomes the only way to achieve status and success. Cloward and Ohlin argued that socially disorganized neighborhoods provide neither the opportunities nor the learning models for skills oriented around property crime enterprises, which would limit the incidence of property-related offenses. The fractured social cohesion and instability of the neighborhood, however, curtails its ability to manage and control violence, thereby allowing violent offending to comprise a greater share of the neighborhood crime distribution. Whereas some theorists find it paradoxical that socially organized areas can have high crime rates, Cloward and Ohlin (1960; Cloward, 1959) argued that criminal enterprise subcultures can flourish in economically deprived neighborhoods that have sufficient social cohesion and interconnectedness of legitimate and illegitimate social networks, which bears out in some empirical work (Chin, 1996; Whyte, 1943). In this way, they also imply that some neighborhoods may have crime profiles that favor nonviolent crime.

Importantly, it does not appear that differential opportunity suggests that *only* violent crime will occur in neighborhoods devoid of social organization; offenders may channel frustration and seek status though occasional vandalism and theft, for example. Still, Cloward and Ohlin are clear in their assertions that, relative to other neighborhoods, violence should be a defining characteristic of socially disorganized areas and not merely part and parcel of high crime rates. In the end, therefore, the traditional social disorganization perspective asserts that structural indicators such as instability and weak social networks should identify high-crime neighborhoods, whereas differential opportunity argues that they should identify neighborhoods dominated by violence.

The literature does highlight an empirical connection between social disorganization and violence. For example, Sampson (1987) found that the key mediator between black unemployment and city-level violence was family breakdown, since it impacted social control and stability at both the neighborhood and individual levels. In this way, the argument is that economic deprivation does not inherently promote violent crime, but rather its effect operates primarily through weakened family and neighborhood social structure. More recent work echoes this point. Ousey (2000) found that deindustrialization, which amplifies economic disparity, promotes violent crime (juvenile homicide) because it increases the amount of female-headed households, which also affects social controls at the neighborhood level. Like Sampson (1987), he argued that neighborhoods with higher rates of female-headed households tend to have lower levels of formal social control, since single mothers tend to be less involved in neighborhood organizations, as well as informal social control, since single parent households tend to be less involved with neighbors. Furthermore, Ousey (2000) hypothesized that fathers who abandon family roles and are also deprived of economic opportunities because of deindustrialization are essentially excluded from legitimate social networks, increasing the odds of violence in the neighborhood. Sampson et al.'s work on collective efficacy also clearly draws a connection between a vacuum of social organization, residential stability, cohesion, and violent crime (Sampson, Raudenbush, & Earls, 1997; see also Clear, Rose, Waring, & Scully, 2003; Rosenfeld, Messner, & Baumer, 2001; Taylor & Covington, 1988).

Collectively, such studies demonstrate that disadvantaged neighborhoods characterized by social instability and a void of cohesion will have higher rates of violence. These notions certainly evoke Cloward and Ohlin's (1960) arguments that a void of integrated and cohesive social networks can promote a violent subculture, since it limits opportunities for other criminal enterprise and the neighborhood has a limited capacity to control youth violence. But it remains unclear whether these factors (1) truly underlie a neighborhood proclivity for violence over other crime types, or (2) instead affect crime in a universal manner. Studies that only focus on violence as an outcome (e.g., Ousey, 2000; Sampson, 1987; Sampson et al., 1997) may miss complementary high nonviolent crime rates. Indeed, studies that do account for property crime often find it too has a relationship with macro-level social instability and social disorganization (Crutchfield, Geerken, & Gove, 1982; Kposowa, Breault, & Harrison, 1995; Raudenbush & Sampson, 1999; Sampson & Groves, 1989). In this way, there remains the question as to what degree malfunctioning neighborhood structure specifically favors violence relative to other crime types or whether neighborhood conditions fuel proportionate growth in all crime.

There are a few indications that structural and organizational factors may affect violent and property crime in different ways. For instance, Stark, Doyle, and Kent (1980) and Stark, Bainbridge, Crutchfield, Doyle, and Finke (1983) found that certain measures of social integration, such as church membership, were more strongly related to property crime than violent crime (see also Kposowa et al., 1995). Hipp's (2007) recent analysis of police data across 19 cities offers perhaps the best evidence on the factors responsible for crime-type differentiation across neighborhoods. One of the research questions he explored was the impact of various structural dimensions of neighborhoods on violent and property crime rates. Running separate models for violent (murder, aggravated assault, robbery) and nonviolent crime (burglary, motor vehicle theft), Hipp found that greater inequality and ethnic heterogeneity resulted in higher crime rates overall, but the effect coefficients were typically more salient for violent crimes than property crimes. Like previous studies investigating both property and violent crime, however, Hipp's (2007) results are still suggestive, as his primary focus was on explaining overall crime rates and not on defining or directly measuring the contrast in violent versus nonviolent offending at the neighborhood level. Thus, extant literature cannot address the key point at which social disorganization and differential opportunity diverge. Disorganization scholars generally assume that disorganized neighborhoods will produce a variety of crimes whereas differential opportunity adopts a view that the same structural and organizational conditions would promote a distribution of crime where violence comprises a much larger share of the criminal activity. Findings to date reveal that a variety of crime and social problems are associated with disorganization, but it is not yet certain if disorganization predicts a relative tendency for violent crimes over other types.

The Current Study

While there is considerable empirical evidence that neighborhood social ties and disorganization influence rates of crime (see e.g., Bursik & Grasmick, 1993; Sampson & Groves, 1989; Sampson et al., 1997), it remains unclear whether a void of integrated and cohesive social networks (1) underlie a neighborhood proclivity for violence over other crime types, or (2) instead affect crime in a universal manner. A proclivity for violence may occur because certain conditions give rise or permit violent crime but not property crime, or because these conditions affect violent and property crime to different degrees (i.e., weak social networks may increase both crime types, but the magnitude may be greater with regard to violence). In this way, neighborhood factors may not only impact the local crime rate, but also predict variations in the relative portion of crime types that comprise this rate.

The current study addresses this issue by using a newly developed analytic method that can detect differential crime profiles at the neighborhood level, drawing on official crime reports from the Chicago PD. After assessing whether there are significant differences in the relative distribution of crime types (i.e., violence and nonviolence) across neighborhoods, this inquiry will determine whether structural factors reflective of a void in social organization predict this differential tendency, independent of local crime rates. If disorganization produces a significantly greater preponderance of violence, then differential opportunity theory is supported, but if the indicators of disorganization do not result in a significant differential impact on the contrast of violence to nonviolence in the neighborhood, then the notion that social disorganization has general effects would be supported.

Data and Measures

Data utilized in this study come from three sources: the PHDCN, the 1990 U.S. Census, and the CPD. Measures of neighborhood social processes come from the

PHDCN 1994–1995 Community Survey of 8,782 Chicago residents. For the purposes of the PHDCN, neighborhood boundaries were operationally defined by combining 847 census tracts into 343 neighborhood clusters, constructed to be internally homogeneous with respect to socioeconomic status, race/ethnicity, housing density, and family structure (Sampson et al., 1997).[1] Survey questions include items about the social organization of neighborhoods, including an emphasis on neighborhood social ties.

Recall Cloward and Ohlin's (1960) assertion that criminal subcultures oriented toward property crimes form in neighborhoods characterized by dense social ties while conflict subcultures situated around violence form in areas lacking integrated social relations. Thus, we utilize a measure of *neighborhood social ties* in our analyses and hypothesize that violence will be relatively more prevalent compared to nonviolent crime in those neighborhoods characterized by weak neighborly social ties. We construct a scale of neighborly ties with the following survey items related to the frequency (i.e., how often) of contact and support among neighbors: (1) Do you and people in your neighborhood do favors for each other? (2) Do you and other neighbors watch over someone's property when they are not home? (3) Do you and people in your neighborhood ask each other for advice? (4) Do you and people in your neighborhood have parties where other people in the neighborhood are invited? and (5) Do you and other people in your neighborhood visit in each other's home or on the street?[2]

Our measure of neighborhood social ties was constructed via a multilevel regression model, with item responses to each survey question nested within a respondent, and respondents nested within neighborhood clusters (see also, Raudenbush & Sampson, 1999; Sampson & Bartusch, 1998). The first level of the model represents an item response model with scale scores adjusted for missing data and unreliability. At the second level of the model, scale scores are adjusted for the individual characteristics of respondents in neighborhood clusters (gender, age, race and ethnicity, marital status, education, employment status, homeownership, years of residence in neighborhood, and the number of residential moves in the five years leading up the survey). At the third level of the model, each neighborhood-specific mean for a given scale is allowed to vary around the mean score for the city as a whole. From this three-level regression

1. In analyses, we follow the standard practice of many PHDCN studies of excluding the neighborhood cluster which contains O'Hare airport.

2. We specifically use this measure in lieu of collective efficacy, which is a combination of social cohesion (e.g., people around here are willing to help their neighbors) and informal social control (which focuses on neighbors' willingness to intervene upon witnessing deviance). In theory, collective efficacy can be applied to achieve any collective goal; yet in practice, measures of collective efficacy are infused with a prosocial and conventional quality. Thus, the traditional measurement of collective efficacy does not match the key point at which differential opportunity and social disorganization differ, which is the notion that neighborhood ties and cohesion are not inherently prosocial. Because some scholars may not view social disorganization in this systemic way, but rather see it as focusing on legitimate ties and networks, we also estimated models with collective efficacy. Supplemental analysis, available upon request, demonstrates that collective efficacy behaves in a manner similar to the neighborhood ties measure. Still, because it is more consistent with our theoretical framework, we present the results with the neighborhood ties variable.

model, a neighborhood-specific empirical Bayes residual is output, which is the neighborhood-specific scale we use in analyses (see Raudenbush & Bryk, 2002, chap. 3).

Neighborhood structural data come from the 1990 U.S. Census. Consistent with research in the social disorganization tradition, we utilize three measures of neighborhood structure: concentrated disadvantage, residential stability, and immigrant concentration. A meta-analysis of the social disorganization literature indicates that these measures generally are predictive of neighborhood crime and disorder (Pratt & Cullen, 2005). These scales are created via factor analyses from resident responses to multiple census questions, where items included in each factor are weighted by their factor loadings. Concentrated disadvantage refers to a scale of economic disadvantage influenced by poverty, family status, age, employment, and race. Specifically, the following census indicators are used to construct the measure: the percentage of families below the poverty line, percentage of families receiving public assistance, percentage of unemployed individuals in the civilian labor force, percentage of female-headed families with children, percentage of residents under age 18, and the percentage of black residents. Residential stability is derived from the following census indicators: percentage of residents five years old and older who lived in the same house five years earlier, and the percentage of homes that are owner-occupied. Finally, immigrant concentration is derived from two census indicators: the percentage of Latino residents and the percentage of foreign-born residents.

Incident-level *reported crime* data for the years 1995 and 1996 were obtained from the CPD.[3] Address information from each incident was used to geocode the location of the crime to the corresponding PHDCN neighborhood cluster. Readers should note that the available data for these two years contain slightly different assortments of offenses. For 1995, violent crimes included assault, homicide, and robbery. Nonviolent crimes included burglary, vandalism, auto theft, theft, drugs, and vice. The 1996 data reported aggravated assault, assault, homicide and robbery (for violence) and vandalism and burglary (for property offending). As detailed in the next section, we combine these measures into latent variables using measurement modeling techniques, which should reduce variations in the results arising from measurement errors. The relevant items and their descriptive information are reported in Appendix A. Though many studies investigating crime at the neighborhood level have relied on official records (e.g., Bursik, Grasmick, & Chamlin, 1990), scholars nonetheless recognize their limitations and provide appropriate caution. Although we know some about individual-level determinants of reporting crime, the extent to which neighborhood level factors impact reporting, and in which direction it operates, remains clouded (see Baumer, 2002). For this reason, even though we believe the current data are the best suited to the question at hand, we acknowledge the limitations of using official records.

3. Data were provided by CPD's Division of Research and Development. Findings from use of these data in no way represent the views of CPD or the City of Chicago.

Analytical Methods

Our analytic strategy consists of two steps: first we employ a modified version of a statistical model developed by Osgood and Schreck (2007) to detect differential crime profiles. Second, after estimating each neighborhood's crime profile (i.e., the relative proportion of violent to nonviolent crimes), we model that profile as a function of neighborhood structural predictors and social ties in a spatial regression model. As the aforementioned article provides a detailed explanation of the technique, this presentation is limited to the main features (see also, Schreck, Stewart, & Osgood, 2008) and our modifications.

Detecting Crime Profiles

Osgood and Schreck's (2007) method derives from an item response theory (IRT) conception of measurement (Osgood, McMorris, & Potenza, 2002) in a multilevel regression framework (Raudenbush, Johnson, & Sampson, 2003). This model provides some important benefits for the current investigation relative to a more traditional regression or, for instance, a geographically identified system analysis that either treats violent and nonviolent crime as separate dependent variables or else uses the ratio of violent to property crime. First, our analysis can assess whether there are significant differences in the crime distributions across neighborhoods, relative to population base rates for each offense type. This allows us to determine the extent to which neighborhoods truly vary and are unique in their crime distributions, as opposed to demonstrating differences generated by chance. Second, our approach addresses any potential confounding between overall crime rates and the tendencies of neighborhoods to differentiate by crime type, as well as controls for the measurement precision of the data. Taken together then, the model can distinguish between (1) neighborhoods with high levels of violence, but where there are also concomitantly high levels of nonviolent crime, and (2) neighborhoods that are significantly different from the mode with regard to the portion of their criminal repertoire that comprises violent crime.

At Level 1, the multilevel regression model specifies a measurement model defining two indices, the first reflecting the combined violent and nonviolent crime rates within neighborhoods and the second reflecting the differential tendency among neighborhoods toward either violent or nonviolent crime. This level therefore will provide insight as to whether there is any evidence of systematic differences in crime type across neighborhoods, or simply differences in crime incidence. The Level 1 unit of analysis is the rate of offending within a neighborhood for a specific type of crime, and the Level 2 unit of analysis is the neighborhood. Integrating these two levels of analysis in a single model enables us to address the variation across neighborhoods in the overall rate of crime as well as the relative proclivity of violent to nonviolent crimes.

In the notation of hierarchical linear modeling (HLM; Raudenbush & Bryk, 2002), our Level 1 regression equation is:

$$Y_{ij} = \beta_{0j} + \beta_{1j} Vio + \sum_{i=2}^{I-1} \beta_{ij} D_{ij} \tag{1}$$

The Level 2 regression equations are:

$$\beta_{0j} = \gamma_{00} + \mu_{0j} \tag{2}$$

$$\beta_{1j} = \mu_{1j} \tag{3}$$

$$\beta_{\text{ij}} = \gamma_{i0} \tag{4}$$

The Level 1 equation serves as the measurement model and it establishes the meaning of the Level 2 equations. IRT models often employ dichotomous item-level data (Osgood et al., 2002); however, neighborhood-level crime rates are continuous measures. HLM can accommodate non-dichotomous data in several ways: via ordinal logistic, Poisson, or linear regression models. Given the continuous nature of our data, we specified linear regression and log-transformed the crime rates in order to normalize their distribution. This converts the Level 1 measurement model from the more complex linear form of IRT models to the more straightforward linear form of classical measurement models (see Baker, 2001). The Level 1 outcome measure thus is neighborhood *j*'s rate or offense type *i*. Should neighborhood *j* report, for instance, that 50 offenses occurred for every 100,000 residents for offense *i*, then Y_{ij} = 50.

Overall crime rate

In Equation (1), the rate for each offense within the neighborhood will depend on three factors. The first is the equation's constant term, β_{0j}, which applies equally to all offense types. This coefficient varies randomly across neighborhoods, as indicated by the residual term in its Level 2 equation (u_{0j} of Equation (2)). Accordingly, β_{0j} is a latent variable that captures neighborhood differences in crime rates across all offenses, or the overall crime rate. The variance of the residual term u_{0j}, or τ_{00}, reflects the extent of neighborhood differences in this tendency. The amount of variance depends on the degree to which higher offense rates for each offense are associated with higher rates for all other offense types.

Differential in violence versus nonviolence

In Osgood and Schreck's (2007) basic model, the second factor determining the rate for a given offense is the neighborhood's level of favoring violent crime. β_{1j} takes on this meaning when the variable *Vio* is coded with a positive value for measures of violent crimes and a negative value for measures of nonviolent crime. To avoid any confound between differential distributions of violence and overall crime, *Vio* is coded to have a mean of zero for every neighborhood (i.e., a group-mean-centered dummy variable). β_{1j} provides an index of this differential tendency calibrated to reflect the difference between a neighborhood's log rate of violent crime versus its log rate of nonviolent crime.

Neighborhoods with a relative preponderance of violent crime to nonviolent crime would have a higher rate of offending for crimes with positive values on *Vio*, and thus a positive value on β_{1j}. Where the distribution of crime rates favors nonviolent crime, the opposite pattern will occur and result in a negative value on β_{1j}. Because the Level 2 equation for β_{1j} includes a residual term, this index of neighborhood violence is a latent variable that varies across neighborhoods, and the corresponding variance term (τ_{11}) will reflect the extent to which neighborhoods systematically differ in their tendency toward violent versus nonviolent crime. An absence of variance would indicate a complete overlap in violent and nonviolent crime, with observed variation across neighborhoods due only to chance. A high level of variance, on the other hand, would be indicative that the two are quite distinct.

Item base-rates

The third factor contributing to the magnitude of a neighborhood's crime rate for a given offense is the base-rate of offenses, expressed by the parameters β_{ij}. Relatively rare forms of crime, which typically are more serious as well (Osgood et al., 2002; Raudenbush et al., 2003), will have lower values of β_{ij} and more common crimes will have higher values. These parameters are incorporated in the model through a series of dummy variables coded to reflect which item is associated with each response (i.e., a value of 1 for that dummy variable and 0 for all others). These base-rate parameters are constant across the sample rather than varying across neighborhoods, as reflected in the absence of a residual term in Equation (4).[4]

Spatial Regression

Neighborhoods are interdependent ecological units, such that the conditions in one neighborhood are influenced by the conditions of spatially proximate neighborhoods. Spatial dependence among neighborhoods arises, in part, because we are artificially dividing a continuous geographic space (i.e., Chicago) into sepa-

4. Our measurement model is a Rasch model, which assumes that all items are equally related to the latent variable, and we assessed the plausibility of this assumption in the same manner as Osgood and Schreck (2007). Consistent with this assumption, (1) all items were positively correlated with each other and had high positive loadings on a first factor in a factor analysis, and (2) violent crime items generally were more strongly associated with one another than with nonviolent offense items (Osgood & Schreck, 2007; Raudenbush et al., 2003). The model also assumes that the residuals of the latent variables (u) have a multivariate normal distribution, and our tests indicated no violations of this assumption.

rate neighborhoods. Thus, it may be the case that: (1) the crime rate in a given neighborhood is influenced by the extent of crime in proximate neighborhoods, and (2) that the proportion of violent to nonviolent crime in a given neighborhood is influenced by the proportion in proximate neighborhoods. Accordingly, prior research suggests that ignoring spatial dependence may lead to biased parameter estimates and erroneous conclusions about statistical significance (Anselin, 1988; Baller, Anselin, Messner, Deane, & Hawkins, 2001; Messner et al., 1999).

In order to estimate a spatial model, we output the Level 2 residuals from Equations (2) and (3) from the multilevel framework previously described, and import those residuals as dependent variables into a software program designed for undertaking spatial regression analyses.[5] With a spatial lag model, we estimate two separate regression equations, one for the overall crime rate (β_{0j}) and another for the violence differential (β_{1j}).[6] In these equations, we model the respective dependent variable as a function of *concentrated disadvantage*, *residential stability*, *immigrant concentration*, and *neighborhood ties*, while also controlling for spatial autocorrelation. Thus, through such an analytic framework, we are able to detect the association between our four measures of neighborhood characteristics and our dependent variables, net of spatial dependencies. Readers should be aware, however, that using predicted scores derived from latent variables in a basic regression analysis has some potential problems of its own, as a large number of items is needed to reduce potential bias in the predicted scores (see Lu, Thomas, & Zumbo, 2005).[7]

Results

Our initial question concerns the significance of the contrast of violent to nonviolent crime across neighborhoods, or whether any observed variations in the patterns can be ruled out as plausibly a byproduct of chance. To address this, Osgood and Schreck (2007) used a *z* test, which employs the relevant variance components (τ_{11}) to assess whether adolescents had different violent offending histories. Here, we use the same strategy to see if individual neighborhoods reveal significantly different violent crime profiles. Note that the information reported in Table 1 omits explanatory (i.e., Level 2) variables, as we are interested in the

5. All spatial models reported to follow were estimated in the GeoDa program.

6. Given the existence of spatial autocorrelation, it must be determined how to incorporate spatial dependence into model specification. There are two general approaches for introducing spatial dependence into regression models: spatial lag terms and spatial error terms. In preliminary analyses, we employed a Lagrange Multiplier test to assess spatial autocorrelation, and to assess the exact form of spatial dependence. We find evidence of spatial autocorrelation with respect to crime (β_{0j}) and violence differentials (β_{1j}), and that a spatial lag model is most appropriate for modeling these dependent variables.

7. To provide some speculative information about whether the bias might affect our substantive results, we also ran a latent variable regression with predictors (as shown in Osgood & Schreck, 2007). This does not control for spatial autocorrelation, however. Even so, the results of this analysis are consistent with those reported here, indicating that the bias does not affect the significance of our key variables.

Table 1 Reliability and variance of overall crime rates and neighborhood violence differentials

	Overall crime rates		Violence differential	
	1995	1996	1995	1996
Reliability	.83	.83	.54	.51
Variance (τ)	.49 (.05)	.69 (.07)	.54 (.08)	.69 (.11)

Note: Standard errors of τ in parentheses.

full variances. The ratio of the variance components for the latent variables to their standard errors must exceed 3.3 if they are to be significant at the .001 level. Since the ratios for both years are 6.8 and 6.3, respectively, for 1995 and 1996, our results show that there is significant differentiation in crime patterns across neighborhoods, and that this is unlikely to have been generated by chance. Moreover, a comparison of the variances of the violent crime differential measures to those for overall crime rates shows that they account for a substantial portion of the overall crime rate within the average neighborhood.[8]

The variance components also speak to the degree of this systematic variation in the proportion of violence for a neighborhood's reported crime rate. The variance in 1995 was .54 with a standard deviation of .74. Exponentiating the standard deviation indicates how much each standard deviation increase in the tendency for violence multiplies the ratio of the rate of violent crime to the rate of nonviolent crime. For 1995, this meant that each standard deviation increase in the violent crime differential resulted in the rate of violent offenses growing by more than two for every unit increase in the rate of nonviolent offenses (exp(.74) = 2.10). For 1996 (τ = .69, *s* = .83), the pattern was very similar (exp(.83) = 2.29).

To provide another perspective on the magnitude of differential distributions of violence, we report in Table 2 the average violent and nonviolent crime rates (per 100,000 people) for all neighborhoods based on their classification as either "violent," "neither violent nor nonviolent," or "nonviolent" neighborhoods.[9] HLM scores each case based on how far that neighborhood's distribution of violent to nonviolent crime deviates from population base rates. Those neighborhoods with a positive score for *Vio* and, moreover, are one standard deviation or greater from the mean are the "violent" neighborhoods. Neighborhoods that are at least one standard deviation from the mean in a negative direction are the "nonviolent" neighborhoods. The remaining cases are classified as "neither," with a distribution of crime generally approximating the overall distribution of

8. Table 1 also reports reliabilities for both latent variables across each wave. The measure for overall crime rates is highly reliable, exceeding .80 for both years. In contrast, the differential violence variable is considerably less reliable (.50 for each wave). A measurement model approach is therefore valuable with respect to addressing limited measurement reliability.

9. The rates reported in Table 2 are not log-transformed. The rates shown here reflect the average rate for the violence and nonviolence items for each year.

Table 2 Observed rates of violent and nonviolent offending, by type of neighborhood

		Observed distribution of crime rates			
Year	Level of differentiation	Violent	Nonviolent	Ratio	*n*
1995	Violent (≥ +1 SD)	3352.60	2415.10	1.41	91
	Neither (≥ −1 SD and ≤ +1 SD)	2148.65	2117.39	1.00	145
	Nonviolent (≤ −1 SD)	1367.78	1523.71	.86	106
1996	Violent (≥ +1 SD)	3794.08	2784.34	1.36	76
	Neither (≥ −1 SD and ≤ +1 SD)	1696.33	1976.07	.83	182
	Nonviolent (≤ −1 SD)	772.08	1494.96	.50	84

violence to nonviolence. These classifications are somewhat arbitrary in that Osgood and Schreck's (2007) technique treats differential crime profiles as a continuous variable, but they are sufficient to provide a rough comparison of crime rates. Within each category, there will not be uniformity among neighborhoods in terms of their distribution of crime.

Table 2 reveals several interesting patterns. The neighborhoods we classified as "violent" tend to have higher crime rates across the board than the other two types of neighborhoods. That is, "violent" neighborhoods had high rates of nonviolent as well as violent crimes. Note, however, that for 1995, the ratio of violent to nonviolent crimes was 1.41 to 1 (and 1.36 to 1 for 1996). For every property crime that the police learned about from these neighborhoods, roughly 1.4 violent crimes were reported. The neighborhoods that tended toward neither violence nor nonviolence typically had a somewhat more even balance of violent to nonviolent crimes, and lower rates of crime overall relative to the "violent" neighborhoods. "Nonviolent" neighborhoods comprise the remainder of cases, and not only did they have the lowest rates of crime generally, the ratio of violent to nonviolent crime distinctly favored nonviolent crimes (i.e., .86 and .50 violent crimes for every nonviolent crime in 1995 and 1996, respectively). In short, as we mentioned earlier, it would be a mistake to characterize violent neighborhoods as places where only violent crime takes place. Rather, such neighborhoods reveal a lot of crimes of all types; however, there is a differential clearly tending toward violence.[10]

If these results are to justify further study, then crime-type differentiation should be an enduring property of the neighborhood and not a transient finding.

10. As discussed earlier, this model detects differential crime profiles/distributions relative to population base rates. This means that if the modal ratio of violent to nonviolent crime was .3 to 1, then neighborhoods that averaged .8 violent crimes for every 1 nonviolent crime might have significantly different profiles and therefore be deemed the relatively "violent" neighborhoods. This may not strike some scholars as having face validity, certainly in comparison to the differential ratios that emerged in the current investigation. Still, because the "average" proportion of violence in the crime rate likely varies from location to location (much like the average crime rate would), having some objective scale of what constitutes relatively violent neighborhoods may be misleading. Such a scenario remains hypothetical, but we nonetheless urge replication of our inquiry outside Chicago in order to frame an empirically informed discussion of this issue.

Table 3 Correlations among 1995 and 1996 measures of overall crime rates and the violence differential (n = 342)

	Overall crime rates		Violence differential	
	1995	1996	1995	1996
Overall crime rates				
1996	.94* (.05)			
Violence differential				
1995	.93* (.06)	.76* (.05)		
1996	.96* (.07)	.99* (.06)	.78* (.07)	

*p < .05.
Note: Standard errors in parentheses.

Given that we have multiple years of crime data, we are able to examine the stability of these differential tendencies for violence. We obtained stability estimates by correlating the latent variables for overall crime and *Vio* with themselves, and these results are reported in Table 3. Overall crime rates for 1995 and 1996 were nearly perfectly correlated, meaning that neighborhoods reported levels of crime virtually identical in magnitude from one year to the next. This result is consistent with those reported in the earliest literature on social disorganization (Shaw & McKay, 1942). The stability of the differential between violence and nonviolence, however, is not as well documented. Our results showed that there is impressive consistency in the tendency of neighborhoods to favor violence between the years 1995 and 1996. Recall that 1995 and 1996 employed slightly different measures, so this correlation probably reflects correction for measurement error. Thus, not only do the "violent neighborhood" crime ratios look remarkably similar from year to year despite some measurement differences, but the neighborhoods are nicely consistent in these ratios over time. The remaining coefficients in Table 3 report the intercorrelation between overall crime rates and crime differentiation for both years. The strong positive correlation values verify what Tables 1 and 2 indicated earlier, which is that neighborhoods with higher crime also tended to have an increasing preponderance of violence within their overall pattern.

Table 4 shows how measures central to social disorganization and differential opportunity theories perform with respect to predicting overall (logged) crime rates and differential distributions of violence, net of our control for spatial autocorrelation. The results for the overall crime models are consistent with earlier work based on PHDCN data using the same or similar measures (e.g., Browning, Feinberg, & Dietz, 2004; Sampson et al., 1997), and we report them here primarily to replicate earlier research and verify that our measures are performing as expected. The coefficients in Table 4, under the "violence differential" columns, report the log-rate differential for violent and nonviolent crime for each unit increase in the independent variable. Should a coefficient

Table 4 Relationships of explanatory variables to overall crime rates and violence differential (*n* = 342)

	1995				1996			
	Crime rates		Violence differential		Crime rates		Violence differential	
	γ^1	SE	γ	SE	γ	SE	γ	SE
Immigrant concentration	−.09*	.02	−.06	.05	−.09*	.03	−.06	.04
Concentrated disadvantage	.24*	.03	.23*	.52	.32*	.03	.30*	.05
Residential stability	−.05*	.02	.09*	.05	−.02	.03	.01	.04
Network ties	−.63*	.13	−1.20*	.28	−.51*	.16	−.85*	.24
Intercept	1.58*	.35	3.05*	.72	1.23*	.40	2.14*	.53

[1]γ is the HLM population average estimate and SE its robust standard error. Spatial lag coefficients excluded from the results reported here.
*$p < .05$.

here not be statistically significant, that would only signify that its effect does not disproportionately influence the log-rates for either violent or nonviolent crime and would thus support the generality of the effects of social disorganization. Variables with differential effects will achieve statistical significance, and thus support differential opportunity theory's predictions. Again, the effects of the coefficients in the violence differential models are independent of overall crime rates.

For both 1995 and 1996, two of the indicators of social disorganization consistently had significant differential effects (with 1995 being a cross-sectional analysis for most measures and 1996 being an analysis with lagged predictors). Recall that differential opportunity theory would predict that stronger social ties within the neighborhood should produce a higher relative incidence of nonviolent crime, where the opposite would be true of neighborhoods where such ties were weak. Our results show that even as stronger neighborhood ties are associated with lower crime rates (based on the overall crime model), the negative coefficient in the violence differential model means that of the crimes that do take place, each unit increase in neighborhood ties corresponds with a greater proportion of nonviolent crime. Greater concentrated disadvantage and residential mobility should result in similarly noticeable differentials of violence to nonviolence. For both 1995 and 1996, increasing concentrated disadvantage was associated with a greater preponderance of violence to nonviolence in a neighborhood's crime distribution. Residential stability, oddly, was associated with violence having a greater share of the crimes in 1995, but its failure to predict a differential in 1996 indicates that this effect might be an artifact of chance. The general tenor of the results indicates that disorganized areas not only have more crime, but they have more violent crime relative to property crime than in organized areas. Reported crime in the more highly organized neighborhoods disproportionately tends to be of a nonviolent nature. The general consistency of both the significance and direction of the effects of the independent variables across waves of data adds credibility to these measures as true predictors of a differential crime profile favoring violence.[11]

Discussion

Park (1936), a forefather of social disorganization theory and the Chicago School, used the term "web of life" as a metaphor for human communities. He argued that the disruption of this web (i.e., the interdependence of people) would result in a complex and maladaptive chain of effects. Research starting with that of Shaw and McKay (1942) would confirm this characterization, as social problems of almost every stripe seem to coalesce in areas of disorganization. Clearly then, social disorganization theory is designed to explain how neighborhood failure yields cascading, yet undifferentiated, varieties of hardship and adversity upon residents (e.g., Browning et al., 2004; Sampson, 2003; Sampson, Sharkey, & Raudenbush, 2008).

At the same time, research far older than that of Park or Shaw and McKay demonstrated that patterns of violence and nonviolence were not homogeneous across areas. Later, scholars, such as Cloward and Ohlin and a string of subculture of violence theorists, would address this inconsistency and implicate factors they saw as specific to explaining violence in the neighborhood. Cloward and Ohlin's differential opportunity theory takes the clearest position with respect to the types of crimes that occur within neighborhoods, going so far as to argue that neighborhoods "specialize" in some types of crime, in much the same way that individuals might.

The objectives of this investigation were to better understand the properties of differential patterns of crime across neighborhoods and to explain why violence might predominate in some neighborhoods but not in others. Specifically, we were interested in documenting the extent, stability, and antecedents of neighborhood crime patterns. Osgood and Schreck's (2007) statistical method is ideal for our purpose, as it is explicitly designed to analyze the balance of violence to nonviolence independently of overall crime rates. In order to study crime rates, it was necessary to modify their technique slightly in order to accommodate continuous interval-level data. One contribution of this research is thus to introduce a new statistical tool to macro-criminology, and one that is well capable of addressing questions that are of substantive importance.

Using data from over 300 Chicago neighborhoods, we found that neighborhoods do clearly distinguish themselves based upon the types of crimes that occur there. Specifically, certain neighborhoods demonstrated crime rates that favored violent crime with ratios that were unlikely due to chance, just as some

11. Though the models predicting 1995 crime data are vulnerable to causal order criticisms, replicating results for the lagged (1996) analysis nonetheless provide a sense of how stable the predictors are.

favored nonviolent crime significantly more so than did the "average" neighborhood. Moreover, there was remarkable stability in both overall crime rates and the distribution of crimes taking place in these neighborhoods over the two years of crime data analyzed. Neighborhoods that had a preponderance of violence to nonviolence in 1995 very often had a similar preponderance in 1996. Although future research should consider longer time windows in order to verify the stability findings reported here, these results are evidence that the contrast of violence to nonviolence across neighborhoods is both distinct from crime incidence and substantively meaningful, which should open up an additional line of empirical inquiry with regard to neighborhoods and crime.

The results predicting these differential crime profiles have some interesting theoretical implications. Our investigation suggests that social disorganization fuels both violent and nonviolent crime, attesting to the notion that the theory does have general effects on the crime rate. At the same time, however, factors indicative of disorganization rather clearly act as accelerants for violent offending (and less so for nonviolent crime). Social disorganization theory, as presently formulated, does not speak to why this might be the case. Alternatively, Cloward and Ohlin's differential opportunity theory, long viewed with skepticism among leading theorists (Hirschi, 1979; Kornhauser, 1978), generally finds support from this finding. To the extent that the PHDCN's measures of disorganization imply weakened collective social control, our results indicate that neighborhood disorganization has clearer implications for the social control of violence than for nonviolence. From our results, we would expect that programs designed to lessen social disorganization (e.g., starting neighborhood organizations) would address local violence more effectively than property crime. Indeed, as social organization improves, there may come a point at which nonviolent crime becomes the dominant crime type (in all likelihood as the levels of both decline generally).

If one were to interpret Cloward and Ohlin's (1960) description of a conflict subculture as defined *solely* by violence, then this is not supported in our results. The void of social organization does not impede nonviolent crime, perhaps because much crime does not require social networks for illegitimate learning and opportunities as Cloward and Ohlin (1960) suggested (e.g., Gottfredson & Hirschi, 1990). Cloward and Ohlin were correct in their assertion that concentrated disadvantage serves as a general risk for crime (i.e., the generalized motivation), but apparently so too does social disorganization. Still, their assertion that social disorganization has a particular tendency to foster and support violence to a degree greater than other crimes finds support. Given our focus on violence, we did not attend to their assertions regarding the other two subcultures (e.g., we did not investigate whether and why drug use might represent a unique neighborhood subculture). In order to provide a broader commentary on differential opportunity as a whole, future research could examine whether Cloward and Ohlin's predictions specifically hold for criminal and retreatist subcultures as well. This would likely be a productive direction, since much literature on differential opportunity has largely lumped it in with strain theories and tended to ignore the proposition that the response to strain is socially structured (Cullen, 1988). By revisiting the unique propositions it offers with regard to both the volume and type of crime across neighborhoods, criminology may well find there is something to Cullen's (1988, p. 233) sentiment that "Cloward and Ohlin's insights … are much ado about something."

Still, like any study, this investigation is not without limitations. Accordingly, we advocate for future research on this topic, both to replicate and expand the current inquiry. In doing so, scholars should first turn to other locations for research sites. A good portion of our theoretical and empirical knowledge about neighborhoods and crime stems from Chicago data and this inquiry joins that group. Thus, it is limited with regard to external validity, and, since this is the first inquiry of crime differentials with the current method, it is important to see whether the results generalize to other locations and contexts. Future research can also productively expand the scope of predictor variables. Earlier, we presented research on opportunity factors and crime differentials (e.g., Sherman et al., 1989). Future work should focus on how opportunity intersects with the balance between violence and nonviolence in a neighborhood. We should also note that this study has not exhausted all of the theoretical possibilities for studying the unique origins of neighborhood violence, relative to other forms of crime. Depending on the availability of suitable data, scholars could derive and test additional relevant predictions from subculture of violence perspectives and strain theories.

Finally, as we noted earlier, our neighborhood crime data come from official reports. The limitations of official data are well known but they have special implications for understanding the patterning of crime within the neighborhood. For crimes to "exist," at least for official purposes, someone must report them to the police. Warner (1992) indicated that the reporting of property crime (but not violence) might depend to some degree on neighborhood disorganization. We do not know if Warner's results persist in Chicago in 1995 and 1996, largely because she indicated in her narrative that crime reporting might be substantially influenced by period effects attributed to levels of intensified social conflict between elites and the lower classes during the Vietnam War and its aftermath (she analyzed 1972 and 1982 crime data). Still, it is noteworthy that Baumer (2002) recently illustrated that the reporting of violent crime does not seem to depend on neighborhood characteristics. Neighborhood biases with respect to nonviolent crime reporting remain unknown, however. Future research should examine neighborhood crime data based upon a broad range of aggregated self-reports of violent and nonviolent offending or victimization.

In the end, despite these limitations, our investigation contributes to the dialogue of macro-level theories of crime, as well as expands knowledge about crime patterns across space. It joins other work in demonstrating that there are numerous dimensions of spatial crime patterns, much like there are for individual-level criminal careers (e.g., Weisburd, Bushway, Lum, & Yang, 2004). We hope it will spark more specific discussions and inquiries about neighborhood crime profiles that extend past the frequency of crime, since this has clear impact for both theory and crime control policy.

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Appendix A. Descriptive Statistics and Item Parameters for Measures of Neighborhood Violent and Nonviolent Crime Measures (n = 342)

	1995			1996		
	Rate	γ_{i0}	SE	Rate	γ_{i0}	SE
Violent offending						
Assault	5459.53	8.35	.04	5419.99	1.66	.02
Homicide	31.39	−6.70	.13	30.71	−5.01	.12
Robbery	1190.01	−1.63	.03	1045.41	−.10	.03
Aggravated assault (1996 only)	—	—	—	1245.86	6.69	.05
Nonviolent offending						
Burglary	1492.98	−1.13	.03	1469.18	.53	.04
Vandalism	2680.25	−.55	.02	2605.85	1.08	.04
Auto theft (1995 only)	1518.16	−1.14	.03	—	—	—
Theft (1995 only)	4052.60	−.25	.04	—	—	—
Drugs (1995 only)	1906.46	−1.72	.05	—	—	—
Vice (1995 only)	425.14	−3.02	.06	—	—	—

Note: Lower values of γ_{i0} reflect greater item "difficulty;" see Equations (1) and (4). γ is the HLM population average estimate, and SE its robust standard error.