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The Corner and the Crew: The Influence of Geography and Social Networks on Gang Violence

Andrew V. Papachristos,[a] David M. Hureau,[b] and Anthony A. Braga[b,c]

Abstract

Nearly a century of empirical research examines how neighborhood properties influence a host of phenomena such as crime, poverty, health, civic engagement, immigration, and economic inequality. Theoretically bundled within these neighborhood effects are institutions' and actors' social networks that are the foundation of other neighborhood-level processes such as social control, mobilization, and cultural assimilation. Yet, despite such long-standing theoretical links between neighborhoods and social networks, empirical research rarely considers or measures dimensions of geography and social network mechanisms simultaneously. The present study seeks to fill this gap by analyzing how both geography and social networks influence an important social problem in urban America: gang violence. Using detailed data on fatal and non-fatal shootings, we examine effects of geographic proximity, organizational memory, and additional group processes (e.g., reciprocity, transitivity, and status seeking) on gang violence in Chicago and Boston. Results show adjacency of gang turf and prior conflict between gangs are strong predictors of subsequent gang violence. Furthermore, important network processes, including reciprocity and status seeking, also contribute to observed patterns of gang violence. In fact, we find that these spatial and network processes mediate racial effects, suggesting the primacy of place and the group in generating gang violence.

Keywords

neighborhoods, street gangs, violent crime, intergroup conflict, social networks, spatial analysis

More than a century of empirical research examines how neighborhoods' emergent properties influence a host of phenomena such as crime, poverty, health, civic engagement, immigration, and economic inequality (for a recent review, see Sampson 2012). These studies typically conceive of such neighborhood effects as influencing behavior through neighborhood characteristics (e.g., population heterogeneity, level of segregation, or economic disadvantage) or social processes (e.g., collective efficacy), or as spatial processes between neighborhoods (e.g., diffusion). Theoretically bundled within these neighborhood effects are the social networks of actors and institutions. In fact, the presence, vitality, and stability of neighborhood social networks are often at the

[a]Yale University
[b]Harvard University
[c]Rutgers University

Corresponding Author:
Andrew V. Papachristos, Yale University, Department of Sociology, PO Box 208265, New Haven, CT 06520
E-mail: andrew.papachristos@yale.edu

foundation of other neighborhood-level processes such as social control, mobilization, and cultural transmission. With respect to neighborhood crime, for example, dense social networks among parents and adults serve as a mechanism for monitoring youth behavior and thereby reducing rates of delinquency (Bursik and Grasmick 1993). Conversely, the absence of kinship and friendship networks, or the presence of criminal networks, can hinder a community's capacity to realize common goals and regulate behaviors (Browning and Dietz 2004).

Despite these long-standing theoretical links between neighborhoods and social networks, empirical research rarely considers *both* geographic and social space simultaneously. Neighborhood research typically employs statistical models that capture spatial influence with little concern for how social networks may transcend or interact with geography. Social network research models how connections among actors shape behavior, yet rarely considers how neighborhood geography shapes such networks. Although research appears to be moving toward integrated approaches to neighborhoods and networks, only a handful of empirical studies actually do so (e.g., Grannis 2009; Hipp, Faris, and Boessen 2012; Sampson 2012). The present study advances this integrated approach by analyzing how both geography and social networks influence an important social problem in urban America: gang violence.

The modern street gang serves as an example *par excellence* of how geography and social networks converge to influence behavior. Gangs are seen as both the byproduct of neighborhood social conditions (Shaw and McKay 1942; Thrasher 1927) and important forms of neighborhood social organization in their own right (Venkatesh 2000; Whyte 1943). Not surprisingly, gang turf and neighborhood attachment are significant sources of group conflict and gang violence (Decker and Van Winkle 1996; Hagedorn 1988; Suttles 1968; Vigil 1988). At their most basic level, gangs are social networks of individuals who come together in time and space, engage in collective activities, and produce a collective identity. It is precisely this "groupness" of the gang that amplifies social processes, such as reciprocity and mutual protection, and makes gang violence so potent (Hughes and Short 2005; Short and Strodtbeck 1965). References to gang turf and social networks abound in the literature, but most empirical studies fail to capture the intertwined nature of geography and social networks or to measure specific spatial or social mechanisms directly linked to violent acts. Rarer still are studies that specify both (for exceptions, see Papachristos 2009; Tita and Greenbaum 2009; Tita and Radil 2011); instead, geography and social networks are poured into a theoretical black box of mechanisms associated with gang behavior.

The present study unpacks this theoretical black box by simultaneously modeling effects of spatial and network processes on gang violence in two cities: Chicago and Boston. Using detailed data on fatal and non-fatal shootings, we recreated the networks of violence that arose from interactions between street gangs. We then constructed a series of statistical models that consider the probability of a gang engaging in an act of violence as a function of gang-level characteristics (e.g., size and racial composition), neighborhood-level characteristics (e.g., poverty and mobility), spatial proximity of gang turf, and several key network processes. Our results go well beyond the sociological truisms that neighborhoods and networks matter by examining (1) which specific spatial and social patterns give rise to gang violence, (2) how such patterns interact, and (3) how such patterns operate in two different cities. In so doing, our results are relevant not only to understanding gang violence, but also to understanding the importance of geography and social network processes more broadly.

NEIGHBORHOODS, NETWORKS, AND GANG VIOLENCE

Street gangs are an enduring feature of many U.S. cities. Today, the most reliable estimates report approximately 28,100 gangs and 731,000 gang members across 3,500 law enforcement jurisdictions—essentially every city with a population greater than 100,000 and 80 percent of all cities with more than 50,000 residents (Egley, Howell, and Major 2004). The extent of gang violence is striking: gang-related homicides account for 20 to 50 percent of all homicides in cities like Boston, Chicago, Detroit, Los Angeles, Pittsburgh, and St. Louis (Howell 2012). Despite variability in levels of gang violence, the circumstances and motives surrounding gang violence are remarkably consistent. The strongest predictors of gang violence are conflicts over gang turf, violations of group norms, threats to identity and honor, and retaliation (Decker 1996; Hughes and Short 2005).

In the present study, we explore several mechanisms that relate to neighborhoods and social networks. As shorthand, we use the term *corner* in reference to neighborhood structural conditions and a gang's use of neighborhood space, and the term *crew* in reference to various interactional processes within and between gangs that amplify violence, such as reciprocity, mutual protection, and status seeking. With few exceptions (e.g., Brantingham et al. 2012; Papachristos 2009; Tita and Radil 2011), empirical research rarely considers the corner and the crew simultaneously, resulting in conceptual confusion over the relative importance of geography vis-à-vis social networks. In the remainder of this section, we discuss the importance of the corner and the crew to specify some of the spatial and social mechanisms driving gang violence.

The Corner: Neighborhood Attachment and the Importance of Turf

Urban ethnographies attest to the significance of neighborhoods for group formation, identity, meaning-making, and individuals' behavioral patterns in disadvantaged communities, especially for young men (e.g., Anderson 1999; Hannerz 1969; Leibow 1967). Gangs are important occupiers and makers of such places; they are woven into the social fabric of many communities in multiple, complex, and, at times, conflicting ways. Gangs simultaneously serve as neighborhood protectors and perpetrators, their members toggling between social positions as regular citizens and gang bangers, neighbors and adversaries (Pattillo 1999; Suttles 1968; Venkatesh 2000; Whyte 1943). This line of work demonstrates how gangs can both support *and* suppress neighborhood social organization. Suttles (1968), for example, describes how conflict among street corner groups serves as a means of protecting and defending neighborhood and ethnic boundaries, but in doing so these groups essentially recreate micro enactments of larger community conflicts. Venkatesh (2000), Whyte (1943), and Pattillo (1999, 2008) describe numerous ways that gangs integrate into and even lead community life, through the underground economy, regulation of resident behavior, and even informal avenues of policing and social support. Connections between a gang and its community can also run in other directions: gangs are often met with opposition and residents can and do mobilize to suppress gang activities such as drug dealing and violence (Pattillo 2008; Venkatesh 2006).

In many ways, gangs more strongly identify with their neighborhoods than does the typical neighborhood resident. Whereas the average resident may take pride in her neighborhood and participate in community life, gangs often view themselves as a symbolic manifestation of the neighborhood itself (Garot 2007; Grannis 2009; Suttles 1968). Gang members venerate their neighborhood—they tattoo its name on their skin and engage in violence to protect the neighborhood and its symbolic value. In many instances, the name of the gang and the name of the neighborhood are synonymous (Garot 2007; Vigil 1988).

The neighborhood or, more precisely, gang turf, thus has a nontrivial and multidimensional value for a gang.[1] Although gangs have no formal legal ownership of these spaces, turf has a straightforward economic value. A gang assumes a piece of turf and determines its land use and value: who can use this basketball court, who can sell drugs on this corner, and so on. However, turf possesses a symbolic value that often trumps its economic value. Turf is typically the setting of a group's collective memories, a meaningful geographic space for young men as they transition from childhood into adulthood (Vigil 1988). Like other symbolic dimensions of a gang, such as honor or respect, possession of gang turf is entirely contingent on the recognition of such ownership claims by others and the actions taken by a gang to reinforce its claims of ownership.

This symbolic value of a neighborhood and its connection to gang identity motivates violence to defend or protect turf (Decker 1996; Horowitz 1983). Unfortunately, very few studies operationalize the manner by which connections to turf lead to violence. Rather, prior work tends to focus on spatial distribution of gang violence (Block 2000; Papachristos and Kirk 2006; Rosenfeld, Bray, and Egley 1999) or the concentration of gangs, gang members, or gang hangouts (Tita et al. 2005). However, two sets of recent studies provide important directions in this area. Papachristos (2009) found that Chicago gangs are more likely to exchange murders when their respective turfs overlap or intersect. Similarly, research by Tita and colleagues (Brantingham et al. 2012; Tita and Greenbaum 2009; Tita and Radil 2011) on gangs in Los Angeles found that geographic concentration of gang violence is highly correlated with the borders of gang territories—that is, gang violence is more likely to erupt at the boundaries where gangs' turf meet (see also Rymond-Richmond 2006). Note that both sets of studies suggest geographic modeling alone is insufficient in understanding the dynamics of gang violence—one must also consider the social networks of gangs and gang members.

The Crew: Group Processes and Social Networks

Gangs are first and foremost social groups. Delinquency tends to be a group phenomenon, but the gang context amplifies crime and delinquency. In other words, something about the gang and gang membership *facilitates* violence above and beyond any individual selection found in joining a gang (Thornberry et al. 2003). Such a facilitation effect is commonly associated with *group processes*: a range of interactional mechanisms and normative processes fostered by the coming together of members and the formation of a collective identity (Short and Strodtbeck 1965; Warr 2002). In the present study, we consider three group mechanisms that facilitate violence: (1) intergroup conflict, (2) reciprocity, and (3) group status seeking.

Intergroup conflict is such a pervasive part of gang identity that members often define their group in opposition to other gangs.[2] In a fundamental sense, gangs use each other as reference groups, judging their own behaviors and competing for status against the other (Decker 1996; Hagedorn 1988; Thrasher 1927). In Chicago, for instance, a common way to signal one's own gang identity is by derisive references to one's adversaries; Latin Saints gang members, for example, claim to be "King Killers" in reference to their longstanding rivalry with the Latin Kings. Such claims are more than symbolic: gang violence often results from direct conflict over status enhancing behaviors (e.g., claims to solidarity or supremacy) or threats to a group or its reputation, be they real or perceived (Decker and Van Winkle 1996; Short and Strodtbeck 1965).

Reciprocity is perhaps the most frequently cited mechanism of gang violence (Decker 1996; Hughes and Short 2005; Papachristos 2009). Here we use the term broadly to refer to an exchange of violence between gangs, although this usage includes more specific forms of reciprocity such as retaliation. Within the gang milieu, violence serves as a form of street justice, a mechanism of social control or self-help that corrects a perceived wrong, addresses a threat, or saves face (Anderson 1999; Jacobs and Wright 2006). An act of violence that reciprocates a transgression or perceived threat serves the dual purposes of protection and vengeance. Retaliation provides evidence of a gang's ability to fulfill a collective promise of mutual protection as well as providing an avenue to mete out justice or correct a perceived wrong.

The final group process of interest here is *status seeking* and management. Early gang research viewed participation in street gangs as a form of status attainment, a way for lower-class youth to achieve social standing within a community and a crew (Cohen 1955; Miller 1958). Status considerations take place within the larger social and ecological world of the gang: a gang must consider how its violent actions (or lack thereof) will be interpreted (Papachristos 2009; Suttles 1968). Violence between gangs represents a classic dominance contest in which groups jockey for social status (Gould 2003). Dominance contests have been looked at more broadly in the social network and aggression literatures (e.g., Chase 1980; Faris and Felmlee 2011) and discussed in the gang literature (e.g., Papachristos 2009), but only a single study actually tests the claim that violence affords a gang a strong reputation. In a study of 17 gangs in one Chicago community, Kobrin, Puntil, and Peluso (1967) found strong and converging evidence of status and prestige rankings among gangs based on their fighting ability and willingness to use violence.

Although few in number, these studies examining group processes find consistent support of the mechanisms discussed here, especially reciprocity and status seeking (see Hughes and Short 2005). Recent developments in social network analysis have rekindled interest in the group processes approach to gang research and further elucidating the mechanisms behind gang violence (e.g., Fleisher 2006; McGloin 2005; Papachristos 2006). For example, the work of Kennedy, Braga, and Piehl (1997), Descormiers and Morselli (2011), Papachristos (2009), and Tita and colleagues (Tita and Greenbaum 2009; Tita and Radil 2011) demonstrates how network patterns of intergroup conflict explain the social and spatial distribution of gang violence in Boston, Montreal, Chicago, and Los Angeles, respectively. These studies illustrate how social network analysis provides an approach to unpack the various group processes at play in gang violence, and for this reason, we employ a network approach here.

Corner and Crew Hypotheses

We formulate four hypotheses to delve deeper into the foundations of gang behavior by modeling specific aspects of the spatial and social network processes driving gang violence. First, we hypothesize that gangs are more likely to engage in violent acts with each other when they are geographically proximate (Hypothesis 1). We make the simple assumption that geographically proximate gangs—groups whose turf boundaries are spatially adjacent—will have more at stake against each other. Moreover, spatially proximate gangs are simply more likely to come into contact—and potentially conflict—during the routine use of resources such as parks, basketball courts, convenience stores, liquor stores, and other local establishments (Felson and Steadman 1983).

Second, because gangs define themselves in relationship to rivals, we argue that past conflicts between gangs influence subsequent acts of violence, particularly through the selection of adversaries (Hypothesis 2). Patterns of dyadic conflict among gangs can generate larger and more enduring social structures. In a sense, gang conflicts become *institutionalized*: regular patterns of conflict create an organizational memory shaping a gang's subsequent violent behavior.[3]

Third, gang violence is more likely to occur when an act of violence reciprocates another act of violence (Hypothesis 3). Here we are arguing something more than just a broad statement that gang violence tends to be retaliatory in nature. Rather, we aim to test the actual effects of reciprocity on the probability of an act of violence occurring—that a gang is more likely to commit an act of violence when that act reciprocates another violent act. As we will discuss, such a process is endogenous to any specific gang because reciprocity (by definition) requires at least one other act of violence to precede it.

Fourth, gangs' status-seeking violence may manifest in the creation of dominance hierarchies, a structural situation in which aggressive gangs obtain higher status and victimized gangs receive lower status (Hypothesis 4). In other words, much like pecking orders in animals and other human social groups (Chase 1980), gangs' use of violence may generate a hierarchy of social status within a population of gangs.

Some prior research supports Hypotheses 1 and 3, but most of these hypotheses have not been considered systematically, and no study, to the best of our knowledge, has examined multiple spatial and social processes in the same analyses. We examine our hypotheses using a social network framework that focuses on observed patterns of gang violence in Chicago and Boston. Our concern here is not with aggregate levels of gang violence, but rather the social patterning of gang violence: who acts violently against whom and what processes generate a specific act of violence. We utilize recent developments in exponential random graph models (ERGMs) that allow us to predict the likelihood of forming a violent tie (i.e., an act of violence between two gangs) as a function of neighborhood and gang attributes, geography, and social network covariates. The ensuing analysis proceeds in two stages. The first stage provides a descriptive analysis of the networks of gang violence in Chicago and Boston; the second stage presents ERGM results predicting the observed networks. A more detailed description of the modeling strategy and variable construction are provided in the relevant analytic sections.

DATA

We test our propositions using data from two cities, Chicago and Boston. Overall, levels of gang violence are substantial in both cities: more than half of all homicides in Chicago and Boston involve a gang member as either a victim or an offender (Braga, Hureau, and Winship 2008; Papachristos, Meares, and Fagan 2007). Gangs in Chicago and Boston differ, however, with regard to their longevity, organizational structures, and collective capacities. A sizable literature classifies street gangs based on composition or organizational characteristics such as age structure, leadership patterns, and the presence of subgroupings (see Howell 2012; Klein and Maxson 2006). Briefly, this literature views gang organizational structure as existing on a spectrum from instrumental-rational gangs with quasi-formalized organizational structures on one end (Jankowski 1991; Venkatesh and Levitt 2000) to diffuse and limitedly organized gangs on the other (Decker and Van Winkle 1996; Fleisher 1998; Hagedorn 1988). Chicago gangs tend to be larger in size, more organizationally sophisticated, and more heavily involved in large-scale drug dealing than gangs in other cities. In contrast, gangs in Boston tend to be smaller in size, without formal organization, limited in age structure, have a shorter organizational lifespan, and are only peripherally involved in group-level drug dealing; in these regards, Boston gangs tend to more closely resemble the typical U.S. street gang (see Kennedy et al. 1997). Analyzing and comparing Chicago and Boston thus affords a unique opportunity to understand not only the mechanisms that generate patterns of gang violence, but also how such mechanisms may vary across geographic and organizational contexts.

The present study derives data from two sets of police records. The primary source of information on gang violence comes from records of fatal and non-fatal gun violence between gang members as recorded between the years 2005 and 2009. These are incident-level data containing demographic, geographic, motive, and gang information as recorded by the investigating detectives. The usual caveats associated with official police data also circumscribe these data, such as bias introduced by police decision-making processes (Black 1970). Some of these problems are unavoidable without replication using original survey data, but homicide data are typically higher quality than other types of official crime records because (1) homicide victims are more likely to be reported/discovered by police, and (2) police agencies expend considerable effort and resources investigating homicides. The same is true of shootings that result in non-fatal injuries: they are more likely to be detected by the police or reported to emergency services (in both cities, medical first responders are legally required to report gunshot injuries to police).

Challenging the notion that police data are mired with biases and measurement errors, a recent study by Decker and Pyrooz (2010) found that police reports of gang homicide in large U.S. cities (1) exhibited strong internal reliability, (2) were consistent with the principles of convergent-discriminant validity tests, and (3) demonstrated considerable external validity. Furthermore, the validity of police-reported gang measures was higher in cities that had specialized policing units directed toward gang problems—a feature of both Chicago and Boston (see also Katz, Webb, and Schaefer 2000). In summary, although police reported data on gang homicide are not perfect, prior research has found such data to be valid and reliable indicators of gang activity and violence.

Chicago data include only homicides, the vast majority (95 percent) committed with firearms; Boston data include fatal and non-fatal gunshot injuries. The availability of non-fatal incident data from Boston allow us not only to replicate previous analyses of homicide in Chicago, but also to extend those models theoretically and empirically to include a wider range of gang violence. Empirical research suggests that gun homicides and non-fatal shootings are not all that different—whether a shooting event becomes lethal is contingent on several uncontrollable factors such as the shooter's aim, distance to the target, a rapid call to the police, and response time of medical assistance (Zimring 1972). Unfortunately, because data on non-fatal shootings were not available in Chicago and the smaller number of total homicides in Boston prohibits an analysis of only homicides in that city, we were unable to model the exact same networks in both cities. However, as we will describe, the similarities between the Chicago and Boston networks suggest that non-fatal and fatal gang violence networks are more alike than they are different.

We further restricted homicide and shooting data in both cities in two ways. First, we analyzed only those violent acts in which police identified the victim and offender as known gang members. Such an approach offers a conservative selection parameter, but our findings parallel those of Papachristos (2009) who included non-gang members in his analysis; this suggests our selection criteria did not bias our results. Second, we analyzed only those homicides and shootings that occurred *between* unique gangs or gang subgroups; we excluded acts of violence committed between members of the same gang. Importantly in the case of Chicago, our analysis includes violent acts between gangs affiliated with each other (e.g., gang factions that might share an alliance) but excludes acts internal to unique gang subgroups (e.g., violence between members of the same faction).[4]

Our second data source is detailed geographic maps of gang turf boundaries generated by gang intelligence officers. In Chicago and Boston, police use geographic information systems (GIS) to map a gang's turf as a polygon that occupies a circumscribed amount of space. Figure 1 displays gang turf boundaries in each city, with each smaller shaded polygon representing a piece of turf occupied by a unique gang. The decision to draw gang turf boundaries is made by police officers with knowledge of particular groups; these map boundaries thus represent the aggregation of local knowledge. Our measurement of the corner is rather straightforward: we created a matrix of turf adjacency in which a tie occurs if any side of a gang polygon touches at least one side of another gang polygon.[5] In Boston, most gangs occupy only a single piece of turf (i.e., each polygon in the right panel of Figure 1 represents the turf of a single gang). In Chicago, however, gangs frequently occupy more than one polygon of turf. In these cases we aggregated a gang's total number of adjacent alters to create a single row/column in the geographic adjacency matrix.[6]

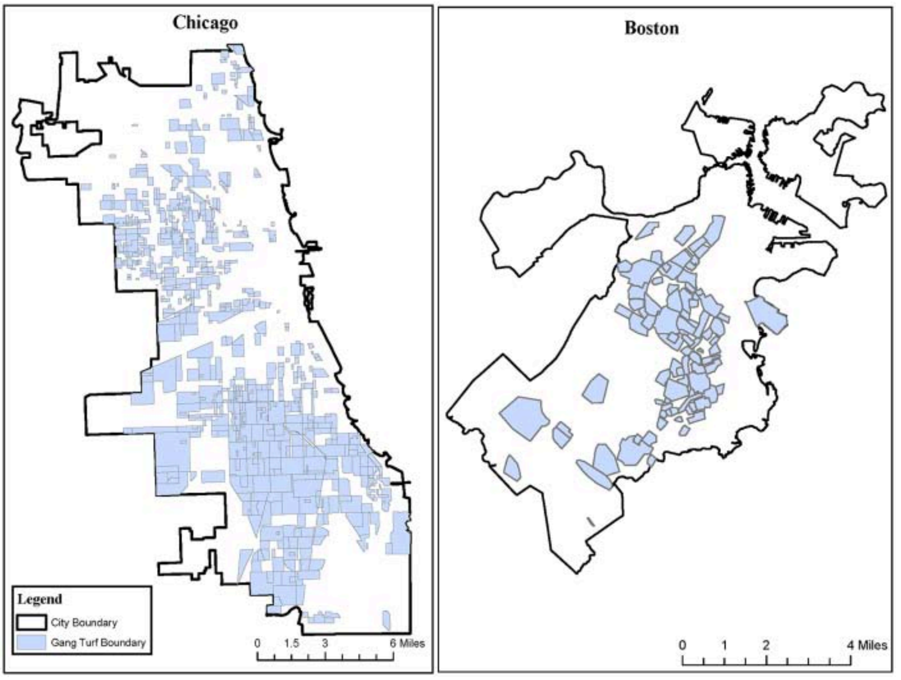

Figure 1. Maps of Gang Turf Boundaries in Chicago and Boston

Our measurement of turf adjacency is not without its limitations. Gangs do not actually occupy the entirety of such turf polygons, but rather micro-locations within them, such as basketball courts and particular residences (Tita et al. 2005). Polygons such as those in Figure 1 more accurately represent the locus of a group's control as perceived by the police and, as such, most likely include several smaller gang spaces. Unfortunately, we were unable to gain access to data at a smaller geographic unit and were therefore prohibited from generating more precise estimates of spatial distances between gangs. However, in support of our measurement, a recent study by Brantingham and colleagues (2012) applied ecological competition models to micro-geographic data on gangs in Los Angeles and found that inter-gang violence clusters around the *boundaries* of gang turf. Our measurement of turf adjacency captures precisely this turf-violence dimension. Nonetheless, future research should consider how alternative measurements of gang geography might alter the findings presented here.

We supplemented homicide/shooting and turf data with additional information on neighborhood structural conditions and gang-level characteristics. As Figure 1 shows, Chicago and Boston have important geographic differences that may lead to different network typologies or patterns of violence. Chicago is not only geographically larger than Boston, but gang turf occupies a larger portion of the total geographic space (two-thirds in Chicago compared to roughly one-third in Boston). Furthermore, differences in racial composition, population size, levels of segregation, and other factors may affect network patterns differently (Butts et al. 2012). Both cities have comparable levels of poverty (approximately 20 percent) and are majority nonwhite, but Chicago's population is more than four times larger than Boston's (2.7 million versus approximately 630,000). Chicago is also a more racially segregated city with a long history of high-rise public housing. Such population and geographic differences might lead to different types and levels of interaction among gangs of different ethnicities and, in turn, different patterns of violence. To control for such factors, we included several covariates derived from the Census to account for neighborhood socio-structural conditions. These measures are concentrated disadvantage (six-item composite), immigrant concentration (two-item composite), and residential stability (two-item composite) (see Tables A1 and A2 in the Appendix).

At the gang level, we considered two important characteristics: racial composition and size of a gang. We assessed a gang's race as the predominant racial or ethnic group represented within the composition of each group's membership as well as the predominant race and ethnicity of each group's victims.[7] In Chicago, nearly all the gangs are racially homogenous, and in most cases gangs self-identify as black or Latino (e.g., the Black Souls or the Latin Eagles). No white gangs or gang homicide victims were reported during the observation period and, in general, the prevalence of white gangs appears to have diminished in Chicago since the late-1980s.[8] For the Boston sample, we determined gangs' racial composition from a law enforcement census conducted in 2007 as well as the predominant race and ethnicity of victims in our data. We coded Boston gangs by a single race or ethnicity when over 75 percent of active gang members were of the same race or ethnicity. Although the majority of gangs fit this description, we also identified a small number of heterogeneous gangs (typically composed of a mix of African Americans and Latinos). As in Chicago, most all-white gangs in Boston are now considered defunct or else do not enter our data as victims in homicides or non-fatal gunshot injuries.

We also included a categorical measure of gang size based on each group's estimated membership. A direct measure of organization that captured leadership structure or the presence of subgroups would have been preferable (Decker and Curry 2000), but such data were not available. Prior research consistently finds that gang structures vary considerably but gang size is correlated with more developed organizational structures (e.g., Fagan 1989; Short and Strodtbeck 1965; Weisel 2002); accordingly, gang size is incorporated into several gang typologies (see Klein and Maxson 2006).[9] We constructed our measure of gang size as a three-category variable relying on police estimates of membership. In Chicago, small gangs had 30 to 100 members, medium gangs had 101 to 350 members, and large gangs had more than 351 members. In Boston, small gangs had fewer than 20 members, medium gangs had between 20 and 49 members, and large gangs had more than 50 members.[10]

OBSERVED NETWORKS: GANG VIOLENCE IN CHICAGO AND BOSTON

Our empirical focus here is the precise patterning of violence between gangs. Our analysis focuses on the social networks created by relationships among gangs in which the ties represent violent acts between groups. Conceiving of and measuring gang violence in this way not only allows us to assess larger group-level patterns of violence, but more importantly facilitates analysis of the generative processes responsible for any given violent act.

For the Chicago case, we used homicides during the 24-month period between January 2008 and December 2009 as the dependent network—the homicide patterns we explore in our statistical models. For the Boston case, we examined all fatal and non-fatal shootings during the 12-month period between January and December 2009.[11] Figure 2 depicts the social networks created by linking together violent events between gangs.[12] The left side of Figure 2 displays the directed-graph of the 244 murders among 32 unique gangs in Chicago from 2008 to 2009. The right side of Figure 2 displays the 207 fatal and non-fatal shootings among 52 gangs in Boston in 2009.[13] Each node represents a unique gang with the color/shape representing the racial composition of the gang: white triangles signify Latino gangs, light-grey circles signify black gangs, darker-grey diamonds signify Cape Verdean gangs, and black circles signify racially/ethnically heterogeneous gangs. Arcs indicate a homicide or non-fatal shooting between gangs with the arrow direction indicating the victim. Bidirectional arcs indicate reciprocal homicides between groups.

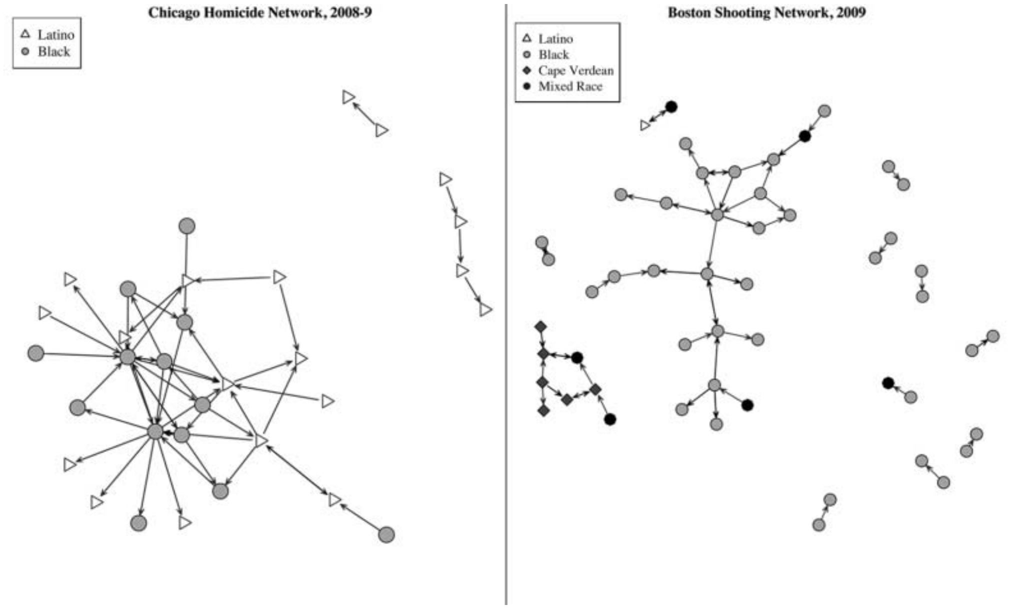

Figure 2. Gang Violence Networks in Chicago (2008 to 2009) and Boston (2009)

Networks in Figure 2 reveal important similarities and differences between gang violence in Chicago and Boston. With regard to connectivity—the extent to which any gang can reach any other gang—both networks were dominated by a single large component. The Chicago network, however, was more connected than the Boston network: 98 percent of all gangs were in the large component in Chicago compared to 66 percent in Boston.

Both networks exhibit clustering along racial lines: approximately 95 percent of all homicides in Chicago and 97 percent of all shootings in Boston were intraracial. Furthermore, network density among black gangs in Chicago (approximately 30 percent) was more than six times higher than Latino network density (4.5 percent).[14] Compared to the Chicago network, the Boston network displayed a higher level of racial clustering and featured greater variation in gangs' racial composition. The Boston network's largest component was almost entirely made up of black gangs, with only two mixed-race gangs in the network; in general, these gangs were more established (many were associated with housing projects) and operated in the historically black neighborhoods of Roxbury, Dorchester, and Mattapan (clustered in the center of the Boston map in Figure 1). In contrast, Boston gangs not involved in the largest component of dyadic conflicts were predominantly from outside these inner-city core neighborhoods and featured more ethnic heterogeneity than their inner-city counterparts. The Cape Verdean groups reside in Boston's historically black neighborhoods, but their violent conflicts form a subnetwork that is almost completely racially homogeneous and entirely isolated from the largest component of inner-city African American gangs (Papachristos, Braga, and Hureau 2012).

Chicago's and Boston's networks had additional structural similarities with regard to the distribution of violence among groups. In network terms, the *in-degree* of any node refers to the number of ties received by that node (Wasserman and Faust 1994), or, in this case, the number of times a gang was a *victim* of a violent act from a unique alter. Conversely, *out-degree* measures the number of ties sent by a node, which, in this study, translates into the number of violent acts *committed* by a gang. Figure 3 plots the in- and out-degree distribution for both networks. In both cities, degree distribution follows a

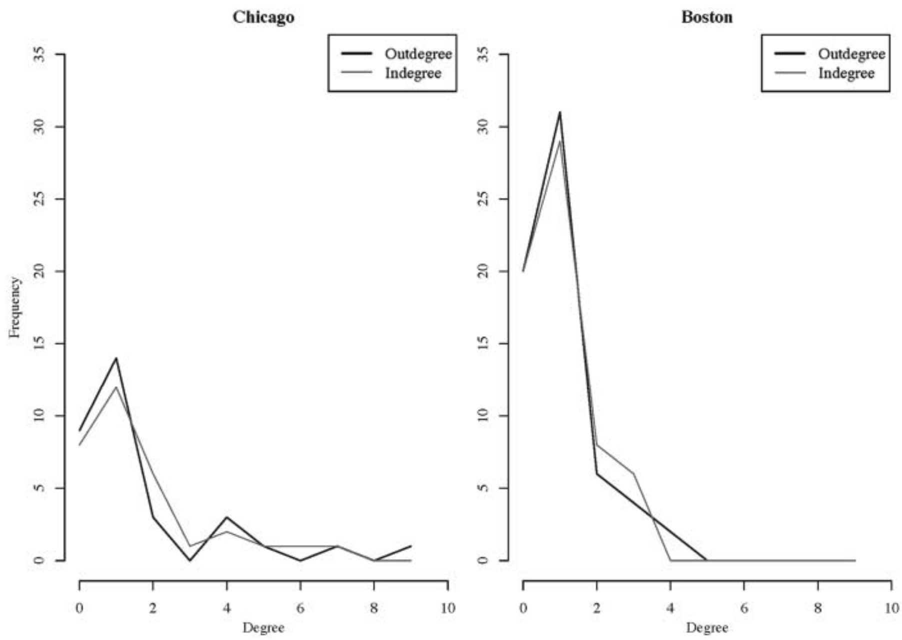

Figure 3. Degree Distribution of Chicago and Boston Gang Violence Networks

similar pattern: most gangs were involved in a violent act as either victim or offender with only a single alter; a very small number of gangs were involved with a large number of alters. The higher total distribution in Boston reflects the inclusion of non-fatal shootings as well as homicides, thus increasing any single gang's level of activity. The degree distribution pattern of gang violence in both networks is extremely similar, suggesting that in both cities violence is a rare event, with most gangs involved in only dyadic conflicts.

The right-hand tail on the degree distribution in Figure 3 points to important outliers in both cities (i.e., groups that engaged in violence with multiple alters). In Chicago, activities of two gangs—the Gangster Disciples (in-degree = 6, out-degree = 9) and the Latin Kings (in-degree = 5, out-degree = 3)—far exceed other gangs in the network. In Boston, the centrality of one gang—Orchard Park (in-degree = 2, out-degree = 4)—is responsible for the right-hand tail on the out-degree distribution. In part, the heightened activities of these gangs may be a function of size or organizational capacity: the Gangster Disciples is Chicago's largest and most organized street gang, and the Orchard Park Trailblazers is one of Boston's largest gangs.

PREDICTING GANG VIOLENCE USING EXPONENTIAL RANDOM GRAPH MODELS

The second stage of analysis employs exponential random graph models (ERGMs) to investigate the generative processes that gave rise to these observed network patterns.[15] The outcome of interest is the probability of tie formation, or, in this case, the probability that a member from one gang will shoot/kill a member from another gang. As a class of statistical models, ERGMs are designed to predict the probability of tie formation in an observed network while incorporating properties of the network itself as well as an array of covariates pertaining to the network actors and sets of ties among them. ERGMs thus allow us to isolate effects of spatial and network parameters in relation to each other as well as in relation to other neighborhood structural, racial, and gang control variables.

ERGMs regard the possible ties among actors in a network as random variables, with the general form of the model based on assumptions about the dependencies among model statistics. The ERGM class specifies the probability of a set of ties, Y, given a set of nodes and their attributes:

$$\Pr(Y = y) = \left(\frac{1}{k}\right)\exp\left\{\sum_{A}\eta_A g_A(y)\right\}$$

The g_A term represents any possible network statistic with A indexing multiple statistics in vector $g(y)$. The η_A term represents coefficients for these terms—the change η_A reflects the change in the conditional log-odds of a tie for each unit increase in $g(y)$ (see Robins et al. 2007). The denominator k represents a normalizing constant over all possible networks with n actors.

Given a proposed set of model statistics, the ideal situation would be to calculate the η_A vector that maximizes model likelihood. However, the normalizing constant prohibits direct evaluation of the likelihood function (see Goodreau 2007; Hunter, Goodreau, and Handcock 2008). For dyad *independence* models—models that include only terms pertaining to dyads (e.g., geographic propinquity and reciprocity) and individual nodes (e.g., race category and neighborhood size)—a normal logistic regression format suffices and the Maximum Pseudolikelihood Estimation (MPLE) is used to estimate the MLE (Robins et al. 2007). For dyad *dependence* models—models that include higher order terms, such as triadic effects or degree distribution—the maximum likelihood can be approximated using Markov Chain Monte Carlo (MCMC) simulation methods that generate a sample of possible networks to estimate the η_A statistic.[16]

Model Specification

We estimated separate ERGMs for the Chicago and Boston networks, where the dependent network was the 2008 to 2009 murder network in Chicago and the 2009 fatal and non-fatal network in Boston.[17] Consistent with our larger argument, we specified a series of ERGMs that consider geography, prior sets of gang conflict, endogenous structural effects, gang-level attributes, and neighborhood sociodemographic characteristics.

Main Theoretical Variables

We captured the corner, the crew, and the interaction between the two as a set of three dyadic covariates, in this case binary social matrices of unique ties between gangs in the observed violence networks.[18] First, as described earlier, we measured the effect of spatial proximity by creating a matrix of geographic adjacency between all gangs in the observed networks; a tie exists if two gangs' turf is immediately proximate. We interpreted the parameter as the probability of a violent tie forming if two gangs share a turf boundary.

Second, to measure the effect of prior conflict we used homicide networks in Chicago for the years 2005 and 2006 and the 2007 network in Boston—essentially, lagged versions of the dependent networks. We omitted a single year between the time periods covered by the dependent variable and the relational covariate to distinguish between reciprocity within the dependent network (a contemporaneous effect) and institutional history (an effect of prior group conflict). Most gang violence, but especially retaliatory violence, tends to be episodic and short-lived (Block and Block 1993), and the average tenure of any individual gang member tends to be less than 3.5 years (Thornberry et al. 2003). Although violent events *within* the time periods are likely to be reciprocal in the sense that event Y is in direct response to event X, it is probably less common that events *across* periods are acts of direct retaliation. We argue that past intergroup conflict drives subsequent violence not simply as retaliation for past wrongs but as a more general guide for group behaviors. The gap between time periods thus offers additional insurance that specific events are not related across those time periods. This parameter measures the probability of a tie forming based on whether two gangs had a past conflict.

Finally, we included an interaction term between gangs that were geographically close and those that had a prior conflict. Conceptually, this interaction captures the idea that gangs spatially closer are also more likely to have some organizational history or conflict. Because all three parameters are represented as binary matrices, this interaction term captures gangs that were geographically proximate *and* had a prior group conflict. When all three dyadic covariates are in the model, the comparison group represents gangs that engaged in a violent act but were *neither* geographically adjacent *nor* had any prior violent history.

Endogenous Structural Effects

An ERGM approach provides the additional benefit of adding parameters for endogenous structural effects within the observed network itself. *Endogenous structural effects* refer to patterns and processes that are entirely contingent upon other ties or features of the network. For example, a gang's race is not contingent on other gangs or sets of ties in a network. Some processes, however, are entirely contingent on pattern ties in a network. Reciprocity, for instance, is only possible as a response to an already existing network tie; likewise, dominance hierarchies are entirely contingent on sets of ties among multiple actors in a network. ERGMs allow for exact specification of such endogenous patterns and we considered four such terms that capture the group processes discussed earlier: (1) reciprocity, (2) delayed reciprocity, (3) transitivity, and (4) distribution of violent ties among the observed gangs.

We included a *reciprocity* parameter that captures the count of reciprocal dyads in the observed network. More precisely, this parameter models the probability that a tie will form if it reciprocates an already existing tie. Given the past research on retaliation discussed earlier, we expect this term to be positive and significant—gangs are more likely to form ties when they reciprocate already existing ties.

To minimize the possibility that the relationship between our dependent network (the network at Time 2) and our measure of prior dyadic tie (the network at Time 1) might be spurious, we supplemented our reciprocity term with a transpose of the Time 1 network essentially as a way to control for any *delayed reciprocity*—that is, an attack from gang j on gang i prior to Time 2 could lead to an attack from gang i on gang j during Time 2. In this way, we can differentiate between reciprocity that happens within time periods (the reciprocity term), the direct effect of a prior dyadic tie between any two groups regardless of whether it is reciprocal (the Time 1 network), and unobserved reciprocity that might happen between time periods (transpose of the Time 1 network). We expect the transpose to be positive and significant and serve as an indication of reciprocity not detected with the other parameters.

To address our hypothesis that gang violence may generate status hierarchies, we included two terms associated with the idea of *transitivity*: geometrically weighted edgewise shared partners (gwesp) and geometrically weighted dyadwise shared partners (gwdsp). The first term, gwesp, captures the classic transitive triad seen in the left side of Figure 4, a situation in which gang i → gang j, gang j → gang k, and gang i → gang k (where → represents the direction of a violent tie). In the context of negative ties, such as aggression, the transitive triad is indicative of a dominance hierarchy or pecking order (Chase 1980). In Figure 4, gang i is at the top of the pecking order because it dominates both of the other gangs—it is the most aggressive of the three—sending two ties and receiving none. Gang j is in the middle of the pecking order because it both receives and gives a violent tie; it is thus below gang i but above gang k in the pecker order. Gang k is in the lowest possible position, what Chase (1980:915) called a "double loser," because it is victimized by both of the other gangs without sending or reciprocating a single violent act.

The gwdsp term captures a triadic pattern seen in the right side of Figure 4 in which gang i → gang j, gang j → gang k, but no tie exists between gangs i and k. In network

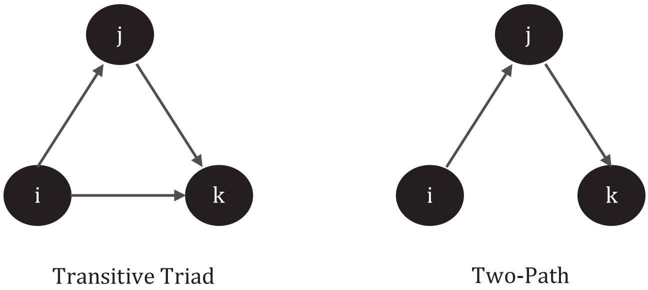

Figure 4. Transitive Triad and Two-Path

terms, the gwdsp term captures an open triangle or a two-path, what Granovetter (1973:1363) called a "forbidden triad." Such two-paths may represent a situation in which (1) a dominance hierarchy is not operating, (2) gangs mutually ignore each other or are not aware of each other, or (3) a functioning alliance keeps gangs from engaging each other. Although we lack data on alliances among gangs and cannot test proposition (3), qualitative data from Chicago suggest that such alliances existed during the 1990s and may have shaped at least some gang behaviors.[19] Therefore, we limit our interpretation to either (1) or (2). More important, though, considering the gwesp and gwdsp in the same model provides direct evidence of transitivity, a situation in which gangs are more likely to form a tie that closes a transitive triangle as opposed to leaving a forbidden triad. Evidence of a dominance hierarchy in a network would thus be supported by a positive gwesp term and a negative gwdsp term in the same model.

To capture the presence of outlier gangs and the skewed distribution of ties (Figure 3), we included two terms equal to the *geometrically weighted degree,* one for the in-degree (gwidegree) and one for the out-degree (gwodegree). Each term captures the extent to which the probability of a tie forming is driven by links to more active gangs. When the coefficient of either term is negative, there is a tendency in the network toward similarity in degree among actors with respect to either receiving (gwidegree) or sending (gwodegree) ties. Put differently, gangs are more likely to kill or be killed by gangs with similar levels of violence. A positive coefficient indicates a preference toward heterogeneity in degree, with some actors sending or receiving more ties than others.

Race and Gang Effects

To account for the racial and gang-specific differences described earlier, our ERGMs also include terms for (1) uniform homophily by gang race and size and (2) sender/receiver effects by gang race and size. *Uniform homophily* refers to the propensity for assortative mixing across attribute categories: the tendency for ties to form among actors with the same attributes (e.g., black gangs engage in violence with other black gangs; large gangs engage in violence with other large gangs). *Sender/receiver* statistics represent the main effect of a particular attribute or characteristic on the direction of a tie. For example, a sender/receiver effect for Latino gangs assesses the baseline probability of Latino gangs committing a murder/shooting (sender) or being a victim of a murder/shooting (receiver) compared to the probability for another racial category. Racial clustering in Figure 2 suggests that racial or gang-level factors may play a role in tie formation.

Neighborhood Structural Characteristics

To control for additional factors often associated with gang violence, we included sociodemographic variables of the turf neighborhoods. Prior research suggests that aggregate levels of gang violence are higher in socially disadvantaged neighborhoods (Papachristos and Kirk 2006; Rosenfeld et al. 1999). Although no research has considered violence networks such as those described here, a recent simulation study by Butts and colleagues (2012) found that the form of one's social networks are partially influenced by neighborhood structural conditions (see also Grannis 2009). Likewise, recent work by Schaefer (2012) using ERGMs demonstrates that structural conditions affect tie formation in co-offending networks between neighborhoods. By extension, neighborhood conditions may influence the shape of observed violence networks by contributing to specific types of ties forming (e.g., intra- versus interracial conflict) or to other properties of the observed networks (e.g., degree distribution).

To ensure that our network and spatial measures are not standing in for more general neighborhood structural conditions, we created several indicators using variables derived from the U.S. Census that prior research suggests are correlated with neighborhood levels of crime. Following extensive research on crime in Chicago (e.g., Sampson, Raudenbush, and Earls 1997), we used principle components factor analysis to combine 10 Census indicators into three unique factors: (1) *concentrated disadvantage,* composed of the percent of the population below the poverty line, on public assistance, in female-headed households with children under age 18, unemployed, and black; (2) *immigrant concentration,* composed of the percent of the population Latino and foreign born; and (3) *residential stability,* composed of the percent of the population in the same house five years prior and owner-occupied housing. In attempting to create identical Census-based variables in Boston, it became apparent that, with the exception of the concentrated disadvantage index, variables did not load on the same factors. Therefore, our Boston model relies on one factor, *concentrated disadvantage,* that loads remarkably similar to that in Chicago, and two individual Census variables: tract-level *vacancy rate,* measured as the percent of housing vacant at the time of the Census, and *residential stability,* measured as the percentage of the population in the same house in the prior five years.[20] Factor loadings of the Chicago and Boston indicators can be found in Tables A1 and A2 in the Appendix.

Additional Considerations

Finally, we considered two additional parameters in our models: an edge statistic and an isolate statistic. The edge parameter is akin to the intercept in standard regression and here represents the baseline probability of tie formation. The isolate term adds a statistic to the model equal to the number of gangs in the network without any ties in a given time period; this controls for gangs that did not commit a violent act in the dependent network but are kept in the data because they are present in the turf data or had a violent exchange in the past.

RESULTS

We used a form of iterative model development that considers several possible combinations of model statistics to observe which combinations yield the best fit for the data—an approach that has proven successful in models of other complex networks (Goodreau, Kitts, and Morris 2009; Wimmer and Lewis 2010). We examined the goodness-of-fit of our models by comparing the Akaike Information Criterion (AIC) between models (Hunter, Goodreau, and Handcock 2008). Additional goodness-of-fit indicators are presented in Part B of the Appendix. For dyad independent models, we used MPLE for estimation (akin to standard logistic regression); we used MCMC estimation for dyad dependent models where the sample size was set at 10,000 and the interval between samples was set at 1,000.

Predicting Violent Ties among Chicago Gangs

Table 1 lists parameter estimates for the Chicago models. Model 1 shows the baseline probability of a tie forming is low, less than

Table 1. ERGM Predicting 2008 to 2009 Chicago Gang Homicide Networks

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Edge Statistic	–5.041***	–5.965***	–6.010***	–5.506***	–5.939***	–6.953***	–6.916***
	(.149)	(.459)	(.400)	(.337)	(.397)	(1.414)	(1.022)
Isolates		1.823***	1.071***	1.640***	1.001***	.966	.941
		(.312)	(.080)	(.075)	(.073)	(.820)	(.579)
Race and Gang Size Effects							
Uniform Homophily (Race)		.889**	.421	.487	.341	.308	.356
		(.342)	(.353)	(.338)	(.335)	(1.270)	(.683)
Uniform Homophily (Size)		.337	.124	.231	.047	.500	.417
		(.321)	(.364)	(.324)	(.334)	(.911)	(.637)
Receiver Effect (Black)		–1.433***	–.596	–1.699***	–1.082**	–1.413	–1.487
		(.428)	(.420)	(.425)	(.416)	(1.055)	(.856)
Sender Effect (Black)		.073	–.155	.344	.116	.675	.573
		(.413)	(.423)	(.369)	(.375)	(.705)	(.600)
Receiver Effect (Medium Gang)		.795*	.410	1.034**	.269	.536	.518
		(.356)	(.452)	(.347)	(.387)	(1.236)	(.933)
Sender Effect (Medium Gang)		1.329**	.105	.683	.818	.084	.117
		(.418)	(.482)	(.367)	(.436)	(.142)	(.096)
Receiver Effect (Large Gang)		2.361***	1.301**	2.529***	1.395**	1.818	1.838
		(.485)	(.494)	(.441)	(.446)	(1.241)	(.971)
Sender Effect (Large Gang)		2.341***	1.273**	1.378***	1.611***	.015	.022
		(.510)	(.496)	(.405)	(.459)	(.066)	(.031)
Spatial and Social Networks							
Turf Adjacency			2.98***		2.537***	2.325***	2.31***
			(.183)		(.063)	(.107)	(.060)
Prior Violent Tie				1.652***	.596***	.873***	.865***
				(.216)	(.134)	(.263)	(.128)
Interaction Prior Tie x Turf Adjacency					.117***	–.054	–.078
					(.027)	(.039)	(.053)

(continued)

Table 1. *(continued)*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Structural (Endogenous) Network Effects							
Reciprocity						.476***	.435***
						(.102)	(.039)
Transpose (Time 1 Network)						.309***	.302***
						(.090)	(.058)
gwdsp (Two-Paths)						.328***	.328***
						(.004)	(.008)
gwesp (Triangles)						–.331***	–.320***
						(.065)	(.030)
gwidegree						.695***	.708***
						(.056)	(.032)
gwodegree						–.813***	–.805***
						(.057)	(.033)
Neighborhood Effects							
Main Effect (Concentrated Disadvantage)							–9.534***
							(.000)
Main Effect (Immigrant Concentration)							–.076
							(.059)
Main Effect (Residential Stability)							2.11
							(.182)
AIC	607.8	451.2	391.88	440.11	394.06	418.20	413.12

Note: N of gangs = 46; N of homicides = 244; N of dyads = 2,070.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$ (two-tailed tests).

50 percent, reinforcing the fact that any act of violence is a rare event. Model 2 adds the isolate term and the race and gang size terms to the baseline model and considerably improves overall model fit. The homophily term provides evidence of racial homophily (violent ties tend to form between gangs of the same race), but provides no evidence of homophily by gang size. The sender and receiver effects show that black gangs are less likely than Latino gangs to receive a violent tie, but they are not significantly different from Latino gangs in sending ties. With regard to gang size, both medium and large gangs are more likely than smaller gangs to send and receive violent ties. Taken together, these findings demonstrate some racial and organizational effects when not considering prior conflict, geography, and higher order network processes.

Models 3 through 5 add the main theoretical parameters. In support of our main hypotheses, results show that both geographic adjacency (Hypothesis 1) and past conflict (Hypothesis 2) significantly predict the probability of a murder occurring between two gangs in Chicago—a finding that holds whether the terms are considered in isolation (Models 3 and 4) or simultaneously (Model 5). In Chicago, the overall effect of geographic adjacency is somewhat higher than prior conflict and provides the greatest reduction to the AIC. When both terms are considered with the interaction in Model 5, the sizes of both terms are slightly moderated and the interaction term is statistically significant. Because we measured these three terms in the same way, we can compare the magnitude of the coefficients. More precisely, Model 5 suggests that although both geography and prior conflict play a role in determining the network structure of gang homicide, gangs that are *only* geographically proximate are more likely to form ties than gangs that *only* have a past conflict. Gangs that are both geographically proximate and have a past conflict are more likely to form ties than gangs that are neither geographically adjacent nor have a past conflict. These results provide strong evidence that social networks and geography are significant predictors of violence and there is an interaction between them.

Model 6 highlights the importance of endogenous network effects when controlling for geographic proximity and prior conflict. All of these terms (1) are statistically significant, (2) slightly moderate the effect of geographic adjacency, (3) bolster effects of prior conflict, and (4) reduce the statistical significance of the interaction term. Perhaps most interestingly, addition of the structural terms reduces the statistical significance of the race and gang size terms. These results support the racial invariance hypothesis: race operates not as a direct cause of violence, but rather as a marker of the ecological dissimilarity of social contexts that are differentially attributable to race in the United States (Sampson and Wilson 1995). In much the same way, our findings indicate that direct effects of race on gang violence are mediated almost completely by network and spatial processes. Whereas prior research has found similar evidence of neighborhood level processes (e.g., Peterson and Krivo 2005), our results are the first to demonstrate a similar racial invariance related to network processes as it applies to violence.

As expected, both the reciprocity and delayed reciprocity terms are positive and statistically significant (Hypothesis 3). The reciprocity term indicates that a gang is more likely to form a tie when it reciprocates an already existing tie, and the delayed reciprocity term indicates that such a process need not be immediate. Furthermore, contrary to the notion that gang violence produces a transitive dominance hierarchy, the gwdsp and gwesp terms indicate that Chicago gangs are unlikely to form ties that complete transitive triads. Taken together, the gwesp term suggests that ties completing transitive triangles are significantly less likely to form and the gwdsp term suggests ties are likely to form that create two-paths. In other words, we find no evidence that gang violence creates dominance hierarchies among Chicago gangs (Hypothesis 4).

The degree distribution terms suggest a tendency toward heterogeneity in the receiving of ties (gwidegree): some gangs are victimized by many adversaries, other gangs are victimized by only a single or small number of adversaries. The negative gwodegree term indicates consistency in sending ties: out-degree is relatively homogenous. This implies a network structure in which most gangs have similar patterns of committing murders but are quite different in their susceptibility as victims.

Model 7 in Table 1 includes neighborhood structural indicators as a robustness check on our main theoretical variables. Of the three neighborhood structural indicators, only the concentrated disadvantage index is statistically significant. However, this negative coefficient requires some clarification. As Papachristos and Kirk (2006) show, gang homicide in Chicago is more likely to occur in disadvantaged neighborhoods to begin with, and virtually all gangs in this sample come from highly disadvantaged communities. Therefore, the negative coefficient in Model 7 suggests that gangs in more severely disadvantaged neighborhoods are less likely to form a violent tie compared to gangs in less disadvantaged communities, but even these latter gangs are still in severely disadvantaged communities. It does not mean that concentrated disadvantage more generally mediates violent ties. Most important for the present study, our main theoretical variables retain their direction and statistical significance, lending further support to our hypotheses.

These results provide insight into the complex processes involved in gang violence. Consistent with our hypotheses, gangs are more likely to engage in murder with gangs that share a geographic border. Prior history in the form of a past dyadic conflict also matters: gangs are more likely to form a violent tie with those whom they share a history of conflict. Moreover, additional endogenous group processes exert considerable influence above and beyond geography and organizational memory. Reciprocity is an essential feature of gang violence, even when controlling for these other factors and even if reciprocity is not immediate. In addition, violence does not appear to establish dominance hierarchies (in the form of transitive triads) among gangs in Chicago. Such structural effects also appear to moderate effects of a gang's racial composition and size. Our final set of analyses examines how such findings hold in a city with a much more typical gang ecology—Boston.

Predicting Violent Ties among Boston Gangs

Table 2 presents the same progression of models for the Boston network. Model 1 presents the baseline model with only the edge statistic, again demonstrating that the probability of a violent tie between any two gangs is low. Model 2 adds race and size terms. Unlike the Chicago models, none of the racial composition terms are statistically significant, thus providing no evidence of racial homophily or sender/receiver effects for gangs of particular races. However, we do see a negative homophily effect based on gang size—gangs are relatively unlikely to form ties with gangs of the same size category. Put another way, gangs shoot at gangs of different sizes.

Models 3 through 5 add the main theoretical variables. Consistent with the Chicago results, the geographic adjacency and prior conflict variables are statistically significant, as is the interaction term. In contrast to the Chicago models, however, the Boston results suggest a stronger relative effect of prior group conflict compared to geographic adjacency. One potential explanation for this finding is that expansive and long-standing school busing in Boston led to the emergence of gang conflicts that are not as geographically bounded as those in Chicago—a question worthy of future research. This point is best illustrated in Model 5 when all three terms are in the same model. Compared to gangs that have neither a prior conflict nor a shared turf boundary, gangs with a prior conflict but without a shared turf border have a greater probability of tie formation than do gangs that share a turf boundary but not a past conflict. In Boston, past conflicts appear to play a more significant role than geographic adjacency in determining who shoots whom.

Table 2. ERGM Predicting 2009 Boston Gang Fatal and Non-fatal Shooting Networks

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Edge Statistic	–4.241***	–5.002***	–5.566***	–5.261***	–5.789***	–6.626***	–6.318***
	(.150)	(.590)	(.771)	(.731)	(.701)	(.692)	(.594)
Isolates		.829	–.038	–.322	–.039	–.037	–.324
		(.435)	(.439)	(.437)	(.451)	(.419)	(.424)
Race and Gang Size Effects							
Uniform Homophily (Race)		.396	.077	–.029	.332	.071	–.015
		(.515)	(.643)	(.593)	(.595)	(.511)	(.484)
Uniform Homophily (Size)		–.869*	–.827	–.618	–1.009*	–1.227**	–.894*
		(.363)	(.441)	(.412)	(.484)	(.381)	(.364)
Receiver Effect (Latino)		.727	.736	–.127	1.296	1.018	.766
		(.638)	(.772)	(1.021)	(.730)	(.861)	(.868)
Sender Effect (Latino)		.981	.748	.834	.883	.569	.727
		(.620)	(.808)	(.729)	(.825)	(.620)	(.588)
Receiver Effect (Cape Verdean)		–.653	–.641	.469	.021	.177	.027
		(.751)	(.792)	(.640)	(.777)	(.737)	(.727)
Sender Effect (Cape Verdean)		–.083	.141	.137	.675	.163	.127
		(.675)	(.709)	(.668)	(.666)	(.595)	(.602)
Receiver Effect (Mixed Race)		–.362	–.735	–.427	–.168	–.344	–.446
		(.605)	(.811)	(.694)	(.762)	(.743)	(.738)
Sender Effect (Mixed Race)		–.204	–.325	–.945	–.371	.014	–.202
		(.615)	(.788)	(.812)	(.788)	(.618)	(.634)
Receiver Effect (Medium Gang)		.936*	1.082*	.953*	.740	1.746***	1.023*
		(.366)	(.448)	(.420)	(.451)	(.527)	(.472)
Sender Effect (Medium Gang)		.721***	.741***	.457***	.637***	.699***	.711***
		(.072)	(.080)	(.089)	(.096)	(.103)	(.092)
Receiver Effect (Large Gang)		–.283	–.390	–.455	–.570**	–.057	–.052
		(.157)	(.204)	(.312)	(.174)	(.255)	(.202)
Sender Effect (Large Gang)		–.354*	–.481**	–.924***	–1.050***	–.573**	–.438**
		(.153)	(.185)	(.178)	(.199)	(.202)	(.165)

(continued)

Table 2. *(continued)*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Spatial and Social Networks							
Turf Adjacency			2.753***		2.173***	1.707***	1.592***
			(.181)		(.208)	(.242)	(.211)
Prior Violent Tie				3.457***	3.120***	2.312***	2.370***
				(.159)	(.1555)	(.246)	(.186)
Interaction Prior Tie x Turf Adjacency					1.309**	1.807***	1.881***
					(.411)	(.349)	(.367)
Structural (Endogenous) Network Effects							
Reciprocity						3.363***	3.431***
						(.297)	(.252)
Transpose (Time 1 Network)						–1.427*	–1.756*
						(.591)	(.685)
gwdsp (Two-Paths)						–.017	–.007
						(.056)	(.054)
gwesp (Triangles)						–1.575	–1.536
						(.865)	(.862)
gwidegree						2.089***	2.085***
						(.101)	(.089)
gwodegree						–1.519***	–1.506***
						(.106)	(.105)
Neighborhood Effects							
Main Effect (Concentrated Disadvantage)							–.501
							(.554)
Main Effect (Immigrant Concentration)							–.836
							(.564)
Main Effect (Residential Stability)							–.793
							(.559)
AIC	474.92	490.56	472.76	447.47	427.12	396.77	401.67

Note: N of gangs = 57; N of fatal and non-fatal shootings = 207; N of dyads = 3,192.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$ (two-tailed tests).

Model 6 adds endogenous effects and shows similarities and differences to the Chicago models. As expected, reciprocity plays a highly significant role in the model: gangs in Boston, just like gangs in Chicago, are much more likely to form a tie that reciprocates an already existing tie. Unlike Chicago, though, the delayed reciprocity term is negative, suggesting that reciprocity in Boston has a shorter shelf life—that is, reciprocity is more likely to occur within the observation period but less likely to occur across observation periods. Supra-dyadic processes, such as transitivity, appear to be less important in Boston than in Chicago (evident in nonsignificant gwdsp and gwesp terms). Like Chicago, Boston shows little evidence of the formation of dominance hierarchies. Taken together, endogenous effects in Model 6 suggest that Boston gangs tend to focus on the here and now and immediate adversaries, unlike in Chicago where reciprocity has a longer memory.

The degree distribution terms in Model 6 mirror those in the Chicago models. Namely, Boston gangs display consistency with respect to outdegree (gwodegree) and heterogeneity with respect to indegree (gwidegree)—gangs have similar patterns of committing murders but are quite different in their susceptibility as victims. Finally, all of the earlier mentioned results hold even after adding neighborhood structural covariates of concentrated disadvantage, vacancy rate, and residentially stability in Model 7, none of which are statistically significant at even the most relaxed levels.

In summary, our ERGMs suggest that many of the processes that drive the structure of gang homicide in Chicago also motivate gang shootings in Boston. Consistent with our hypotheses, the corner and the crew appear to be the primary drivers of gang violence in both cities, even mediating racial and gang-level effects in Chicago. Reciprocity is foundational for violence in both cities and exerts a more durable effect in Chicago, spanning a longer period of time. Contrary to our hypothesis, gang violence did not appear to establish dominance hierarchies or pecking orders in either city. The importance of the corner and the crew remained even when considering higher order network processes and neighborhood structural conditions.

DISCUSSION AND CONCLUSIONS

Geography and social networks intersect and intertwine to produce many effects associated with urban neighborhoods. We argue that street gangs provide an excellent point of departure from which to examine such spatial and social processes, especially with regard to urban violence. Our primary objective was to unpack such spatial and social processes to better explain the observed patterns of violence in Chicago and Boston. While by no means exhaustive, our study modeled multiple geographic and social processes, including geographic proximity, organizational memory, reciprocity, and status seeking.

Descriptive analyses revealed striking similarities in Chicago's and Boston's networks of violence. In both cities, the majority of violent acts created a single large network that linked the majority of gangs either directly or indirectly. In this sense, gang violence is a highly connected and structured phenomenon. Gangs—and the violence they engage in—tend to cluster along racial and ethnic cleavages, with a higher density of interaction among black gangs. In addition, the presence of highly active gangs skews the distribution of violence in a network.

The larger question under consideration was *what* spatial and social processes produce the observed patterns of violence? To answer this question we employed a series of ERGMs that included parameters for geographic and network processes. With respect to our main theoretical conceptualization, the findings indicate that geography plays a central role in determining the nature of gang violence: gangs with adjacent turf are more likely to engage in violence compared to gangs without adjacent turf or gangs with only a prior conflict. Yet, space alone does not explain gang violence. Indeed, prior conflicts—even when gangs do not share turf boundaries—also drive violence. That is, a history of conflict between groups exerts an effect above and beyond spatial proximity. The interaction between spatial adjacency and organizational memory in both cities is positive, suggesting that effects of the corner and the crew are interactive in nature.

We also considered additional social processes beyond prior conflict that might generate the observed structure of violence. First, we found continued support for the importance of reciprocity: gangs are more likely to commit an act of violence when it reciprocates another gang's violent act. Second, evidence from both cities shows that gang violence does *not* create a dominance hierarchy or pecking order. Many theories posit that gang violence is a way to jockey for relative status, but it appears that no such dominance hierarchy is ever achieved through shootings or killings.[21]

As an important point for future research, all these results held even when controlling for gang-level characteristics, groups' racial and ethnic composition, and neighborhood structural characteristics. This is of particular relevance for the racial invariance hypothesis—the underlying mechanisms associated with violence are the same across races (Sampson and Wilson 1995). Indeed, our findings suggest that many direct effects of race are mediated by spatial and network processes. Whereas most prior work in this area focuses on ecological conditions and processes, our results suggest that network processes play an important and underexamined role in how we understand the mechanisms behind violence vis-à-vis race and ethnicity.[22]

Our study is not without limitations. First, our data are circumscribed by the availability and limitations of available police data. In particular, our measurements of gang presence and activity are derived from police records. Thus, we most likely underestimated the actual extent of gang activity in both cities. Second, we also likely underestimated aggression because gang animosity and conflict manifests more often in non-violent (or less violent) acts than in homicide or gunshot injury. Third, as mentioned earlier, our measures of gang turf were limited to the polygons seen in Figure 1. We were thus unable to consider additional spatial processes (e.g., spatial diffusion) that might influence the observed structure. Future research would do well to consider additional methods of data collection to expand this line of inquiry to include a wider range of gang networks, spatial processes, and collective behaviors. Finally, our empirical investigation was designed to uncover structural patterns generating gang violence in two different cities in a very specific historical period. The extent to which such patterns hold under different historical, geographic, and organizational considerations is an important matter for future research.[23]

These results have important implications for research on neighborhoods, social networks, and urban violence. In support of recent work by Sampson (2012), Grannis (2009), and others (e.g., Hipp et al. 2012; Tita and Greenbaum 2009), our results clearly demonstrate that social networks and neighborhood ecology work in concert to influence social behavior. Our study advances this line of research by demonstrating the utility of adding measures of geographic space to social network models to parse out competing and complementary processes. In particular, studies of the spatial diffusion of social behaviors across neighborhoods would do well to consider—and, more importantly, *measure*—the mechanism of transmission. The goal should be to capture more precise modes of transmission as they might relate to social networks and space. In the case of violence, most contemporary studies model how crime rates (in the aggregate) somehow spill across geopolitical boundaries of neighborhoods (e.g., Cohen and Tita 1999; Morenoff, Sampson, and Raudenbush 2001). Many of these spatial analyses hypothesize that social networks are responsible for the transmission of crime across neighborhood boundaries, but studies rarely measure these networks and, instead, model via the airborne pathogen assumption. Similar implications may hold for other public health epidemics and social phenomena.

APPENDIX

Part A. Factor Loading of Census Variables in Chicago and Boston

Table A1. Chicago Factor Loadings

Variable	Factor Loading
Concentrated Disadvantage	
% Below poverty line	.93
% On public assistance	.94
% Female-headed household	.93
% Unemployed	.86
% Under age 18	.94
% Black	.61
Immigrant Concentration	
% Latino	.88
% Foreign Born	.70
Residential Stability	
% Same house in 1995	.77
% Owner-occupied house	.86

Table A2. Boston Factor Loadings

Variable	Factor Loading
Concentrated Disadvantage	
% Below poverty line	.74
% On public assistance	.91
% Female-headed household	.89
% Unemployed males age 18 years or older	.86
% Black	.71
Vacancy Rate	
% Vacant housing	n/a
Residential Stability	
% Same house in 1995	n/a

Part B. Additional Goodness-of-Fit Indicators

Following Hunter, Goodreau, and Handcock (2008), one way to evaluate model fit in ERGMs is to generate a sample of networks based on the fit model and calculate the model parameters of interest on both the original and the sample of networks. Plots of the distribution of statistics from the MCMC sample are compared with the statistic from the observed network. If the simulated networks differ drastically from the original network, the model is not well fit and possibly degenerate. Figures A1 and A2 provide such plots for the final models for Chicago and Boston. Both figures suggest well fit models as evidenced by the fact that the observed model statistics (the solid lines) fall roughly at the mean value of the sampled networks (the box-and-whisker plots indicate the mean and the 95% Confidence Intervals). In both cases, the MCMC processes produced a sample of networks conducive to model assumptions and specifications. In other words, both the Chicago and Boston models accurately reproduce basic characteristics of the observed networks, in this case the in-degree, out-degree, and edgewise shared partners. The near-perfect fit of the edgewise shared partner statistic in the Boston model reflects the rarity of that process in the model—that is, our models and visual inspection of the Boston models find that higher order triadic and network processes do not play an important role in the observed network structure in Boston.

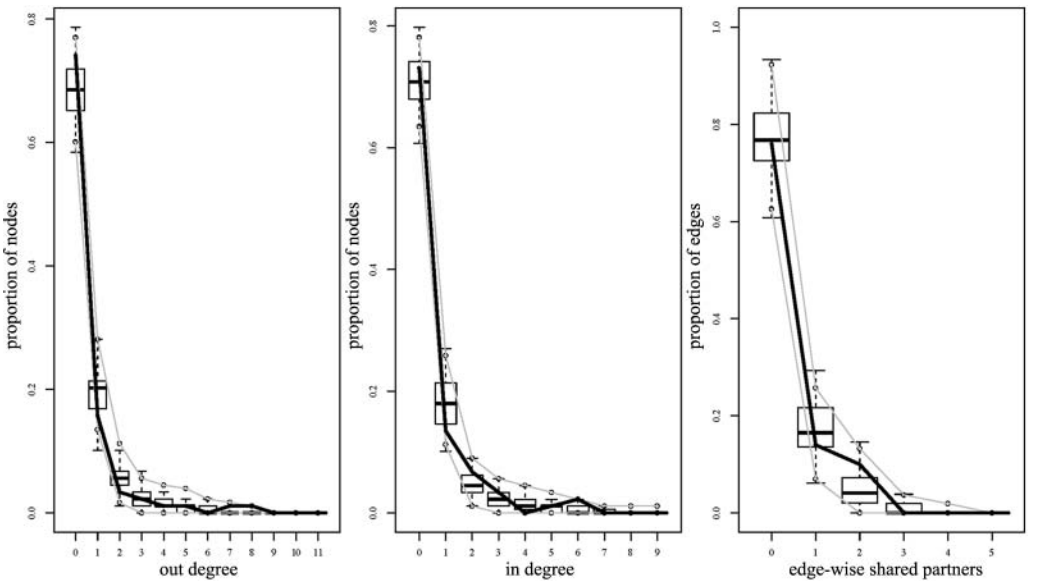

Figure A1. Model-Fit Plots for Final Chicago Models

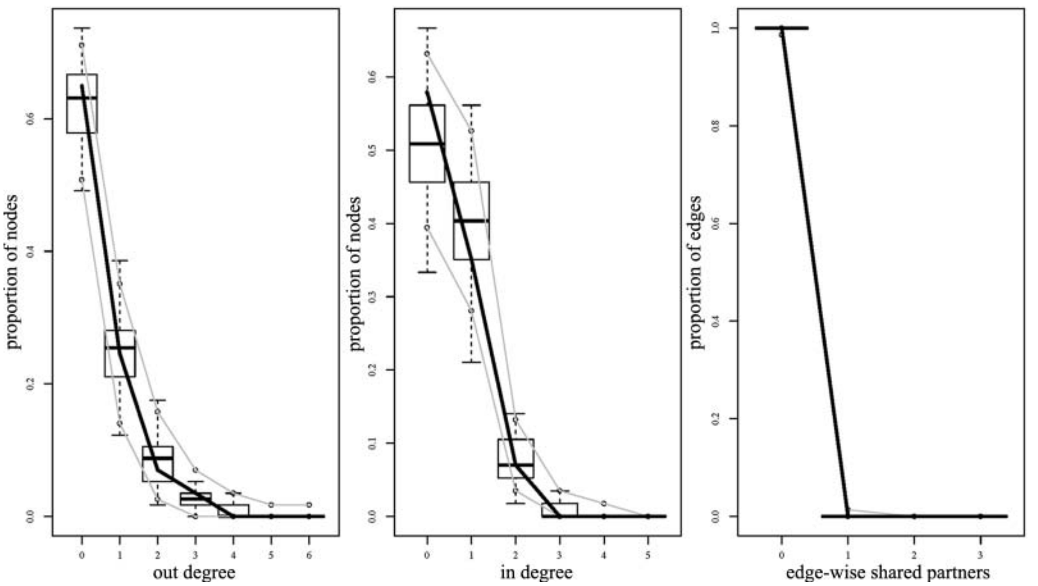

Figure A2. Model-Fit Plots for Final Boston Models

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Notes

1. Other dimensions of geography (e.g., school catchment areas, location of public housing, and geography of tertiary streets) also influence gang behavior (Grannis 2009; Rymond-Richmond 2006; Tita, Cohen, and Engberg 2005). These dimensions are all worthy of additional research, but we retain a focus on turf because, (1) consistent with prior research, we believe turf to be one of the primary spatial dimensions related to gang violence, and (2) our data were only available in a format that precluded any reduction beyond an identified parcel of turf.
2. The question of what defines a "gang" is much debated (see Howell 2012; Klein and Maxson 2006). An important tension is between sociological definitions that stress collective identity, group processes, and social structures versus legalistic definitions that stress the criminal activities and deviant behaviors of gangs and their members (Bursik and Grasmick 1993). Our arguments pertaining to the corner and the crew are conceptually, theoretically, and methodologically consistent with sociological definitions such as Thrasher's (1927:18) that define a gang as "[a]n interstitial group originally formed spontaneously and then integrated through conflict. . . . The result of this collective behavior is the development of a tradition, unreflective internal structure, esprit de corps, solidarity, morale, group awareness, and attachment to a local territory." Our assessment, based on prior ethnographic research and our own qualitative research, is that the groups identified in our sample are consistent with the sociological orientation. However, as we will describe, we collected our data from police records that are likely biased toward legal definitions. In short, while we agree that the distinction between the sociological and legalistic definitions of gangs is an important one (and we are proponents of the sociological definition), we believe data in the present study represent an area of overlap and perhaps agreement between these two definitions.
3. The extent to which gang structures and behavior patterns are institutionalized or form organizational memory is a matter of debate (Short and Hughes 2006). On one hand, research on gangs in Chicago and Los Angeles suggests that some gangs have rich organizational and cultural identities that span decades (e.g., Hagedorn 2008; Jankowski 1991). However, research in other cities (Decker and Van Winkle 1996; Fleisher 1998) as well as survey research (Esbensen and Huizinga 1993) suggests that the vast majority of street gangs in the United States have limited organizational capacity and memory.
4. Although prior research by Decker and Curry (2002) in St. Louis found that the majority of gang homicides during the 1990s were internal, levels of intragroup homicides in Chicago and Boston during the study period were relatively low—less than 10 percent in Chicago and 5 percent in Boston (see the online supplement [http://asr.sagepub.com/supplemental]). Exclusion of these events does not significantly alter our findings on the overarching patterns of gang violence in both cities.
5. We generated the adjacency matrix as a spatial weight matrix (Queen's contiguity) using the GeoDa software package (Anselin, Syabri, and Kho 2006).
6. For example, if the Gangster Disciples had two pieces of turf (location A and location B) and two adversaries in location A and one adversary in location B, we combined these locations to say that the Gangster Disciples were geographically adjacent to three different gangs.
7. Some prior research provides evidence of racial biases in police reporting on stop-and-frisk interactions, traffic stops, crime incident data, and arrest data (e.g., Fagan et al. 2009; Warren et al. 2006). However, three facts suggest that such biases are minimal in our study. First, original academic-collected data show that gang involvement is highly concentrated in minority communities (Hagedorn 1988, 2008; Venkatesh 2000; Vigil 2002). Second, as discussed earlier, these biases are less likely in homicide and shooting data because racial categorization in these data is derived from the actual body of the victim. Unlike simple assaults or traffic stops where individual police officers exert great discretion over the reporting process, police have virtually no discretion on reporting and recording of homicides and gunshot injuries. Finally, the greatest potential source of bias is a false-negative of white gang homicides or a false-positive of black and Latino homicides. Although we cannot accurately estimate the potential rates of such biases in the available data, the vast majority of victims in

gang homicides and non-fatal gun violence in both cities are black and Latino. During the study period, 73 percent of all homicide victims in Chicago were non-Hispanic black, 19 percent were Hispanic/Latino, and 8 percent where non-Hispanic white or "other." Of events deemed to be gang-related by the Chicago police department, less than 1 percent involved a white homicide victim, the last of which appeared in the data in 2000. In Boston, non-Hispanic blacks accounted for 69 percent of all homicide victims during this period, Latino/Hispanics accounted for 17 percent, and non-Hispanic whites accounted for less than 11 percent.

8. An autobiography by a member of a white Chicago street gang during this time describes precisely this process (Scott 2005).
9. Decker, Katz, and Webb (2008) demonstrate that even modest increases in organizational structure are correlated with increases in patterns of victimization and offending.
10. We also considered a continuous version of this variable. However, significant clustering around certain sizes and important outliers suggested that an ordinal variable more accurately captured effects of size and provided an overall better fit of the data. Our specification of gang size acts mainly as a control variable and does not significantly influence our findings; in fact, removing any measurement of size from our models does not affect parameter estimates of our main theoretical variables or overall model fit (see the online supplement).
11. We used different time intervals for two reasons. First, as described in the text, we wanted to leave a single-year gap between the dependent variable and the independent variable of intergroup conflict to account for any delayed reciprocity. However, only four years of data were available for Boston (2006 to 2009), making it impossible to create 24-month windows that would allow a one-year gap between the two time periods. Second, there were fewer homicides in any given year in Chicago relative to the total N of shootings in Boston. A two-year time frame of homicides for Chicago produced a comparable number of incidents as a one-year time frame of shootings in Boston.
12. We used the Fruchterman and Reingold (1991) force-directed placement algorithm to determine placement of nodes in both figures. Isolates are not displayed in the figure.
13. Both cities had gangs that were not involved in a murder/shooting during the observation period. The observed networks used in our ERGMs capture 60 percent of all reported gangs in Chicago and 65 percent of all reported gangs in Boston. If the observation period were expanded to an additional two years, 100 percent of all gangs would be captured in both cities, but doing so would lose the temporal information of interest here.
14. Density refers to the number of ties present in a network divided by the number of possible ties (Wasserman and Faust 1994). The greater the density, the more connected the network actors. In the present case, network density embodies the extent that exchange of violence among gangs creates a situation where gangs engage with each other; a higher density suggests a greater proportion of all gangs engage in violence with each other.
15. The general theory and methodologies of ERGMs have received considerable attention (e.g., Robins et al. 2007) with important advancements in regard to directed graphs (Robins, Pattison, and Wang 2009).
16. MCMC simulation is not without problems and its estimates can produce empirically implausible networks, such as completely connected or empty graphs. To deal with this issue, called model degeneracy, we followed Hunter and Handcock (2006) by including the geographically weighted versions of several of our model parameters.
17. We used the statnet and ergm suite of packages for statistical network analysis for all models and goodness-of-fit assessments (Handcock et al. 2008; Hunter, Handcock, et al. 2008).
18. We treated all networks as binary even though we could, in principle, treat them as weighted (i.e., the number of violent events between groups). We do so because, to the best of our knowledge, only binary networks can be used as dependent variables, and we wanted to facilitate a simpler interpretation between the dependent and independent networks—that is, a prior murder/shooting in a dyad or geographic adjacency is related to a subsequent murder/shooting.
19. In the 1990s, most of Chicago's corporate-style gangs resulted from alliances and complex gang federations formed during the preceding decades (Venkatesh and Levitt 2000). These federations were premised on explicit normative expectations that gangs would come to each other's aid should other federation members be attacked. Yet, to the best of our knowledge, no study directly tests whether a gang comes to the mutual aid of its allies in violent episodes—that is, whether a gang will seek vengeance on the enemy of its friends.
20. Unfortunately, we lack quantitative studies on the relationship between crime and sociodemographic characteristics in Boston neighborhoods similar to the Chicago studies cited here. Ongoing research by the authors is currently exploring these issues. Although we were able to align our Boston research with much of the existing literature in the macrosocial research paradigm (through use of the disadvantage index and residential stability), we determined that concentrated immigration (particularly the way it was constructed in prior Chicago research) was not analytically appropriate in Boston. In part this may stem from Boston's greater proportions of (1) non-Latino immigrants and (2) Latino populations (i.e., Puerto Ricans and Dominicans) that had longer tenure in the United States. In keeping with the spirit of these macrosocial analyses, we added the tract-level measure of vacancy rate. This variable

is frequently employed as an additional measure of social disorganization, and in Boston, it is much more closely linked with levels of neighborhood violence than are proportion of Latinos or immigrants, after controlling for other relevant factors.

21. The first author is currently completing a study on the issue of transitivity and dominance hierarchies in violence networks.
22. One potential avenue for advancing this line of inquiry would be to consider how ecological-focused research might incorporate findings from network studies demonstrating that individual-level racial effects are often amplified network-centered processes (e.g., Goodreau et al. 2009; Wimmer and Lewis 2010).
23. As we describe at greater length in the online supplement, we believe our data accurately reflect patterns of violence during this time period. Although specific organizational traits might vary and new patterns might emerge under different scope conditions, one might hypothesize that the role of the corner and the crew are enduring traits that make the gang a worthy subject of sociological investigation. Of course, this too is subject to empirical investigation.

References

Anderson, Elijah. 1999. *Code of the Street: Decency, Violence, and the Moral Life of the Inner City*. New York: W.W. Norton & Company.

Anselin, Luc, Ibnu Syabri, and Youngihn Kho. 2006. "GeoDa: An Introduction to Spatial Data Analysis." *Geographical Analysis* 38:5–22.

Black, Donald J. 1970. "The Production of Crime Rates." *American Sociological Review* 35:733–48.

Block, Carolyn R. and Richard Block. 1993. *Street Gang Crime in Chicago*. Research in Brief, NCJ 144782. Washington, DC: U.S. Department of Justice, National Institute of Justice.

Block, Richard. 2000. "Gang Activity and Overall Levels of Crime: A New Mapping Tool for Defining Areas of Gang Activity Using Police Records." *Journal of Quantitative Criminology* 16:369–83.

Braga, Anthony A., David Hureau, and Christopher Winship. 2008. "Losing Faith? Police, Black Churches, and the Resurgence of Youth Violence in Boston." *Ohio State Journal of Criminal Law* 6:141–72.

Brantingham, P. Jeffrey, George E. Tita, Martin B. Short, and Shannon E. Reid. 2012. "The Ecology of Gang Territorial Boundaries." *Criminology* 50:851–85.

Browning, Christopher R. and Robert D. Dietz. 2004. "The Paradox of Social Organization: Networks, Collective Efficacy, and Violent Crime in Urban Neighborhoods." *Social Forces* 83:503–534.

Bursik, Robert J. and Harold G. Grasmick. 1993. *Neighborhoods and Crime: The Dimensions of Effective Community Control*. Lanham, MD: Lexington Books.

Butts, Carter T., Ryan M. Acton, John R. Hipp, and Nicholas N. Nagle. 2012. "Geographical Variability and Network Structure." *Social Networks* 34:82–100.

Chase, Ivan D. 1980. "Social Process and Hierarchy Formation in Small Groups: A Comparative Perspective." *American Sociological Review* 45:905–924.

Cohen, Albert K. 1955. *Delinquent Boys: The Culture of the Gang*. Glencoe, IL: Free Press.

Cohen, Jacqueline and George Tita. 1999. "Diffusion in Homicide: Exploring a General Method for Detecting Spatial Diffusion Process." *Journal of Quantitative Criminology* 15:451–93.

Decker, Scott H. 1996. "Collective and Normative Features of Gang Violence." *Justice Quarterly* 13:243–64.

Decker, Scott H. and G. David Curry. 2000. "Addressing Key Features of Gang Membership: Measuring Involvement of Young Gang Members." *Journal of Criminal Justice* 28:473–82.

Decker, Scott H. and G. David Curry. 2002. "Gangs, Gang Homicides, and Gang Loyalty: Organized Crimes or Disorganized Criminals?" *Journal of Criminal Justice* 30:343–52.

Decker, Scott H., Charles M. Katz, and Vincent J. Webb. 2008. "Understanding the Black Box of Gang Organization: Implications for Involvement in Violent Crime, Drug Sales, and Violent Victimization." *Crime & Delinquency* 54:153–72.

Decker, Scott H. and David C. Pyrooz. 2010. "On the Validity and Reliability of Gang Homicide: A Comparison of Disparate Sources." *Homicide Studies* 14:359–76.

Decker, Scott H. and Barrik Van Winkle. 1996. *Life in the Gang: Family, Friends, and Violence*. New York: Cambridge University Press.

Descormiers, Karine and Carlo Morselli. 2011. "Alliances, Conflicts, and Contradictions in Montreal's Street Gang Landscape." *International Criminal Justice Review* 21:297–314.

Egley, Arlen, James C. Howell, and Aline K. Major. 2004. "Recent Patterns of Gang Problems in the United States: Results From the 1996–2002 National Youth Gang Survey." Pp. 90–108 in *American Youth Gangs at the Millennium,* edited by F. Esbensen, S. G. Tibbetts, and L. Gaines. Long Grove, IL: Waveland Press.

Esbensen, Finn-Aage and David Huizinga. 1993. "Gangs, Drugs, and Delinquency in a Survey of Urban Youth." *Criminology* 31:565–89.

Fagan, Jeffrey A. 1989. "The Social Organization of Drug Use and Drug Dealing among Urban Gangs." *Criminology* 27:633–70.

Fagan, Jeffrey A., Amanda Geller, Garth Davies, and Valerie West. 2009. "Street Stops and Broken Windows Revisited: The Demography and Logic of Proactive Policing in a Safe and Changing City." Pp. 309–348 in *Race, Ethnicity, and Policing: New and Essential Readings,* edited by S. K. Rice and M. D. White. New York: New York University Press.

Faris, Robert and Diane Felmlee. 2011. "Status Struggles: Network Centrality and Gender Segregation in Same- and Cross-Gender Aggression." *American Sociological Review* 76:48–73.

Felson, Richard B. and Henry J. Steadman. 1983. "Situational Factors in Disputes Leading to Criminal Violence." *Criminology* 21:59–74.

Fleisher, Mark S. 1998. *Dead End Kids: Gang Girls and the Boys They Know*. Madison: University of Wisconsin Press.

Fleisher, Mark S. 2006. "Youth Gang Social Dynamics and Social Network Analysis: Applying Degree Centrality Measures to Assess the Nature of Gang Boundaries." Pp. 85–98 in *Studying Youth Gangs,* edited by J. F. Short and L. A. Hughes. Lanham, MD: AltaMira Press.

Fruchterman, Thomas M. J. and Edward M. Reingold. 1991. "Graph Drawing by Force-Directed Placement." *Journal of Software: Practice and Experience* 21:1129–64.

Garot, Robert. 2007. "'Where You From!': Gang Identity as Performance." *Journal of Contemporary Ethnography* 36:50–84.

Goodreau, Steven M. 2007. "Advances in Exponential Random Graph (*p**) Models Applied to a Large Social Network." *Social Networks* 29:231–48.

Goodreau, Steven M., James A. Kitts, and Martina Morris. 2009. "Birds of a Feather, or Friend of a Friend? Using Exponential Random Graph Models to Investigate Adolescent Social Networks." *Demography* 46:103–125.

Gould, Roger V. 2003. *Collision of Wills: How Ambiguity about Social Rank Breeds Conflict*. Chicago: University of Chicago Press.

Grannis, Rick. 2009. *From the Ground Up: Translating Geography into Community through Neighbor Networks*. Princeton, NJ: Princeton University Press.

Granovetter, Mark S. 1973. "The Strength of Weak Ties." *American Journal of Sociology* 78:1360–80.

Hagedorn, John M. 1988. *People and Folks: Gangs, Crime, and the Underclass in a Rustbelt City*. Chicago: Lake View Press.

Hagedorn, John M. 2008. *A World of Gangs: Armed Young Men and Gangsta Culture*. Minneapolis: University of Minnesota Press.

Handcock, Mark S., David R. Hunter, Carter T. Butts, Steven M. Goodreau, and Martina Morris. 2008. "Statnet: Software Tools for the Representation, Visualization, Analysis, and Simulation of Network Data." *Journal of Statistical Software* 24:1–11.

Hannerz, Ulf. 1969. *Soulside: Inquiries into Ghetto Culture and Community*. Chicago: University of Chicago Press.

Hipp, John R., Robert W. Faris, and Adam Boessen. 2012. "Measuring 'Neighborhood': Constructing Network Neighborhoods." *Social Networks* 34:128–40.

Horowitz, Ruth. 1983. *Honor and the American Dream: Culture and Identity in a Chicano Community*. New Brunswick, NJ: Rutgers University Press.

Howell, James C. 2012. *Gangs in America's Communities*. Los Angeles, CA: Sage.

Hughes, Lorine A. and James F. Short. 2005. "Disputes Involving Youth Street Gang Members: Micro-Social Contexts." *Criminology* 43:43–76.

Hunter, David R., Steven M. Goodreau, and Mark S. Handcock. 2008. "Goodness of Fit of Social Network Models." *Journal of the American Statistical Association* 103:248–58.

Hunter, David R. and Mark S. Handcock. 2006. "Inference in Curved Exponential Family Models for Networks." *Journal of Computational and Graphical Statistics* 15:565–83.

Hunter, David R., Mark S. Handcock, Carter T. Butts, Steven M. Goodreau, and Martina Morris. 2008. "Ergm: A Package to Fit, Simulate, and Diagnose Exponential-Family Models for Networks." *Journal of Statistical Software* 24:1–29.

Jacobs, Bruce A. and Richard Wright. 2006. *Street Justice: Retaliation in the Criminal Underworld*. New York: Cambridge University Press.

Jankowski, Martin Sanchez. 1991. *Islands in the Street: Gangs and American Urban Society*. Berkeley: University of California Press.

Katz, Charles M., Vincent J. Webb, and David R. Schaefer. 2000. "The Validity of Police Gang Intelligence Lists: Examining the Differences in Delinquency between Documented Gang Members and Nondocumented Delinquent Youth." *Police Quarterly* 3:413–37.

Kennedy, David M., Anthony A. Braga, and Anne M. Piehl. 1997. "The (Un)Known Universe: Mapping Gangs and Gang Violence in Boston." Pp. 219–62 in *Crime Mapping and Crime Prevention,* edited by D. Weisburd and T. McEwen. Monsey, NY: Criminal Justice Press.

Klein, Malcolm W. and Cheryl L. Maxson. 2006. *Street Gang Patterns and Policies*. New York: Oxford University Press.

Kobrin, Solomon, Joseph Puntil, and Emil Peluso. 1967. "Criteria of Status among Street Groups." *Journal of Research in Crime and Delinquency* 4:98–118.

Leibow, Elliot. 1967. *Tally's Corner: A Study of Negro Streetcorner Men*. Boston, MA: Little, Brown and Company.

McGloin, Jean Marie. 2005. "Policy Intervention Considerations of a Network Analysis of Street Gangs." *Criminology & Public Policy* 4:607–635.

Miller, Walter B. 1958. "Lower Class Culture as a Generating Milieu of Gang Delinquency." *Journal of Social Issues* 14:5–19.

Morenoff, Jeffrey D., Robert J. Sampson, and Stephen W. Raudenbush. 2001. "Neighborhood Inequality, Collective Efficacy, and the Spatial Dynamics of Urban Violence." *Criminology* 39:517–58.

Papachristos, Andrew V. 2006. "Social Network Analysis and Gang Research: Theory and Methods." Pp. 99–116 in *Studying Youth Gangs,* edited by J. F. Short and L. A. Hughes. Lanham, MD: AltaMira Press.

Papachristos, Andrew V. 2009. "Murder by Structure: Dominance Relations and the Social Structure of Gang Homicide." *American Journal of Sociology* 115:74–128.

Papachristos, Andrew V., Anthony A. Braga, and David M. Hureau. 2012. "Social Networks and the Risk of

Gunshot Injury." *Journal of Urban Health* 89:992–1003.

Papachristos, Andrew V. and David S. Kirk. 2006. "Neighborhood Effects on Street Gang Behavior." Pp. 63–84 in *Studying Youth Gangs,* edited by J. F. Short and L. A. Hughes. Lanham, MD: AltaMira Press.

Papachristos, Andrew V., Tracey L. Meares, and Jeffrey Fagan. 2007. "Attention Felons: Evaluating Project Safe Neighborhoods in Chicago." *Journal of Empirical Legal Studies* 4:223–72.

Pattillo, Mary E. 1999. *Black Picket Fences: Privilege and Peril among the Black Middle Class*. Chicago: University of Chicago Press

Pattillo, Mary E. 2008. *Black on the Block: The Politics of Race and Class in the City*. Chicago: University of Chicago Press.

Peterson, Ruth D. and Lauren J. Krivo. 2005. "Macrostructural Analyses of Race, Ethnicity, and Violent Crime: Recent Lessons and New Directions for Research." *Annual Review of Sociology* 31:331–56.

Robins, Garry, Philippa Pattison, and Peng Wang. 2009. "Closure, Connectivity, and Degree Distributions: Exponential Random Graph (p*) Models for Directed Social Networks." *Social Networks* 31:105–117.

Robins, Garry, Tom Snijders, Peng Wang, Mark Handcock, and Philippa Pattison. 2007. "Recent Developments in Exponential Random Graph (p*) Models for Social Networks." *Social Networks* 29:192–215.

Rosenfeld, Richard, Timothy M. Bray, and Arlen Egley. 1999. "Facilitating Violence: A Comparison of Gang-Motivated, Gang-Affiliated, and Nongang Youth Homicides." *Journal of Quantitative Criminology* 15:495–516.

Rymond-Richmond, Wenona C. 2006. "Transforming Communities: Formal and Informal Mechanisms of Social Control." Pp. 295–312 in *The Many Colors of Crime: Inequalities of Race, Ethnicity, and Crime in America,* edited by R. D. Peterson, L. J. Krivo, and J. Hagan. New York: New York University Press.

Sampson, Robert J. 2012. *Great American City: Chicago and the Enduring Neighborhood Effect*. Chicago: University of Chicago Press.

Sampson, Robert J., Stephen W. Raudenbush, and Felton Earls. 1997. "Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy." *Science* 277:918–24.

Sampson, Robert J. and William Julius Wilson. 1995. "Toward a Theory of Race, Crime, and Urban Inequality." Pp. 37–54 in *Crime and Inequality,* edited by J. Hagan and R. D. Peterson. Stanford, CA: Stanford University Press.

Schaefer, David R. 2012. "Youth Co-offending Networks: An Investigation of Social and Spatial Effects." *Social Networks* 34:141–49.

Scott, Michael. 2005. *Lords of Lawndale: My Life in a Chicago White Street Gang*. Bloomington, IN: Authorhouse.

Shaw, Clifford R. and Henry D. McKay. 1942. *Juvenile Delinquency and Urban Areas*. Chicago: University of Chicago Press.

Short, James F. and Lorine A. Hughes, eds. 2006. "Moving Gang Research Forward." Pp. 225–38 in *Studying Youth Gangs*. Lanham, MD: AltaMira Press.

Short, James F. and Fred L. Strodtbeck. 1965. *Group Process and Gang Delinquency*. Chicago: University of Chicago Press.

Suttles, Gerald D. 1968. *The Social Order of the Slum: Ethnicity and Territory in the Inner City*. Chicago: University of Chicago Press.

Thornberry, Terence P., Marvin D. Krohn, Alan J. Lizotte, Carolyn A. Smith, and Kimberly Tobin. 2003. *Gangs and Delinquency in Development Perspective*. New York: Oxford University Press.

Thrasher, Frederic M. 1927. *The Gang: A Study of 1,313 Gangs in Chicago*. Chicago: University of Chicago Press.

Tita, George E., Jacqueline Cohen, and John Engberg. 2005. "An Ecological Study of the Location of Gang 'Set Space.'" *Social Problems* 52:272–99.

Tita, George E. and Robert T. Greenbaum. 2009. "Crime, Neighborhoods, and Units of Analysis: Putting Space in its Place." Pp. 145–70 in *Putting Crime in its Place,* edited by D. Weisburd, W. Bernasco, and G. Bruinsma. New York: Springer.

Tita, George E. and Steven M. Radil. 2011. "Spatializing the Social Networks of Gangs to Explore Patterns of Violence." *Journal of Quantitative Criminology* 27:521–45.

Venkatesh, Sudhir Alladi. 2000. *American Project: The Rise and Fall of a Modern Ghetto*. Cambridge, MA: Harvard University Press.

Venkatesh, Sudhir Alladi. 2006. *Off the Books: The Underground Economy of the Urban Poor*. Cambridge, MA: Harvard University Press.

Venkatesh, Sudhir Alladi and Steven D. Levitt. 2000. "Are We a Family or a Business? History and Disjuncture in the Urban American Street Gang." *Theory and Society* 29:427–62.

Vigil, James Diego. 1988. *Barrio Gangs: Street Life and Identity in Southern California*. Austin, TX: University of Texas Press.

Vigil, James Diego. 2002. *A Rainbow of Gangs: Street Cultures in the Mega-City*. Austin: University of Texas Press.

Warr, Mark. 2002. *Companions in Crime: The Social Aspects of Criminal Conduct*. New York: Cambridge University Press.

Warren, Patricia, Donald Tomaskovic-Devey, Marcinda Mason, William Smith, and Matthew Zingraff. 2006. "Driving While Black: Bias Processes and Racial Disparities in Police Stops." *Criminology* 44:709–738.

Wasserman, Stanley and Katherine Faust. 1994. *Social Network Analysis: Methods and Applications*. New York: Cambridge University Press.

Weisel, Deborah Lamm. 2002. *Contemporary Gangs: An Organizational Analysis*. El Paso, TX: LFB Scholarly Publishing.

Whyte, William Foote. 1943. *Street Corner Society: The Social Structure of an Italian Slum*. Chicago: University of Chicago Press.

Wimmer, Andreas and Kevin Lewis. 2010. "Beyond and Below Racial Homophily: ERG Models of a Friendship Network Documented on Facebook." *American Journal of Sociology* 116:583–642.

Zimring, Franklin E. 1972. "The Medium Is the Message: Firearm Caliber as a Determinant of Death from Assault." *Journal of Legal Studies* 1:97–123.

Andrew V. Papachristos is Associate Professor in the Department of Sociology at Yale University. His research examines neighborhood social organization, street gangs, interpersonal violence, illegal gun markets, and social networks. He is currently involved in a multi-city study on the diffusion of gun violence within high-risk social networks, as well as a historical project examining the evolution of criminal and political networks during Prohibition Era Chicago.

David M. Hureau is a doctoral student in Sociology and Social Policy at Harvard University and also serves as a Research Fellow at the Harvard Kennedy School's Program in Criminal Justice Policy and Management. He is broadly interested in urban sociology and crime. His present research project is an ethnographic exploration of a network of individuals who have experienced disproportionate exposure to homicide.

Anthony A. Braga is the Don M. Gottfredson Professor of Evidence-Based Criminology in the School of Criminal Justice at Rutgers University and a Senior Research Fellow in the Program in Criminal Justice Policy and Management at Harvard University. His research involves collaborating with criminal justice, social service, and community-based organizations to address illegal access to firearms, reduce gang and group-involved violence, and control crime hot spots. He is currently the President and an elected Fellow of the Academy of Experimental Criminology.