

Rules of the Game: Exponential Random Graph Models of a Gang Homicide Network

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Gang members frequently refer to street life as a “game” (or “*The Game*”): a social milieu in which status is lost or won by the way individuals and groups manage their reputations. Like other games, successfully participating in the street game may demand adherence to certain rules, such as the willingness to violently redress threats, the avoidance of “weak” behaviors, and the protection of one’s allies. This paper draws on detailed police records of violent exchanges among gangs in Chicago to ascertain which rules of the game in fact contribute to the relative social standing of groups. Specifically, we use exponential random graph models to identify the underlying micro-arrangements among gangs that collectively generate macro-level patterns of homicide. Findings illuminate a large and diverse array of generative mechanisms based on gangs’ attributes and structural positions. However, these mechanisms vary depending on which two gangs are at hand; provide evidence of a contested hierarchy with few intergroup alliances; and are surprisingly inconsistent over time. As all gangs engage in local and ongoing struggles for dominance—and as the rules constantly change—the street game is continually played but never truly won.

“Nobody fucks with the Latin Kings, man. Nobody... If someone steps up, calls you a ‘bitch’ or something, or messes with one of your boys, your crew better throw down [fight]... If you back down, everyone’ll think you’re weak... You best believe the Kings’ll show any fools what we about... That’s the way it is in the game. And, the Kings run it up in here! For real.”

~ Rascal, 24 year-old member of the Latin Kings

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Introduction

Gang members frequently refer to street life as a “game” (or “*The Game*”): a milieu in which social status is lost or won by the manner in which individuals and groups manage their reputations. Like other games, the street game has rules that determine who wins and who loses. Some rules relate to mannerisms, style, language, patterns of consumption, and even one’s eye movements and saunter (Anderson 1999; Fagan and Wilkinson 1998; Katz 1988). But, as Rascal’s words make abundantly clear, many rules of the street game explicitly prescribe the use of violence as a status conferring mechanism.

One pervasive rule of the street game is *retaliation*, the use of violence as a form of impression management to correct perceived wrongs, losses of face, or other transgressions (Anderson 1999; Decker 1996). Retaliation provides a sort of “street justice” that not only restores lost status, but signals to other would-be assailants that the avenger adheres to the street code and is willing to use violence to protect or advance his reputation (Jacobs 2004; Jacobs and Wright 2006). Yet retaliation is imperfect; if it were the only rule of the game, the majority of gangs would be losers. For example, among organized street gangs in Chicago, only 30 percent of homicides are reciprocated (Papachristos 2009). According to Rascal’s remarks, such a failure to seek retribution would amount to status suicide—a surefire way for a gang to sink to the detested position of “punk” or “bitch.”

Gangs thus navigate their precarious social situation by turning to additional rules besides retaliation—rules related to the interactive and public nature of street violence. One such rule is *generalized reciprocity*. This refers to a scenario where a gang that has lost a particular violent exchange seeks to redress the loss not by engaging the initial adversary, but by attacking a third party (Chase 1980; Tsvetkova and Macy 2015). Such an outward act of aggression demonstrates publicly that the losing gang still adheres to the street code, i.e., is an active status-seeking player in the street game, despite the previous loss of face. Importantly, such outward acts of aggression can also lead to the diffusion of violence and the generation of enduring networks of conflict over time (Papachristos 2009; Papachristos, Hureau, and Braga 2013).

While prior research has documented the importance of both retaliation and generalized reciprocity for inter-gang violence, their implications remain poorly understood. While both mechanisms address fundamental issues pertaining to social status, they lead to quite different outcomes and arrangements. Retaliation is often conceived as a dyadic, zero-sum process. Like notches on a belt, one’s street credibility amasses in a cumulative fashion whereby each act of vengeance, successful competition, or display of street savvy enhances one’s reputation. Generalized reciprocity, meanwhile, broadens the scope of the street game to include a greater number of actors and a greater number of possible status orderings. In particular, it can lead to the creation of *dominance hierarchies* that sort groups into various status categories, some of which may be purely hierarchical while others may be less clearly ordered (Davis 1970). In such a world, the reputation of any gang is a result of dynamic processes of exchange

with multiple social actors—the intricacies of which are challenging to empirically disentangle.

Using detailed police records, this paper explores the rules of the street game and their implications for social standing among the known population of gangs in Chicago. Specifically, we use exponential random graph models (ERGMs) to statistically discern which interactional principles govern the network of inter-gang homicides. Results suggest that a large and diverse set of rules are responsible for observed patterns of violence. Some of these rules are clearly documented in the ethnographic literature, while others seem to represent “invisible yet consequential” structures (Bearman, Moody, and Stovel 2004:60) imperceptible to gang members themselves. Further, our results suggest (1) important heterogeneity in rules based on gang racial composition; (2) evidence of a contested hierarchy with few horizontal alliances; and (3) surprising inconsistency in these rules over time. As all gangs engage in ongoing local dominance struggles where the rules constantly change, the street game is continually played but never truly won.

We begin by outlining the basic parameters of the street game: its boundaries, players, and potential rules. We next describe our quantitative data and approach to statistical modeling. Results from ERGMs are presented first for our entire five-year study period and second for overlapping two-year intervals. We conclude by discussing implications and directions for future research.

The Street Game and Its Players

To say street life is a game implies there are boundaries, players, and rules. While each of these dimensions can be rather amorphous, a “code of the streets” is frequently thought to govern public interactions in disadvantaged urban neighborhoods (Anderson 1999). Broadly conceived, this code refers to a set of informal behavioral rules that regulate public interaction and stress a willingness to use violence to gain or maintain respect. Symbolic matters such as toughness, honor, charisma, and criminal prowess are major determinants of social standing. Individuals wishing to maintain respect must walk, talk, and act in a manner that sends an “unmistakable, if sometimes subtle, message that one is capable of violence, and possibly mayhem, when the situation requires it” (p. 72). Successfully navigating the streets requires one to continually assess and react to myriad interactional cues—especially important in potentially threatening encounters.

The boundaries of the street game encompass residents of disadvantaged neighborhoods, but especially those individuals who subscribe to the code of the street as a dominant cultural frame. Importantly, Anderson (1999) tells us the majority of residents in such neighborhoods do *not* subscribe to the code—i.e., only a small fraction of residents are active “players” in the game. For instance, a recent study showed that 85 percent of all gun homicides in Boston occurred in a network of less than 5 percent of the community’s population (Papachristos, Braga, and Hureau 2012). Still, the actions of this small but active network can have severe consequences for others who walk the same streets. As

such, even non-players must possess a modicum of street savvy, if only to navigate their daily routines (e.g., [Garot 2010](#)).

Players in the street game are demarked by two crucial elements: *geographic residence* and *group membership*. When an unknown individual—especially a young minority male—is encountered on the street, one of the first questions he is inevitably asked is, “Where you from?” ([Anderson 2011](#); [Martinez 2016](#)). Though seemingly innocuous in other social situations (e.g., among freshmen at college or between singles on a first date), this question is extremely loaded in the street game ([Garot 2010](#)). “Claiming” a particular neighborhood associates an individual with a collective identity, thus affording him some baseline status of being “in the game” (i.e., from a neighborhood with a street reputation) or not. In some instances, the names of particular neighborhoods are synonymous with the names of delinquent groups and gangs.

A related question—one that precedes or follows “Where you from?”—is “Who you with?” or “Who you claim?” Questions such as these directly assess whether an individual belongs—or “claims” to belong—to a street gang or other group. As [Garot \(2010\)](#) points out, such questions profoundly impact the daily interactions of youth in disadvantaged communities. Claiming to be part of a group carries with it the burdens (and perhaps the benefits) of the collective, including associations with its allies and adversaries, its reputation, and its overall worldview. Thus, just like claiming to be from a particular neighborhood, claiming to associate with a particular group demarks an individual as a “player” in the street game; and being from “someplace” or belonging to “some group” amplifies any baseline level of playership.

One of the most frequently cited reasons for joining a gang is protection—often from other gangs ([Howell 2012](#); [Warr 2002](#)). Quite simply, young people turn to gangs to mitigate their fears about walking through their own neighborhoods or schools. This notion of mutual protection is just one of many processes that lead to group conflict ([Peterson, Taylor, and Esbensen 2004](#); [Thornberry et al. 2003](#)). At its core, the gang is a group whose identity is tied to the streets and whose internal dynamics surrounding loyalty, protection, reputation, and cohesion generate individual and collective behavior. This “group processes” perspective underscores that such collective elements of the gang amplify the likelihood of intergroup violence.

The Golden Rule of the Street: Retaliation and Social Status

Retaliation—otherwise known as *direct reciprocity*—is one of the most pervasive and most studied rules of the street game ([Jacobs and Wright 2006](#); [Papachristos 2009](#)). Direct reciprocity is a relevant norm in numerous social contexts (for the classic statement on reciprocity, see [Gouldner 1960](#)). In the street game, retaliation refers to the enactment of direct reciprocity against someone who has committed a perceived transgression or caused some related loss of status, face, or reputation ([Anderson 1999](#)). The street code demands that such threats necessitate revenge—often a tit-for-tat, dyadic exchange whereby the offended extracts their pound of flesh from the offender. Violence, in this sense, is

not only a manner of self-help (Black 1983); it also serves to enforce status differences and similarities (Gould 2003). If the offended retaliates, status is saved or won. If the offended does nothing, the loss of status may be severe.

In this view of the street game, credibility is the sum total of one's "wins" or successful encounters—a status piggy bank of sorts in which each encounter represents a potential deposit or withdrawal. But the game is not only dyadic—far from it. Most encounters, including violence, are highly performative, taking place in front of an audience and often (quite literally) *on the street*.¹ Consequently, one is "honorable" or "dishonored" only insofar as such distinctions are credibly bestowed by one's larger frame of reference (Gould 2003; Horowitz 1983). For gangs, this frame largely consists of other gangs—possible opponents who might threaten a gang's safety or status (Decker 1996; Short and Strodtbeck 1963). Conflicts thus occur within a broader social *system*, as seemingly isolated acts of violence string together to form enduring social networks (Papachristos 2009; Papachristos et al. 2013). In this way, the accumulation of status is less like a windfall won in a scratch-off lottery ticket and more like parlaying one's bets across multiple types of activities and encounters.

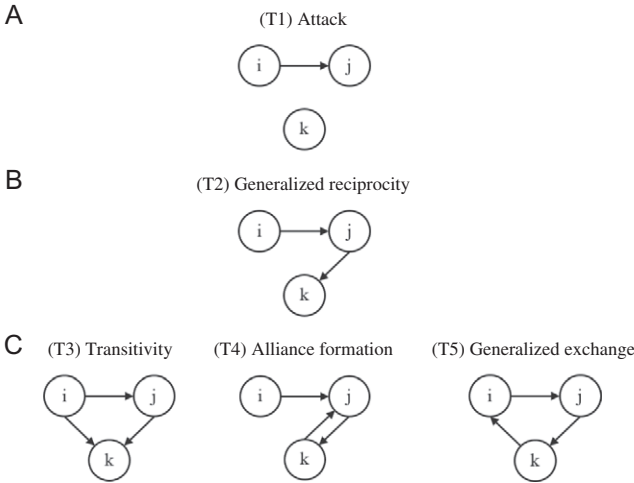
One way gangs deal with the performative nature of violence is through *generalized reciprocity*. In the context of the street game, this refers to a situation when direct reciprocity is not possible and a violent act is instead directed to a gang that was not involved in the initial transgression. Specifically, if gang A attacks gang B, gang B attacks gang C (cf. Gray, Ward, and Norton 2014). Thus, B displaces some status loss by demonstrating that it still adheres to the code and refuses to be victimized in a more general sense; no gang wants to be in a situation where they experience no wins and move to the bottom of a ranking system.²

The Consequences of Imperfect Retaliation

Generalized reciprocity has significant consequences for street status. In particular, moving away from a purely dyadic notion of reciprocity implies that the street game involves a complex series of interactions in which multiple actors vie for dominance. The triad in Panel A of Figure 1, T1, shows an act of dyadic aggression in which gang i attacks gang j. While the norm of reciprocity demands retribution, the performative nature of street violence and the presence of additional adversaries might lead to an act of generalized reciprocity, T2. The implications of T2 are profound. By extending violence outward to include a third gang k, gang j turns the original (dyadic) contest into a potential (triadic) dominance hierarchy (specifically, a "two-path")—a transformation that opens new and qualitatively distinct possibilities (Simmel 1902).³

In T2, gang k finds itself in the same dyadic position of gang j in T1. How k responds, however—or how *other* gangs respond to k—has ramifications for the entire social system. While many different configurations might emerge, the triads in Panel C represent three empirical violent arrangements identified by qualitative research.⁴ In the remainder of this section, we discuss these

Figure 1. Some basic lines of action in gang violence networks



configurations—each representing a potential “rule of the game”—and their implications for social status in the broader gang system.

Is Murder Transitive?

T3 represents a classic transitive triad—a situation in which gangs form a dominance hierarchy or “pecking order” (Chase 1980). T2 implies a nascent hierarchy in which gang i is the winner, gang k is the loser, and gang j plays an intermediate role. T3 carries this hierarchy to its natural conclusion: gang i further asserts its dominant position by also attacking gang k. While perfect transitive hierarchies are uncommon in human groups, less restricted forms of dominance are commonplace, even in egalitarian settings. Indeed, a long tradition of research documents a mixture of transitive triads and direct reciprocity in human groups, suggesting a loose hierarchy of status positions (Davis 1970; Davis and Leinhardt 1972).

Dominance of one group over all others is a common theme among gang members. Gangs frequently boast of being the “top dog” or else of their supremacy and fighting prowess (Decker 1996; Short and Strodbeck 1963; Vigil 1988). Rascal’s bold claim of “the Kings run it” was made in reference to his gang being at the “top” of a pecking order—the gang with the strongest status claims. When gangs are acutely aware that the outcome of each conflict provides additional status information for all gangs in the population, the situation of the transitive triad represents a clear status hierarchy of unequivocal winners (gang i) and losers (gang k).

A recent study by Papachristos et al. (2013) found some evidence that transitive triads are uncommon in networks of gang homicides and shootings. However, the authors did not examine whether other triadic configurations

were present (or whether transitive triads were common or uncommon controlling for such alternatives).

Down with the Nation: Alliance Formation

A second potential consequence of generalized reciprocity is seen in T4, or what we call “alliance formation.” Grounded in Heider’s (1946) balance theory and the old adage of “the enemy of my enemy is my friend,” T2 could lead to the formation of an alliance between gangs i and k. In this instance, gang k retaliates against gang j—thereby avoiding conflict with gang i. The result, to use Chase’s (1980) term, is a form of “double attack” against gang j. The absence of ties between gangs i and k may or may not be related to a formal alliance or agreement. It might simply be a byproduct of mutual avoidance—the need to stay clear of additional conflicts (Martinez 2016). But even the latter implies a tacit understanding that i and k will not attack each other, and therefore an implicit alliance as far as patterns of violence are concerned.

Alliances among gangs are not without precedent. Qualitative and historical data suggest that complicated alliance systems have developed among gangs in Chicago (Hagedorn 2015; Venkatesh 1997), in Los Angeles (Maxson and Klein 2001; Vigil 1988), and within prisons (Jacobs 1977; Skarbek 2014). During the 1980s, Chicago gangs developed an intricate system dividing the gang world into two federations, the People and the Folks, intended to minimize intra-federation violence and offer mutual protection against the competing federation (Dawley 1973; Jacobs 1977). Chicago gangs also describe a “Nation” system whereby smaller gangs with similar geographic or cultural origins pledge their allegiance to each other. For instance, the Conservative Vice Lords, the Insane Vice Lords, the Traveling Vice Lords, and approximately 10 other “Vice Lord” gangs collectively constitute the “Almighty Vice Lord Nation.”

The key distinction between T3 and T4 is that the former is decidedly hierarchical. In contrast, while gang j in T4 is on the losing end of two ties, it also has one victory—and, as such, can claim some status (unlike gang k in T3). The status ranking in T4 is therefore less clearly defined, and more closely resembles a “two against one” than a rigidly ordinal system.

Cycles of Violence and Generalized Exchange

The final pattern we consider is called a 3-cycle. Like gang j in T2, gang k in T5 does not directly reciprocate gang j’s attack, but instead engages in generalized reciprocation with gang i. The result is a completed circle of violence that works its way through the network: from the first gang to a second, from the second to a third, and from the third back to the first.

The triadic configuration in T5 is an example of *generalized exchange* (Bearman 1997). Generalized exchange is a process in which one person gives to another with the understanding that she will be repaid by someone, but not necessarily the original receiver. In other words, one gives without the expectation of direct reciprocity, but rather the expectation that the group will provide

through indirect exchange patterns. In small societies, this process leads to a sense of solidarity and cohesion. Chains of generalized exchange can emerge even without the explicit formulation of norms to govern them and, once established, are often difficult to break.

In the context of “negative” ties like violence, however, generalized exchange would suggest not cohesion but ordered chaos—literal cycles of violence that are decidedly egalitarian. Everyone in T5 is both a winner and a loser; it is a status washout of sorts. “That’s the way it is in the game,” Rascal stated matter-of-factly: violence begets more violence. Generalized exchange likewise suggests you reap what you sow—but that it may or may not come at the hands of the original victim. In a sense, it represents the opposite social situation from the transitive structure of T3: the nascent hierarchy of the two-path is contested, not reinforced.

Summary

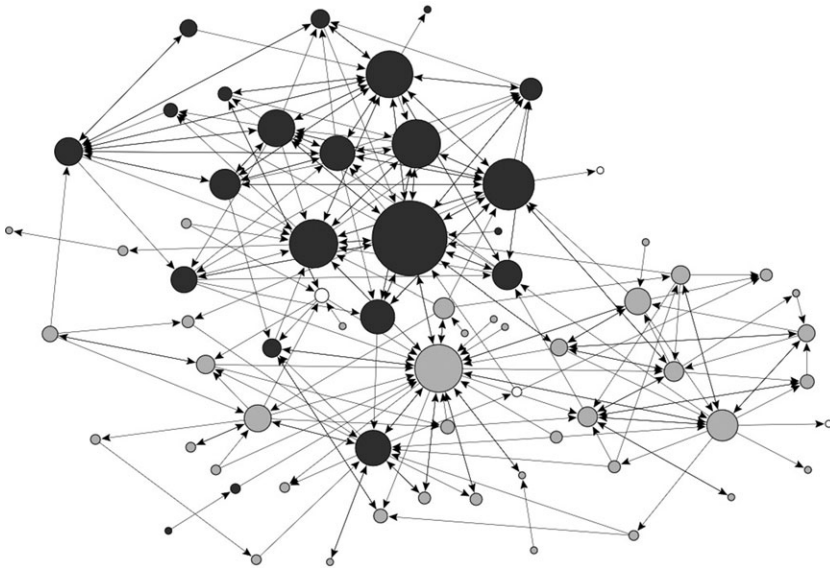
In the preceding sections, we described dyadic and triadic rules that emerge from prior research on street gangs and gang violence. Though we have emphasized, for each rule, a specific temporal ordering, most important for our purposes are the *micro-arrangements* among gangs that are ultimately produced: one hierarchical, one involving a horizontal alliance, and one egalitarian. Our objective is to statistically ascertain which (if any) of these rules actually influence patterns of gang violence in Chicago—specifically, which gangs kill members of which other gangs.

Data and Method

A Gang Homicide Network in Chicago

Our data include all “gang involved” homicides that occurred in Chicago over the 60-month period from January 1996 to December 2000.⁵ A homicide is considered gang involved only if *both* the victim *and* the offender were identified by the police as a member of a street gang. Decker and Pyrooz (2010) document that data on gang homicides display strong internal and external validity even given known limitations on definitions of the term “street gang.”

During our time window, 636 homicides among 68 gangs were committed in Chicago.⁶ Following Papachristos (2009), we established the network structure of gang homicide by letting nodes represent gangs and ties represent instances of *at least* one homicide, with the direction of the tie pointing from perpetrator to victim. This resulted in 248 ties with a unique combination of “sender” and “receiver,” i.e., the network examined in this paper.⁷ Figure 2 displays the ensuing social structure. The shading of each node corresponds to the predominant racial background of the gang: darkly-shaded nodes signify black gangs, lightly-shaded nodes signify Latino gangs, and unshaded nodes signify white gangs. The size of each node corresponds to the number of unique neighborhoods (police beats) in which each gang was reported as either perpetrator or victim,

Figure 2. The social structure of gang homicide in Chicago, 1996–2000

Note: Darkly shaded nodes represent black gangs; lightly shaded nodes represent Latino gangs; unshaded nodes represent white gangs. Node size is proportionate to gang size.

which we use as a proxy for gang size. Since no reliable estimates of gang size exist, we assume gangs occupying more geographic space tend to have greater membership and organizational sophistication—an assumption consistent with prior research (see [Klein and Maxson 2006](#)).

Accompanying descriptive statistics are provided in Table 1. The network includes 23 black gangs, 41 Latino gangs, and only 4 white gangs. The majority of ties (79 percent) are intra-racial, although there are clear racial differences in network structure (with a smaller number of much larger black gangs clustered together compared to a greater number of small Latino gangs loosely surrounding one central gang, the Latin Kings). The network is rather sparse: only 5 percent of possible ties are present. About half of all ties are reciprocated.⁸ Finally, Figure 3 presents the in- and out-degree distributions, i.e., (respectively) the distributions of the quantity of incoming and outgoing ties. Most common are gangs that have only one incoming or outgoing tie (recall that all gangs must be involved in at least one murder to be included in our data) and both distributions are right-skewed, particularly in-degree (the Latin Kings are an outlier with 21 incoming ties).

Exponential Random Graph Models

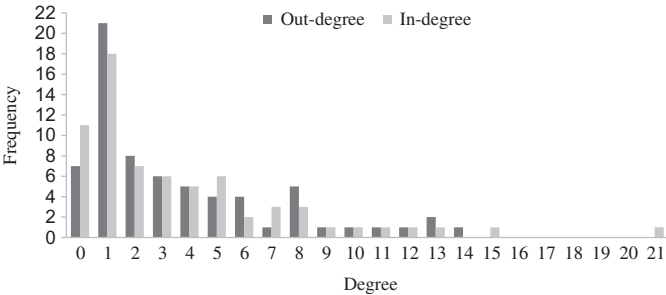
In recent decades, network analysts have focused less on describing network structures and more on identifying underlying micro-level mechanisms whereby such structures are generated ([Lewis 2015](#)). One exciting area of development is

Table 1. Descriptive statistics of the Chicago gang homicide network, 1996–2000

Quantity of gangs	
Black gangs	23
Latino gangs	41
White gangs	4
Total	68
Quantity of network ties	
Black-black ties	113
Latino-Latino ties	82
White-white ties	0
Interracial ties	53
Total	248
Average gang size	
Black gangs	22.7
Latino gangs	5.1
White gangs	2.0
Overall	10.9
Dyad census	
Mutual	64
Asymmetric	120
Null	2,094
Total	2,278

Note: Gang size is measured by the quantity of unique neighborhoods (police beats) in which each gang was reported in our homicide data. The dyad census refers to the observed distribution of the three possible states an (unordered) pair of gangs can occupy: both ties are present (mutual), only one tie is present (asymmetric), or neither tie is present (null).

Figure 3. Degree distribution of the Chicago gang homicide network, 1996–2000



the class of exponential random graph models (ERGMs). These models have the following general form:

$$\Pr(\mathbf{Y} = \mathbf{y}) = \left(\frac{1}{\kappa}\right) \exp \left\{ \sum_A \eta_A g_A(\mathbf{y}) \right\}$$

Here, the possible ties in a network are regarded as binary random variables, where \mathbf{Y} is the matrix of all such variables and \mathbf{y} the matrix of realized ties. In the above formula, $g_A(\mathbf{y})$ is a statistic representing how frequently configuration A occurs in network \mathbf{y} ; η_A is a parameter indicating whether A is more or less common than we would expect by chance (controlling for all other configurations in the model); and κ is a normalizing constant.

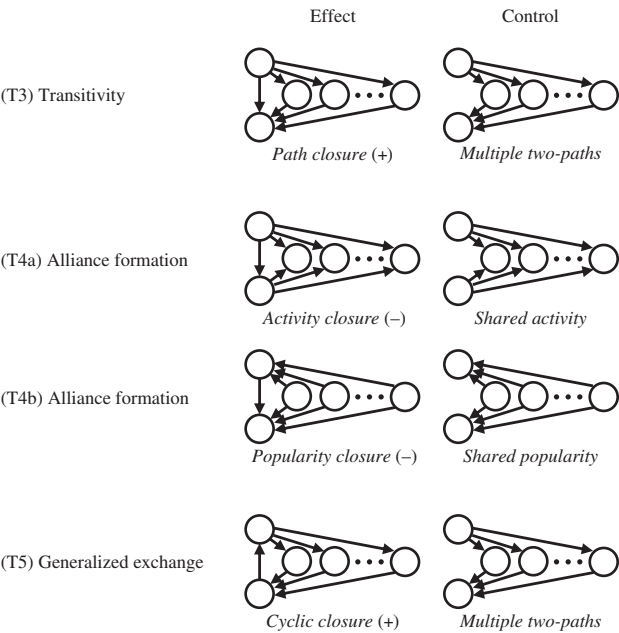
Configurations are the building blocks of social networks; indeed, many can be visualized as small network “micro-structures.” Conceptually, some configurations also correspond to “tie-generating mechanisms” (Wimmer and Lewis 2010), or possible reasons why a homicide tie might arise between two gangs. In other words, they represent potential “rules of the game.” A central strength of ERGMs is their flexibility: configurations can represent a variety of monadic, dyadic, and higher-order structures. Consequently, such models cannot be estimated in closed form and require special simulation-based estimation techniques. For an accessible introduction to ERGMs, we recommend Robins et al. (2007). For a thorough discussion of the configurations employed in this paper, see Robins, Pattison, and Wang (2009) and Snijders et al. (2006).

Modeling Strategy

ERGMs are different from mainstream statistical techniques in that they explicitly model the interdependencies among observations (as opposed to assuming observations are independent). Additionally, many ERGM practitioners advocate an analytic approach that prioritizes *fit* as much as (if not more than) hypothesis-testing. Such an approach coincides with the goals of this paper: we seek to identify those rules of interaction that are *necessary* and *sufficient* to explain the observed structure of homicide. As commonly practiced, these standards are unusually high—where a “good-fitting model” is capable not only of accurately predicting some outcome variable (here, the presence or absence of individual network ties) but also of reproducing any number of macro-level structural features of the empirical network (Hunter, Goodreau, and Handcock 2008; for illustrations, see Goodreau 2007; Wimmer and Lewis 2010).

While there is no universally accepted modeling strategy, the methodological literature recommends an approach guided by both theory and inductive exploration. We pursue a strategy derived from the standards of fit employed by Robins et al. (2009).⁹ Specifically, we began with a model containing all potentially relevant terms, based on prior research using ERGMs and also the gang research described earlier. Our focal theoretical mechanisms are represented using the four effects in Figure 4. The “path closure” effect represents transitivity (the tendency to victimize the victims of our victims); the “cyclic closure” effect

Figure 4. Focal mechanisms and controls



Note: The name of the corresponding model term appears beneath each visualization in italics (with the predicted direction of the effect in parentheses). “Multiple two-paths” serve as a control term for both path closure and cyclic closure.

represents generalized exchange (the tendency to be victimized *by* the victims of our victims); and two terms (“activity closure” and “popularity closure”) represent alliance formation (the tendency of gangs who victimize the same gangs or are victimized *by* the same gangs to victimize each other—effects we expect to be *negative* if gangs establish alliances). These effects are parameterized in such a way as to have diminishingly cumulative effects.¹⁰ As recommended by [Snijders et al. \(2006\)](#), each effect is accompanied by a control term to help distinguish the tie that “closes” a triangle from its two “walls.”

Beyond these terms, we include seven other effects recommended by [Robins et al. \(2009\)](#) for directed networks: a “density” term (representing the baseline likelihood of tie creation), a “reciprocity” term (representing the tendency to retaliate), terms representing “sinks,” “sources,” and “isolates” (respectively, gangs that send no ties, receive no ties, and neither send nor receive ties), and higher-order terms representing the overall distribution of incoming ties (“popularity spread”) and outgoing ties (“activity spread”). Ten terms represent the effects of gang “attributes” on homicide activity: two for tie formation among Latino and black gangs, respectively (“Latino- interaction” and “black- interaction”); two for reciprocity among Latino and black gangs, respectively (“Latino- interaction- reciprocity” and “black- interaction- reciprocity”); and six for the impact of racial background and gang size on the overall tendency to send and receive ties (“Latino- sender,” “Latino- receiver,” “black- sender,” “black- receiver,” “gang size- sender,” and

“gang size- receiver”).¹¹ Finally, six terms capture the behavior of two outliers in our network, the Latin Kings and the Gangster Disciples (respectively, the largest Latino and black gangs, each by a considerable margin): their tendency to send (“Latin Kings- sender” and “Gangster Disciples- sender”), receive (“Latin Kings- receiver” and “Gangster Disciples- receiver”), and reciprocate (“Latin Kings- activity- reciprocity” and “Gangster Disciples- activity- reciprocity”) ties.

The ensuing model contains a total of 29 terms and is presented as Model 1, below.¹² To assess its fit, we simulated a large number of networks from the fitted model and compared these simulations with the observed network across 118 distinct statistics. These include Markov graph configuration counts (and their intersection with gang attributes), properties of the degree distribution, clustering coefficients, and the full triad census (the complete list is available from the authors). The *t*-ratios for these statistics—defined as the ratio of the difference between the observed value and the mean from the simulated sample to the standard deviation—were less than 0.1 in absolute value for all features explicitly modeled, as required for model convergence. Moreover, the *t*-ratios for 115 out of 118 statistics were less than 1 in absolute value—which Robins et al. (2009) consider a “good fit for features not in the model”—and for all statistics were less than 2 in absolute value—meaning “the observed feature is not unusual in the estimated graph distribution” (p. 112). In other words, simulations of Model 1 very closely resemble the observed network with respect to a large number of macro-level characteristics; the terms in this model are *sufficient* to account for the structure of gang homicides in Chicago.

This does not require, however, that all 29 terms are *necessary* to achieve the same level of fit. Our next step was to pare Model 1 to its most parsimonious form. To do this, we eliminated effects one by one, starting with the effect with the smallest ratio of parameter estimate to standard error. After each elimination, we estimated a new model and examined the same array of fit statistics—continuing in this manner until we could not eliminate another term without at least one *t*-ratio rising above 2 in absolute value (in fact, in our final model, 111 of 118 *t*-ratios were still beneath 1 in absolute value). In other words, Model 2 represents those mechanisms minimally necessary to account for the observed structure of homicides from 1996 to 2000.¹³

As a final analytic step, we replicated this entire modeling strategy for 4 subsets of data: the overlapping two-year windows consisting of data from 1996 to 1997, 1997 to 1998, 1998 to 1999, and 1999 to 2000 (see Table 2). One concern this addresses is that 5 years is a sufficiently long period such that actually unrelated homicides (e.g., from gang A to gang B in 1996 and from B to A, or B to C, in 2000) appear related (thereby driving up rates of e.g., direct and generalized reciprocity).¹⁴ Rather than take an absolute stance on the appropriate time horizon of network configurations, we make this an empirical question: do rules appear in the aggregate that do not appear in shorter windows? Second, this approach allows us to examine possible *variation* in configurations over time that might otherwise be obscured. In other words, do rules appear in some periods but not others? Finally, while it is impossible to perfectly address the issue of censoring (i.e., the fact that homicide data prior to 1996 and subsequent to

Table 2. Descriptive statistics of the Chicago gang homicide network, 2-year windows

	1996–1997	1997–1998	1998–1999	1999–2000
Quantity of network ties				
Black-black ties	82	67	55	50
Latino-Latino ties	40	41	46	41
White-white ties	0	0	0	0
Interracial ties	33	28	18	20
Total	155	136	119	111
Dyad census				
Mutual	33	28	25	24
Asymmetric	89	80	69	63
Null	2,156	2,170	2,184	2,191
Total	2,278	2,278	2,278	2,278
Jaccard coefficient				
1996–1997	1.00			
1997–1998	0.53	1.00		
1998–1999	0.18	0.41	1.00	
1999–2000	0.19	0.22	0.56	1.00

Note: The dyad census refers to the observed distribution of the three possible states an (unordered) pair of gangs can occupy: both ties are present (mutual), only one tie is present (asymmetric), or neither tie is present (null). The Jaccard coefficient is a measure of network stability—it is calculated by dividing the quantity of network ties shared in common between any two periods by the total number of unique ties that appear in both periods combined. The total quantity of gangs is constant across periods, as are gang attributes (race and size).

2000 are not available, and yet these homicides certainly impact and are impacted by those in our data), our approach means that configurations truncated by one two-year window might instead be captured in the next. The “full” models for each time period are presented as Models 3, 5, 7, and 9; Models 4, 6, 8, and 10 are the “reduced” models and the focus of our interpretation below. As before, *t*-ratios for all 118 statistics in all models are below 2 (and the overwhelming majority below 1) in absolute value.

Results: The Rules of the Street Game

Of the 30 effects we assessed, 25 appeared in at least one reduced model. To provide the reader with a concise overview of results, these 25 configurations—the empirically verified “rules of the game”—are summarized in Table 3. A detailed examination of results follows.¹⁵

Table 3. Rules of the street game

	Effect	Sign	Overall	96–97	97–98	98–99	99–00	Interpretation
1.	Density	-	X	X	X	X	X	Homicide ties are relatively uncommon.
2.	Reciprocity	+	X	X	X	X	X	Homicide ties tend to be reciprocated.
3.	Sinks	-				X		There are relatively few gangs who are exclusively victims of homicide.
4.	Sources	+				X		There are relatively many gangs who are exclusively perpetrators of homicide.
5.	Isolates		N/A					
6.	Popularity spread	+					X	The in-degree distribution is skewed such that most gangs receive relatively few homicide ties, while some gangs receive relatively many.
7.	Activity spread	+	X		X	X		The out-degree distribution is skewed such that most gangs send relatively few homicide ties, while some gangs send relatively many.
8.	Path closure	-					X	If gang A murders someone from gang B and gang B murders someone from gang C, gang A is unlikely to murder someone from gang C.
9.	Cyclic closure	+					X	If gang A murders someone from gang B and gang B murders someone from gang C, gang C is likely to murder someone from gang A.

(Continued)

Table 3. continued

Effect	Sign	Overall	96–97	97–98	98–99	99–00	Interpretation
10. Popularity closure	+	X	X				Gangs that are attacked by the same set of third-party gangs tend to attack each other.
11. Activity closure							
12. Multiple two-paths	+		X				“Two-paths” are relatively common, where gang A murders someone from gang B and gang B murders someone from gang C
13. Shared popularity	-	X	X	X	X		Gangs are relatively unlikely to be attacked by the same set of third-party gangs.
14. Shared activity	-					X	Gangs are relatively unlikely to attack the same set of third-party gangs.
15. Latino-sender	-				X		Latino gangs send relatively few homicide ties.
16. Latino-receiver	-	X			X	X	Latino gangs receive relatively few homicide ties.
17. Latino-interaction	+	X			X	X	Latino gangs tend to murder members of other Latino gangs.
18. Latino-interaction-reciprocity							
19. Black-sender	-		X	X			Black gangs send relatively few homicide ties.
20. Black-receiver	-	X	X	X		X	Black gangs receive relatively few homicide ties.
21. Black-interaction	+	X	X	X		X	Black gangs tend to murder members of other black gangs.

(Continued)

Table 3. continued

Effect	Sign	Overall	96–97	97–98	98–99	99–00	Interpretation
22. Black-interaction-reciprocity	-	X		X		X	Homicide ties among two black gangs are especially likely to be reciprocated.
23. Gang size-sender	+	X	X	X	X	X	Larger gangs tend to send more homicide ties.
24. Gang size-receiver	+	X	X	X	X	X	Larger gangs tend to receive more homicide ties.
25. Latin Kings-sender							
26. Latin Kings-receiver	+			X	X	X	The Latin Kings receive relatively many homicide ties.
27. Latin Kings-activity-reciprocity	-			X			The Latin Kings are involved in relatively few reciprocal ties.
28. Gangster Disciples-sender	-	X	X	X			The Gangster Disciples send relatively few homicide ties.
29. Gangster Disciples-receiver	-	X				X	The Gangster Disciples receive relatively few homicide ties.
30. Gangster Disciples-activity-reciprocity							

Note: All interpretations are *conditional on all other effects in the model*. Shaded effects did not appear in any reduced model.

Overall Model

Fourteen effects appear in Model 2, our reduced model for the entire time period (Table 4). The very large, negative “density” parameter—like the intercept in a regression—indicates that ties in this network are more likely to be absent than present when all other terms in the model are 0. Although setting all terms to “zero” is not so straightforward as in standard regression, this still indicates that the overall network is relatively sparse. The only other basic structural effect is

Table 4. Coefficients and standard errors for ERGMs of the Chicago gang homicide network, 1996–2000

	Model 1	Model 2
Basic structural effects		
Density	−4.19 (0.64)	−4.56 (0.41)
Reciprocity	3.38 (0.56)	2.68 (0.33)
Sinks	0.00 (0.94)	
Sources	1.56 (0.90)	
Higher-order structural effects		
Popularity spread	−0.33 (0.52)	
Activity spread	0.58 (0.57)	0.25 (0.24)
Path closure	−0.07 (0.36)	
Cyclic closure	0.03 (0.15)	
Popularity closure	0.47 (0.27)	0.49 (0.11)
Activity closure	0.00 (0.26)	
Multiple two-paths	0.11 (0.07)	
Shared popularity	−0.21 (0.11)	−0.11 (0.05)
Shared activity	−0.12 (0.10)	
Attribute effects		
Latino- sender	−0.21 (0.48)	
Latino- receiver	−0.87 (0.50)	−1.11 (0.36)
Latino- interaction	1.11 (0.51)	1.44 (0.28)
Latino- interaction- reciprocity	−0.49 (0.63)	
Black- sender	−1.03 (0.59)	
Black- receiver	−0.90 (0.53)	−0.97 (0.41)
Black- interaction	1.93 (0.57)	1.15 (0.29)
Black- interaction- reciprocity	−1.82 (0.63)	−1.14 (0.48)
Gang size- sender	0.03 (0.01)	0.03 (0.01)
Gang size- receiver	0.03 (0.01)	0.03 (0.01)
Individual gang effects		
Latin Kings- sender	−0.49 (0.93)	
Latin Kings- receiver	1.93 (1.04)	
Latin Kings- activity- reciprocity	−1.36 (0.77)	
Gangster Disciples- sender	−2.83 (1.22)	−2.07 (0.88)
Gangster Disciples- receiver	−1.64 (1.09)	−1.94 (0.64)
Gangster Disciples- activity- reciprocity	0.79 (1.00)	

Note: Standard errors are in parentheses. *N* = 68 for both models.

the large and positive “reciprocity” effect. This is unsurprising given the qualitative literature on gangs and retaliatory violence as well as past network studies of gang homicides. However, this does *not* refer to reciprocity between two black gangs—a situation we discuss below.

Three higher-order structural effects are featured in this model. First is a positive “activity spread” effect. Corresponding with Figure 3, this means that the out-degree distribution is right-skewed: most gangs send relatively few ties but some send relatively many (Robins et al. 2009). Second, the negative “shared popularity” effect means that two gangs are unlikely to be attacked by the same third-party gangs. In the unlikely event that they *are*, however, the positive “popularity closure” effect means that such gangs are likely to attack *each other*. This is opposite to what we would expect if gangs formed alliances. In other words, rather than “team up” against their mutual opponent, “structurally equivalent” victims instead attack their own attackers’ other victim to ensure they don’t become “double-losers” (Papachristos 2009:78).

Very few studies compare the structure and behavior of gangs by ethno-racial background. Those studies suggest black gangs may be slightly more organized and more involved in organized drug dealing than Latino gangs (Decker and Curry 2002; Fagan 1989; Jankowski 1991). Such differences may also reflect differences between Latino and black neighborhoods (see Papachristos and Kirk 2006). We find several network effects related to gang size and racial composition. Larger gangs both send and receive more ties than smaller gangs (positive “gang size- sender/receiver” effects). Homicide ties between two black gangs and (especially) between two Latino gangs are more common than interracial homicide ties (positive “black/Latino- interaction” effects). Black gangs and Latino gangs are less likely to be victimized than white gangs (negative “black/ Latino- receiver” effects). Finally, the “black- interaction- reciprocity” effect is *negative* ($\eta = -1.14$). However, it is important to remember that this effect is essentially a combination of the general reciprocity effect and the “black- interaction” effect—the former of which ($\eta = 2.68$) is large and positive and the latter of which ($\eta = 1.15$) is approximately equal in magnitude but opposite in direction to the combination effect. What this means in practice is that (all else equal) retaliations *among* black gangs are about as common as *between* a black gang and a Latino gang, both of which are less common than retaliations among Latino gangs.¹⁶

Lastly, two effects specific to an individual gang are present: negative “sender” and “receiver” effects for the Gangster Disciples. These effects mean that the Gangster Disciples are *less* likely to both send and receive ties than we would expect based on their racial classification (black) and size (115 beats, by far the largest in the dataset) alone.

Two-Year Models

Decomposing the network into two-year periods, we find that very few rules are consistent over time (Table 5). In fact, the *only* effects that appear in the reduced models for all four periods are a (negative) density effect; a (strongly positive)

Table 5. Coefficients and standard errors for ERGMs of the Chicago gang homicide network, 2-year windows

	1996–1997		1997–1998		1998–1999		1999–2000	
	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Basic structural effects								
Density	–4.16 (1.43)	–4.55 (0.18)	–6.18 (1.46)	–5.17 (0.28)	–5.99 (1.61)	–5.77 (0.36)	–5.58 (1.73)	–5.74 (0.56)
Reciprocity	2.41 (0.84)	1.99 (0.36)	3.58 (0.78)	3.41 (0.52)	3.61 (0.96)	2.29 (0.41)	4.36 (0.92)	3.85 (0.46)
Sinks	1.76 (1.26)		–1.31 (1.24)		–2.02 (1.30)	–1.84 (0.54)	0.20 (1.33)	
Sources	–0.08 (1.18)		–0.05 (1.31)		1.40 (1.33)	0.95 (0.45)	0.13 (1.47)	
Isolates	0.67 (1.49)		–0.87 (1.55)		–0.14 (1.52)		0.94 (1.69)	
Higher-order structural effects								
Popularity spread	0.56 (0.78)		0.39 (0.94)		–0.11 (0.90)		1.31 (1.12)	1.54 (0.31)
Activity spread	–0.61 (0.81)		1.62 (0.87)	0.93 (0.28)	1.69 (0.97)	1.59 (0.28)	–0.01 (0.95)	
Path closure	–0.72 (0.49)		–0.34 (0.52)		–0.96 (0.68)		–1.98 (0.76)	–0.65 (0.18)
Cyclic closure	–0.18 (0.18)		–0.03 (0.17)		0.10 (0.19)		0.52 (0.20)	0.71 (0.16)
Popularity closure	0.78 (0.34)	0.43 (0.14)	0.51 (0.39)		0.68 (0.47)		0.86 (0.55)	
Activity closure	0.43 (0.36)		–0.33 (0.36)		0.27 (0.45)		0.55 (0.58)	
Multiple two-paths	0.19 (0.10)	0.12 (0.04)	0.08 (0.10)		–0.02 (0.10)		0.02 (0.12)	
Shared popularity	–0.24 (0.14)	–0.22 (0.09)	–0.44 (0.18)	–0.39 (0.10)	–0.42 (0.21)	–0.44 (0.10)	–0.07 (0.19)	
Shared activity	–0.21 (0.15)		–0.22 (0.19)		–0.13 (0.18)		–0.57 (0.29)	–0.56 (0.11)
Attribute effects								
Latino- sender	–0.59 (0.69)		–0.53 (0.72)		–0.81 (0.89)	–1.20 (0.44)	0.73 (1.13)	
Latino- receiver	–0.38 (0.73)		–0.78 (0.71)		–1.11 (0.77)	–1.64 (0.39)	–1.83 (0.86)	–1.49 (0.65)
Latino- interaction	0.81 (0.81)		1.42 (0.81)		2.52 (1.10)	3.35 (0.50)	1.90 (1.01)	1.77 (0.46)

Latino- interaction- reciprocity	0.61 (0.98)		−0.79 (0.93)		0.01 (1.02)		−0.94 (1.01)	
Black- sender	−1.09 (0.74)	−1.52 (0.39)	−1.34 (0.81)	−2.02 (0.40)	−0.43 (1.27)		0.23 (1.41)	
Black- receiver	−0.70 (0.76)	−1.28 (0.32)	−0.80 (0.80)	−0.97 (0.37)	−0.24 (1.15)		−1.38 (0.81)	−1.16 (0.68)
Black- interaction	1.77 (0.83)	2.55 (0.43)	2.13 (0.90)	3.01 (0.47)	1.32 (1.17)		1.81 (1.08)	1.42 (0.42)
Black- interaction- reciprocity	−0.50 (0.94)		−2.39 (0.86)	−1.85 (0.67)	−2.80 (1.05)		−2.67 (1.07)	−1.58 (0.69)
Gang size- sender	0.05 (0.02)	0.06 (0.01)	0.05 (0.02)	0.07 (0.01)	0.05 (0.02)	0.05 (0.01)	0.03 (0.02)	0.02 (0.01)
Gang size- receiver	0.03 (0.01)	0.01 (0.01)	0.04 (0.02)	0.02 (0.00)	0.02 (0.01)	0.01 (0.01)	0.04 (0.02)	0.05 (0.01)
Individual gang effects								
Latin Kings- sender	0.81 (0.83)		0.69 (1.08)		0.87 (1.26)		−0.38 (1.05)	
Latin Kings- receiver	1.20 (0.87)		2.20 (1.14)	1.71 (0.46)	2.78 (1.39)	1.47 (0.44)	2.90 (1.48)	2.33 (1.02)
Latin Kings- activity- reciprocity	−1.65 (0.97)		−2.16 (1.02)	−2.13 (0.90)	−2.04 (1.02)		−0.67 (1.19)	
Gangster Disciples- sender	−3.74 (1.49)	−4.61 (1.05)	−2.31 (1.52)	−2.78 (1.24)	−1.07 (1.61)		−2.30 (1.37)	
Gangster Disciples- receiver	−1.10 (1.22)		−0.55 (1.54)		−0.11 (1.39)		−3.21 (1.76)	−2.81 (1.39)
Gangster Disciples- activity- reciprocity	0.68 (1.02)		1.50 (1.15)		1.11 (1.18)		2.30 (1.55)	

Note: Standard errors are in parentheses. $N = 68$ for all models.

reciprocity effect (though its magnitude varies); and (positive) effects of gang size on the tendency to send and receive ties. Further, a number of rules appear in at least one two-year model that do *not* appear in the overall model—such as a negative “sinks” effect and a positive “sources” effect in 1998–99. These effects suggest, respectively, that there are *fewer* gangs that receive ties but do not send any, and *more* gangs that send ties but do not receive any, than we would expect based on other effects in the model.

A variety of higher-order effects appear and disappear over the years. Like in the overall model, a positive “activity spread” effect appears in 1997–98 and 1998–99; a negative “shared popularity” effect appears in all periods *except* 1999–2000; and a positive “popularity closure” effect appears in 1996–97. Also in 1996–97—and *only* in this period—we see a positive “multiple two-paths” effect, indicating unusually many instances of gang A being connected to gang C *via* multiple intermediaries B. Finally, 1999–2000 is particularly noteworthy because all four higher-order effects in this period do *not* appear in any other period. First, there is a positive “popularity spread” term—identical in interpretation to “activity spread,” except that it refers to the skew in *in*-degree. Second, there is a negative “shared activity” term. This means that two gangs A and B are unlikely to attack the same victims—i.e., they avoid “structurally competing” with each other. Third, the negative “path closure” effect indicates that transitive triads are unusually *uncommon*. Fourth, the positive “cyclic closure” effect indicates that cycles of generalized exchange are unusually common. Specifically, whether or not the receiver of a homicide tie retaliates, that tie is likely to be “paid back” by the victim of one’s victim. In fact, the higher-order parameterization not only captures the tendency for C to attack A if A attacks B and B attacks C, but also for the magnitude of this effect to strengthen the greater the number of distinct “B’s” involved.

Beyond the persistent effects of gang size on homicide involvement described above, we observe interesting patterns regarding the importance of race over time. In both 1996–97 and 1997–98, black gangs are less likely to both send and receive ties compared to white and Latino gangs (collectively the reference category in these models). Also in both models, homicide ties among black gangs are more likely than *either* interracial ties *or* ties among Latino gangs. The absence of a “Latino- interaction” effect in these periods is striking. The fact that a good-fitting model can be achieved without it suggests gangs’ tendency to self-segregate according to race is much more contingent on both the time period and the racial background of the gangs than prior work has recognized. Also in 1997–98 (and again in 1999–2000), the negative black- interaction- reciprocity effect that was observed in the overall model reappears. After this time period, there is a shift: in 1998–99, there are no effects related to black gangs. Instead, *Latino* gangs are less likely to both send and receive ties (compared to black and white gangs) and *more* likely to attack each other (compared to interracial ties and ties among black gangs). Finally, in 1999–2000, there are positive interaction effects for both black and (especially) Latino gangs and both black and (especially) Latino gangs are less likely to receive ties than white gangs.

Individual gang effects, too, vary considerably over time. In 1996–97 and 1997–98, the Gangster Disciples are less likely to send ties than we would expect given their size and racial composition. In all periods *except* 1996–97, the Latin Kings are *more* likely to *receive* ties than we would expect given their size and racial composition. In 1999–2000 alone, a negative “receiver” effect appears for the Gangster Disciples. Finally, in 1997–98 alone, there is a negative “Latin Kings- activity- reciprocity” effect. Somewhat similar to the earlier interaction-reciprocity effect, this effect indicates that the Latin Kings are less likely to be involved in mutual exchanges than we would expect given other effects in the model: their own attacks are *relatively* less likely to be reciprocated and/or they are *relatively* less likely to retaliate when other gangs attack them.

Discussion

Gang members live in a social milieu they often describe as a “game.” In this game, the status of one’s group is tied to specific rules surrounding the use of violence as a form of status enhancement and maintenance. While prior qualitative work describes various street codes and how individuals enact them in public behavior (Anderson 1999; Decker 1996; Katz 1988), the present study utilized detailed quantitative data and advances in statistical modeling to uncover which “rules” actually account for observed patterns of violence. Results from ERGMs identified a large and diverse array of mechanisms responsible for inter-gang homicide in Chicago. From these findings, we draw three central conclusions that both confirm and qualify prior research.

First, certain rules are *contingent* on the racial composition of the gang. While we observe the same racially segregated network structure as previous research, we find that the strength of racial homophily varies tremendously between black gangs and Latino gangs (and in some periods does not exist at all), as does the baseline tendency to commit and be victims of murder. Further, although direct reciprocity—a tit-for-tat exchange of homicides between two gangs—plays an important role, the strength of this rule also varies depending on which two gangs are involved. This finding may, in part, relate to organizational differences. Unlike Latino gangs, black gangs in Chicago consolidated into a fewer number of larger federations as early as the late-1960s. The result, as Venkatesh and Levitt (2000) have argued, is these federations became more “business-like,” including in their responses to violence. Such factors could impact a gang’s capacity to respond to threats vis-à-vis groups of the same or a different racial background—a possibility future comparative historical research would have to explore.

Second, several features of the observed network point to status differences among gangs: in particular, the skew in both in- and out-degree distributions (indicating some gangs are much more central than others); the presence of many “sources” (gangs that send homicide ties but do not receive any) in 1998–99; and even the fact that only 52 percent of all ties are reciprocated (suggesting some degree of status asymmetry). However, this hierarchy is *contested* in a variety of ways: in 1999–2000, we find that generalized exchanges with no

discernable status ordering are an important feature of the network; we do not find evidence of transitivity in *any* period (including a negative effect in 1999–2000), reflecting the absence (if not avoidance) of strictly hierarchical arrangements; and even the negative “sinks” effect in 1998–99 suggests there are few gangs who are exclusively victims of homicide and never perpetrators. Further, we find evidence (in our overall model and in 1996–97) that gangs in the same “structural position” (i.e., attacked by the same third-party gangs) are especially likely to attack each other—the opposite of alliance formation. Although not all gangs are equal participants in the structure of homicide—and notwithstanding the central theme of dominance in the qualitative literature (and institutionalized oaths of mutual protection in Chicago)—the evidence shows that gangs resist subordination by others and engage in ongoing, localized struggles to assert superiority.

Third, perhaps our most unexpected finding was how *inconsistent* are the rules of the game across the various two-year windows: not only did we document an evolving landscape of violence, but also dynamic change in the mechanisms that generated it. Absent further data, it is challenging for us explain this variation. It could be that the strategies gangs pursue to advance their positions are much more opportunistic than enduring. If so, even the rules of engagement become objects of contestation—and any gang’s ascendancy to “top dog” becomes that much more precarious. This variation also provides important lessons for qualitative and quantitative researchers alike: the organizing principles of violence may be less cohesive in practice than they are in the minds of gang members; and we should be cautious against assuming “time homogeneity” when we model network determinants (cf. [Lewis and Kaufman 2018](#)).

More broadly, our results show how networks of violence might contribute to the diffusion of victimization within cities, neighborhoods, and other local settings ([Green, Horel, and Papachristos 2017](#); see also [Tsvetkova and Macy 2015](#)). Identifying the rules and conditions under which gangs engage in conflict might be leveraged to prevent other kinds of harm, such as gun violence, through either targeted or systematic interventions (e.g., [Braga, Hureau, and Papachristos 2014](#); [Engel, Tillyer, and Corsaro 2013](#); [Kennedy, Braga, and Piehl 1997](#)). Our results also have implications for social network research. Recent empirical and theoretical work tends to focus on “dynamics of dyads” in friendship and collaboration networks ([Rivera, Soderstrom, and Uzzi 2010](#)). We not only extend this work to “negative” ties ([Everett and Borgatti 2014](#)), but assess the importance of multiple higher-order, triadic mechanisms for the genesis of network structure. Just as prior work may have misdiagnosed the importance of some mechanisms by failing to account for others (see [Block 2015](#); [Goodreau, Kitts, and Morris 2009](#)), so the broader relevance of other supra-dyadic configurations (including, but not limited to, those considered here) remains to be explored—including variation in these configurations across individuals, groups, and time.

This study has several limitations. First, the granular data used here were only available for a single city, Chicago, from 1996 to 2000. While other cities have been subjected to similar analyses, future research should consider how different

city, neighborhood, or gang contexts might affect the types of rules that generate gang violence, particularly in an increasingly digital society (Lane 2018). Second, this study considered only homicide ties among gangs. It is plausible that alternative, unmeasured relationships—such as violent but non-lethal interactions, educational or employment affiliations with institutions, or social support ties among individuals—influence homicide as well, such that we have likely underestimated relevant tie-generating mechanisms. The extent to which the rules documented here might also explain non-lethal violent events as important outcomes in their own right should also be considered.

Finally, we here used ERGMs to understand how the macro-level structure of homicide was generated by a variety of micro-level configurations among gangs. Of course, these static configurations of relationships were themselves derived from *sequences* of underlying *events* that unfolded in real time. While our choice of approach was motivated by limitations in available methods—and by an interest in providing theoretical and empirical “first steps” on which others can build—future research could productively explore the questions of temporal ordering that were here elided. Even basic analyses examining the distribution of events across relationships and variation in triadic mechanisms (see e.g., notes 3 and 4) could make far-reaching contributions to the literature. Combined with recent advances in analytic tools for longitudinal and valued networks (e.g., Hanneke, Fu, and Xing 2010; Krivitsky 2012), the possibilities are greater still.

Notes

1. See Warr (2002) on the importance of third parties in the outcomes of violent encounters and Luckenbill (1977) on the role of third parties in homicidal encounters.
2. To be clear, this is distinct from acts of “displaced aggression” whereby a victim in one context (e.g., someone who is picked on by their boss at work) takes out their frustration on a target in a different context (e.g., one’s spouse at home). Generalized reciprocity occurs among similar players all actively involved in the same game.
3. An alternative, theoretically distinct possibility is that the two-path is produced not by generalized reciprocity but by *indirect reciprocity*—in other words, the j-to-k tie precedes rather than succeeds the i-to-j tie (Simpson et al. 2018). While indirect reciprocity has primarily been examined in the context of prosocial exchanges, it is easy to see how (in the case of indirect reciprocity) gang i might attack gang j to ascend to the top of the hierarchy, just as (in the case of generalized reciprocity) gang j attacks gang k to avoid falling to the bottom.
4. While additional triadic arrangements could be of interest in the context of violence (see Balian and Bearman 2018), we only consider those that build on the notion of generalized reciprocity.
5. The corresponding author also conducted 20 interviews with current or former members of street gangs in Chicago. While these interviews are the source of our opening quotation, their utility here is otherwise limited because they occurred later (from 2004 to 2006) and thus do not refer to the same set of homicides in our network data.
6. Murders *within* the same gang—“loops” in network terminology—are here excluded.

7. While there were an average of 2.6 homicides per tie, the distribution is highly skewed: most ties (61.3 percent) represent a single homicide and the highest observed quantity of homicides (40) occurred between the Black Disciples (perpetrator) and Gangster Disciples (victim). Although we cannot share the original homicide data due to identifiability concerns, a copy of the network and attribute data examined in this paper are available at: www.kevinlewis-sociology.com.
8. Because ties represent *at least* one homicide, one concern is that mutual dyads (i.e., A sends a tie to B and B sends a tie to A) may mask underlying power asymmetries (e.g., there are many *more* A-to-B than B-to-A homicides) that belie our “zero-sum” interpretation of direct reciprocity. In practice, however, the difference in the quantity of A-to-B and B-to-A homicides is less than two for 67 percent of all mutual dyads (and less than three for 81 percent of all mutual dyads); and we are more interested in whether B has retaliated at all than in quantifying the scale of this response.
9. All models were estimated using PNet (Wang, Robins, and Pattison 2009). Estimations were run with 5 subphases, a multiplication factor of 100, and 1,000 phase 3 steps. Goodness-of-fit analyses used 10,000,000 simulations, a sample size of 10,000, and an initial burn-in of 10,000,000 steps.
10. For instance, in T3 in Figure 1, gang *i* is *more* likely to victimize gang *k* the more transitive triads this would “close,” but the magnitude of this increase diminishes with each additional gang *j*. Past research has shown that such “higher-order parameterizations” offer dramatically improved fit to real-world social networks (Hunter et al. 2008; Robins et al. 2009; Snijders et al. 2006).
11. White gangs are the reference category for Latino and black sender and receiver effects. Effects for interaction and reciprocity among white gangs are not included because no such ties exist in our network, and thus these coefficients could not be estimated.
12. The “isolates” term is omitted because there were no isolates in the overall network. It is included in subsequent models, however, when reducing our purview to two-year intervals induced at least one isolate in each interval.
13. We recognize that our approach contrasts sharply with conventional wisdom, where stepwise regression with backward selection is suspect insofar as it may impact the size and significance of remaining coefficients in ways that are obscured from the reader (Young and Holsteen 2017). We reiterate that this difference stems from our fundamentally different aims—where we are not interested in testing hypotheses about any specific variable(s), but rather in answering a question that has no analogue in standard regression: “Can the global structural features observed in a network be generated by a modest number of local rules?” (Hunter et al. 2008:248). Further, we hope that our transparency (with respect to data and modeling strategy) eliminates the information asymmetry between analysts and readers; in fact, we encourage readers to replicate our approach and identify an equally fitting but more parsimonious model, if one exists.
14. Unfortunately, there is no way for us to discern whether revenge is a “dish best served cold” or whether it tends to quickly follow victimization; we lack direct evidence of whether a B-to-A or B-to-C murder is *motivated* by an A-to-B murder—only that these homicides occurred. Further complicating matters is that any given network tie might represent multiple possible homicides. Empirically, in mutual dyads in our dataset, the median delay between the first A-to-B homicide and the first B-to-A homicide is 150.5 days. In two-paths in our dataset, the median delay between the first A-to-B homicide and the first B-to-C homicide (regardless of which came first) is 406 days. However, both distributions are heavily right-skewed and

there is no natural cutoff for either. Future research might follow Bouchard and Hashimi (2017) for ways to unpack this issue.

15. As in standard regression, the interpretation of each effect is *conditional* on all other effects in the model. This means the same effect might have a slightly different interpretation in different models (depending on what other effects are included).
16. Specifically, the log-odds of retaliation among black gangs is $-2.84 (-4.56 + 2.68 - 0.97 + 1.15 - 1.14)$, among Latino gangs is $-1.55 (-4.56 + 2.68 - 1.11 + 1.44)$, from a Latino gang to a black gang is $-2.85 (-4.56 + 2.68 - 0.97)$, and from a black gang to a Latino gang is $-2.99 (-4.56 + 2.68 - 1.11)$. In addition to reciprocity, interaction, and interaction- reciprocity effects, these calculations also include the density effect and appropriate receiver effects.

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References

- Anderson, Elijah. 1999. *Code of the Streets*. New York: Norton.
- . 2011. *The Cosmopolitan Canopy: Race and Civility in Everyday Life*. New York: Norton.
- Balian, Hrag, and Peter Bearman. 2018. "Pathways to Violence: Dynamics for the Continuation of Large-Scale Conflict." *Sociological Theory* 36:210–220.
- Bearman, Peter. 1997. "Generalized Exchange." *American Journal of Sociology* 102:1383–1415.
- Bearman, Peter S., James Moody, and Katherine Stovel. 2004. "Chains of Affection: The Structure of Adolescent Romantic and Sexual Networks." *American Journal of Sociology* 110:44–91.
- Black, Donald. 1983. "Crime as Social Control." *American Sociological Review* 48:34–45.
- Block, Per. 2015. "Reciprocity, Transitivity, and the Mysterious Three-Cycle." *Social Networks* 40: 163–173.
- Bouchard, Martin, and Sadaf Hashimi. 2017. "When Is a 'War' a 'Wave?' Two Approaches for the Detection of Waves in Gang Homicides." *Canadian Journal of Criminology and Criminal Justice* 59: 198–226.
- Braga, Anthony A., David M. Hureau, and Andrew V. Papachristos. 2014. "Deterring Gang-Involved Gun Violence: Measuring the Impact of Boston's Operation Ceasefire on Street Gang Behavior." *Journal of Quantitative Criminology* 30:113–139.
- Chase, Ivan D. 1980. "Social Process and Hierarchy Formation in Small Groups: A Comparative Perspective." *American Sociological Review* 45:905–924.
- Davis, James A. 1970. "Clustering and Hierarchy in Interpersonal Relations: Testing Two Graph Theoretical Models on 742 Sociomatrices." *American Sociological Review* 35:843–851.
- Davis, James A., and S. Leinhardt. 1972. "The Structure of Positive Interpersonal Relations in Small Groups." In *Sociological Theories in Progress*, vol. 2, edited by J. Berger, 218–251. Boston: Houghton Mifflin.

- Dawley, David. 1973. *A Nation of Lords: The Autobiography of the Vice Lords*. Garden City, N.Y.: Anchor Press.
- Decker, Scott, and G. David Curry. 2002. "Gangs, Gang Homicides, and Gang Loyalty: Organized Crime or Disorganized Criminals." *Journal of Criminal Justice* 30:343–352.
- Decker, Scott H. 1996. "Collective and Normative Features of Gang Violence." *Justice Quarterly* 13: 243–264.
- Decker, Scott H., and David C. Pyrooz. 2010. "On the Validity and Reliability of Gang Homicide: A Comparison of Disparate Sources." *Homicide Studies* 14:359–376.
- Engel, Robin S., Marie Skubak Tillyer, and Nicholas Corsaro. 2013. "Reducing Gang Violence Using Focused Deterrence: Evaluation the Cincinnati Initiative to Reduce Violence (Cirv)." *Justice Quarterly* 30:403–439.
- Everett, Martin G., and Stephen P. Borgatti 2014. "Networks Containing Negative Ties." *Social Networks* 38:111–120.
- Fagan, Jeffrey. 1989. "The Social Organization of Drug Use and Drug Dealing among Urban Gangs." *Criminology* 27:633–670.
- Fagan, Jeffrey, and Deanna L. Wilkinson 1998. "Guns, Youth Violence, and Social Identity in Inner Cities." *Crime and Justice* 24:105–188.
- Garot, Robert. 2010. *Who You Claim? Performing Gang Identity in School and on the Streets*. Princeton, NJ: Princeton University Press.
- Goodreau, Steven M. 2007. "Advances in Exponential Random Graph (P*) Models Applied to a Large Social Network." *Social Networks* 29:231–248.
- 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.
- Gouldner, Alvin W. 1960. "The Norm of Reciprocity: A Preliminary Statement." *American Sociological Review* 25:161–178.
- Gray, Kurt, Adrian F. Ward, and Michael I. Norton 2014. "Paying It Forward: Generalized Reciprocity and the Limits of Generosity." *Journal of Experimental Psychology: General* 143:247–254.
- Green, Ben, Thibaut Horel, and Andrew V. Papachristos. 2017. "Modeling Contagion through Social Networks to Explain and Predict Gunshot Violence in Chicago, 2006 to 2014." *JAMA Internal Medicine* 177:326.
- Hagedorn, John M. 2015. *The in\$Ane Chicago Way: The Daring Play by Chicago Gangs to Create a Spanish Mafia*. Chicago, IL: The University of Chicago Press.
- Hanneke, Steve, Wenjie Fu, and Eric P. Xing 2010. "Discrete Temporal Models of Social Networks." *Electronic Journal of Statistics* 4:585–605.
- Heider, F. 1946. "Attitudes and Cognitive Organization." *Journal of Psychology* 21:107–112.
- 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*. Thousand Oaks, CA: Sage.
- Hunter, David R., Steven M. Goodreau, and Mark S. Handcock 2008. "Goodness of Fit of Social Network Models." *Journal of the American Statistical Association* 103:248–258.
- Jacobs, Bruce A. 2004. "A Typology of Street Criminal Retaliation." *Journal Of Research In Crime And Delinquency* vol 41:295–323.
- Jacobs, Bruce A., and Richard Wright. 2006. *Street Justice: Retaliation in the Criminal Underworld*. New York: Cambridge University Press.

- Jacobs, James B. 1977. *Stateville: The Penitentiary in Mass Society*. Chicago: University of Chicago Press.
- Jankowski, Martin Sanchez. 1991. *Islands in the Street: Gangs and American Urban Society*. Berkeley: University of California Press.
- Katz, Jack. 1988. *Seductions of Crime: Moral and Sensual Attractions in Doing Evil*. New York: Basic Books.
- Kennedy, D. M., Anthony A. Braga, and Anne. M. Piehl. 1997. "The (Un)Known Universe: Mapping Gangs and Gang Violence in Boston." In *Crime Mapping and Crime Prevention*, edited by D. Weisburd, and T. McEwen, 219–262. Monsey, NY: Criminal Justice Press.
- Klein, Malcolm W., and Cheryl L. Maxson 2006. *Street Gang Patterns and Policies*. New York: Oxford University Press.
- Krivitsky, Pavel N. 2012. "Exponential-Family Random Graph Models for Valued Networks." *Electronic Journal of Statistics* 6:1100–1128.
- Lane, Jeffrey. 2018. *The Digital Street*. New York: Oxford University Press.
- Lewis, Kevin. 2015. "How Networks Form: Homophily, Opportunity, and Balance." In *Emerging Trends in the Social and Behavioral Sciences*, edited by R. Scott, and S. Kosslyn, Hoboken, NJ: John Wiley & Sons.
- Lewis, Kevin, and Jason Kaufman. 2018. "The Conversion of Cultural Tastes into Social Network Ties." *American Journal of Sociology* 123:1684–1742.
- Luckenbill, David F. 1977. "Criminal Homicide as a Situated Transaction." *Social Problems* 25:176–186.
- Martinez, Cid Gregory. 2016. *The Neighborhood Has Its Own Rules: Latinos and African Americans in South Los Angeles*. New York: NYU Press.
- Maxson, Cheryl, and Malcolm W. Klein. 2001. "'Play Groups' No Longer: Urban Street Gangs in the Los Angeles Region." In *From Chicago to L.A.: Making Sense of Urban Theory*, edited by M. J. Dear, 235–266. Thousand Oaks, CA: Sage.
- 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., David Hureau, and Anthony A. Braga. 2013. "The Corner and the Crew: The Influence of Geography and Social Networks on Gang Violence." *American Sociological Review* 78: 417–447.
- Papachristos, Andrew V., and David S. Kirk. 2006. "Neighborhood Effects on Street Gang Behavior." In *Studying Youth Gangs*, edited by J. F. S. Jr. and L. A. Hughes, 63–84. Walnut Creek, CA: AltaMira Press.
- Peterson, Dana, Terrance J. Taylor, and Finn-Aage Esbensen. 2004. "Gang Membership and Violent Victimization." *Justice Quarterly* 21:793–815.
- Rivera, Mark T., Sara B. Soderstrom, and Brian Uzzi. 2010. "Dynamics of Dyads in Social Networks: Assortative, Relational, and Proximity Mechanisms." *Annual Review of Sociology* 36:91–115.
- Robins, Garry, Pip Pattison, Yuval Kalish, and Dean Lusher. 2007. "An Introduction to Exponential Random Graph (P*) Models for Social Networks." *Social Networks* 29:173–191.
- Robins, Garry, Pip Pattison, and Peng Wang. 2009. "Closure, Connectivity and Degree Distributions: Exponential Random Graph (P*) Models for Directed Social Networks." *Social Networks* 31:105–117.
- Short, James F., Jr., and Fred L. Strodbeck. 1963. "The Response of Gang Leaders to Status Threats: An Observation on Group Process and Delinquent Behavior." *American Journal of Sociology* 68:571–579.
- Simmel, Georg. 1902. "The Number of Members as Determining the Sociological Form of the Group. I." *American Journal of Sociology* 8:1–46.

- Simpson, Brent, Ashley Harrell, David Melamed, Nicholas Heiserman, and Daniela V. Negraia 2018. "The Roots of Reciprocity: Gratitude and Reputation in Generalized Exchange Systems." *American Sociological Review* 83:88–110.
- Skarbek, David. 2014. *The Social Order of the Underworld: How Prison Gangs Govern the American Penal System*. London: Oxford University Press.
- Snijders, Tom A. B., Philippa E. Pattison, Garry L. Robins, and Mark S. Handcock. 2006. "New Specifications for Exponential Random Graph Models." *Sociological Methodology* 36:99–153.
- Thornberry, Terence P., Marvin D. Krohn, Alan J. Lizotte, Carolyn A. Smith, and Kimberly Tobin. 2003. *Gangs and Delinquency in Developmental Perspective*. Cambridge: Cambridge University Press.
- Tsvetkova, Milena, and Michael W. Macy 2015. "The Social Contagion of Antisocial Behavior." *Sociological Science* 2:36–49.
- Venkatesh, Sudhir Alladi. 1997. "The Social Organization of Street Gang Activity in an Urban Ghetto." *American Journal of Sociology* 103:82–111.
- 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* 29:427–462.
- Vigil, James Diego. 1988. *Barrio Gangs: Street Life and Identity in Southern California*. Austin: University of Texas Press.
- Wang, Peng, Garry Robins, and Philippa Pattison. 2009. "Pnet: Program for the Simulation and Estimation of Exponential Random Graph Models." The University of Melbourne: Melbourne School of Psychological Sciences.
- Warr, Mark. 2002. *Companions in Crime: The Social Aspects of Criminal Conduct*. New York: Cambridge University 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.
- Young, Cristobal, and Katherine Holsteen. 2017. "Model Uncertainty and Robustness: A Computational Framework for Multimodel Analysis." *Sociological Methods & Research* 46:3–40.