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Ethnic Homophily and Triad Closure: Mapping Internal Gang Structure Using Exponential Random Graph Models

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Abstract

Previous studies indicate the importance of similarities between street gang members in terms of ethnicity for mapping the patterns of co-offending relationships within gangs. Individual members are more likely to co-offend with other members who are from the same ethnicity. Past studies, however, do not appropriately account for the fact that correlation between attributes of co-offending gang members may be driven by alternative mechanisms. Most importantly, the presence of clustering in networks can dramatically affect the assessment and make us believe that homophily—the deliberate choice to co-offend with others from the same ethnic group—is important while in fact it is not. In this article, we recreate the internal structure of a London-based street gang with exponential random graph (ERG) models. Our results refine the role of ethnicity for co-offending within gangs. While homophily is still prevalent, the effect diminishes when triad closure—the tendency for two individuals to offend with each other when they also offend with a common third person—is considered. Furthermore, we extend existing ERG specifications and investigate the interaction between ethnic homophily and triad closure. Findings indicate that ethnic homophily is even stronger when it is embedded in co-offending triads.

Keywords

street gangs, group processes, exponential random graph models, homophily, triad closure, clustering

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Introduction

Despite consensus that the vast majority of crime is committed in pairs or in groups, a process known as co-offending (Andresen & Felson, 2010; Felson, 2009; van Mastrigt & Farrington, 2009; Warr, 2002), the statistical modeling of co-offending networks is still surprisingly rare (for a discussion, see Carrington, 2011; McGloin & Kirk, 2010; Papachristos, 2011). Such modeling relates observed network statistics (e.g., count of reciprocated ties) to the distribution of potential network statistics derived from a stochastic process (e.g., Barrat, Barthélemy, & Vespignani, 2008; Carrington, Scott, & Wasserman, 2005). This strategy explicitly addresses the uncertainty that follows when networks are considered the outcome of both regularities and randomness, facilitating simultaneous analyses of various potential antecedents of criminal structure. Network models further allow inferences to be drawn regarding whether certain network substructures or configurations are more commonly observed than one would expect by chance.

Criminologists have used the social network paradigm to describe the (in)stability of co-offending connections (McGloin & Piquero, 2010; McGloin, Sullivan, Piquero, & Bacon, 2008; Reiss & Farrington, 1991; Sarnecki, 2001; van Mastrigt & Farrington, 2009), the relationship between weapon carrying and friendship ties (Dijkstra et al., 2010), the structure of peer influence (Haynie, 2001; Weerman & Smeenk, 2005), heroin distribution patterns (Natarajan, 2006), organized crime syndicates (Campana & Varese, 2012; Klerks, 2001; McIllwain, 2000; Morselli, 2003, 2009), and of course, street gangs (Grund & Densley, 2012; Fleisher, 2006; McGloin, 2005; Papachristos, 2006, 2009). Recent methodological advances and the advent of more sophisticated techniques for modeling criminal networks mean this body of work can only grow. Most prominently, exponential random graph (ERG) models, sometimes referred to as p* models (Anderson, Wasserman, & Crouch, 1999; Frank & Strauss, 1986; Robins, Pattison, Kalish, & Lusher, 2007a; Robins, Snijders, Wang, Handcock, & Pattison, 2007b; Snijders, 2002; Snijders, Pattison, & Robins, 2006; Wasserman & Pattison, 1996), offer new opportunities to investigate social networks and disentangle the countless concurrent theoretical mechanisms that contribute to network structure (Lusher, Koskinen, & Robins, 2013). Few studies apply ERG models to co-offending networks (see Malm, Bichler, & Van De Walle, 2010; Papachristos, Hureau, & Braga, 2013; Schaefer, 2012; Young, 2011).

The present study builds on these recent developments and extends an earlier investigation of co-offending relations within an ethnically heterogeneous Black street gang in London, which found evidence of ethnic homophily—the tendency that individuals co-offend more with others from the same ethnic group (Grund & Densley, 2012). We put emphasis on co-offending triads and demonstrate that homophily is even more pronounced in such configurations.

Literature Review

Gangs and Social Network Analysis

Network criminologists have studied the patterns of alliance, clustering, conflict, dominance, and violence within and between gangs (Descormiers & Morselli, 2011;

Kennedy, Braga, & Piehl, 1997; Papachristos, 2009; Papachristos, Braga, & Hureau, 2012; Papachristos et al., 2013; Tita & Greenbaum, 2009; Tita & Radil, 2011). Results indicate gangs are not necessarily "bounded" organizations (Fleisher, 2006), but rather "individuals who come together in time and space, engage in collective activities, and produce a collective identity" (Papachristos et al., 2013, p. 418). Recreating the gang as a social network—linking each of the units, either gang or gang member, by the type of relation being examined (see Wasserman & Faust, 1994)—is indeed shedding new light on "gang processes" that shape organizational structure, create solidarity, and strengthen ties among gang members (see Decker, Melde, & Pyrooz, 2013).

Gang interactions and processes enable gang members to do things—particularly violent things—they would not do alone (Decker, 1996; Decker & Pyrooz, 2010; Decker & Van Winkle, 1996; Densley, 2012, 2013; Pizarro & McGloin, 2006). But gang interactions and processes are typically assumed rather than observed by criminologists (Papachristos, 2013). For Klein (1995), gang cohesion is the "quintessential group process" (p. 45). Social network analyses enable criminologists to get closer to the mechanisms underlying gang cohesion. Homophily and triad closure are two candidate explanations.

Homophily

Homophily—the tendency for "birds of a feather to flock together" (Glueck & Glueck, 1950, p. 164)—is an established pattern in social network analysis (Lazarsfeld & Merton, 1954; Marsden, 1987, 1988; McPherson, Smith-Lovin, & Cook, 2001; Moody, 2001). Individuals tend to form network relationships with similar others. The literature on co-offending demonstrates strong tendencies toward homophily in general (Reiss, 1988; Reiss & Farrington, 1991; van Mastrigt & Carrington, 2013; van Mastrigt & Farrington, 2009; Warr, 2002; Weerman, 2003) and racial and ethnic homophily in particular (Daly, 2005; Pettersson, 2003; Sarnecki, 2001). Grund and Densley (2012) argue explicitly, "ethnicity matters for who offends with whom" (p. 388) within a heterogeneous Black street gang.

There are two dominant explanations for homophily in a criminal context. Three recent, related, criminological perspectives capture the first explanation, *opportunities*. Rational choice theory (Cornish & Clarke, 1986), routine activities theory (Cohen & Felson, 1979), and crime pattern theory (Brantingham & Brantingham, 1993) are predicated on the notion crime is not random, but rather planned or opportunistic. Crime occurs when the everyday *activity space* (e.g., schools, workplaces, or neighborhoods) of a victim or target both intersects with the activity space of a motivated offender and capable controllers (i.e., intimate handlers, guardians, or place managers) are absent. Co-offending networks likewise emerge within an individual offender's activity or *awareness space* because offenders are commonly sorted into shared environments (e.g., prisons) that are frequently more homogeneous than the population at large, thus resulting in greater opportunities to associate with similar others (Blau, 1977; Feld, 1982).

Second, individuals might have a psychological *preference* to co-offend with similar people. This may reflect processes of social categorization and comparison, which in turn validate one's own social status and identity (Tajfel & Turner, 1986). Mayhew, McPherson, Rotolo, and Smith-Lovin (1995, p. 19) argue heterogeneity in terms of age, gender or ethnicity, acts as an "energy barrier" to communication and coordinated action. The implication is homophily may assist gangs in negotiating the "problems of trust" inherent in criminal cooperation (Densley, 2012; Gambetta, 2009; Tremblay, 1993; Weerman, 2003). This leads to our first hypothesis:

Hypothesis 1: Gang members are more likely to offend with each other when they have the same ethnic background.

Triad Closures

In general, one must think of co-offending ties between gang members as the outcome of a dynamic process of tie formation. Several micro-level mechanisms play a role at the same time in producing homogeneous mixing patterns in gangs (Grund & Densley, 2012). An important concept is that of two individuals, who share another co-offender, are likely to commit an offense together as well. For example, Georg Simmel (1950) suggested that a strong social tie could not exist without being part of a triangle of ties between network nodes. In other words, a person's close contacts are more likely to know each other than peripheral contacts. In network studies, such *triad closure* is consistently found to be a relevant micro-mechanism (e.g., Dijkstra et al., 2010; Mercken, Snijders, Steglich, Vartiainen, & de Vries, 2010).

Scholars only recently began to acknowledge that triad closure contributes to homogeneity in networks due to "dyadic dependence." In other words, when there already exists a tendency toward homophily, friends-of-friends (or co-offenders of co-offenders) are likely to be similar. Hence, closing triads increases the number of ties between similar network nodes. Assortative mixing can produce transitivity, since increasing the likelihood of within-category ties enhances the opportunity for completed triangles within categories (Goodreau, Kitts, & Morris, 2009). Consequently, if one does not account for the role of triad closures in social networks one is likely to overestimate homophily effects. Based on this we hypothesize the following:

Hypothesis 2: Triad closure accounts for some ethnic homogeneity in co-offending in gangs.

Furthermore, triad closure and homophily could interact. Being embedded in structural configurations, such as triads, could provide an important context in which homophily unfolds. When two nodes *A* and *B* have a common friend C, the attributes of the nodes are likely to be more salient. Disentangling such different effects from each other, this is where ERG models come in.

Hypothesis 3: Gang members are even more likely to offend with each other when they have the same ethnic background AND share another co-offender from the same ethnic background.

Method

Sample and Data Collection

The gang under investigation is a "durable, street-oriented youth group whose involvement in illegal activity is part of their group identity" (Klein & Maxson, 2006, p. 4). The gang formed in 2005 and its members have since adopted a common name and other discernible "conventional" or "symbolic" signals of gang membership (Gambetta, 2009). The gang's "set space" (Tita, Cohen, & Engberg, 2005, p. 280) is the area in and around a social housing estate in a socioeconomically deprived inner London borough.

Data stem from anonymized police arrest and conviction records for all "confirmed" members of this gang, as obtained from the relevant Borough Operational Command Unit of London's Metropolitan Police Service.[1] The records stretch from 2005 to 2009 and include the gang members' demographic profiles (e.g., age, ethnicity, gender) as well as information regarding their illicit activities, including whether two gang members had ever been arrested together for a single offense. We focus on 48 individuals who had been members of the gang between 2006 and 2009. All of these were Black men. We represent the gang as a one-mode, undirected, binary social network, where the nodes represent individual gang members and a tie between nodes implies that two gang members co-offended at least once (see Figure 1).[2] In total, there are 133 undirected co-offending ties.

Although the gang forms a well-defined group and all members clearly identify with the gang, members can be categorized beyond racial attributes according to a common place of birth and national heritage, which we take as a proxy measure for ethnic background, as follows: (a) Somali (n = 6), (b) West African (Congo, Ghana, Ivory Coast, Nigeria, and Sierra Leone, n = 11, including two siblings), (c) Jamaican (n = 10), and (d) British (n = 21). We recognize that when two individuals come from the same geographic region, they do not necessarily share the same ethnicity with regard to history, language and literature, religion, or other cultural items, but our fieldwork with the gang confirms the validity of this categorization (for a discussion, see Grund & Densley, 2012).

ERG Model Specification

At the core of ERG models stands the notion that potential ties between individuals are random. Let Y_{ij} be the potential that a co-offending connection exists between individual i and j, which takes the value 1 if a relation is assumed to exist and 0 if it is not. The matrix $\mathbf{Y}$ of these random variables, then, represents all potential co-offending networks. In contrast, y_{ij} is defined as the observed relationship between gang members i and j, and the matrix $\mathbf{y}$ as the observed co-offending network.

The general form of an ERG model, which indicates the probability to observe a particular co-offending network $\mathbf{y}$ as a function of other variables, is

$$\text{prob}(\mathbf{Y} = \mathbf{y}) = \left(\frac{1}{c}\right)\exp\left[\sum_A \eta_A g_A(y)\right],$$

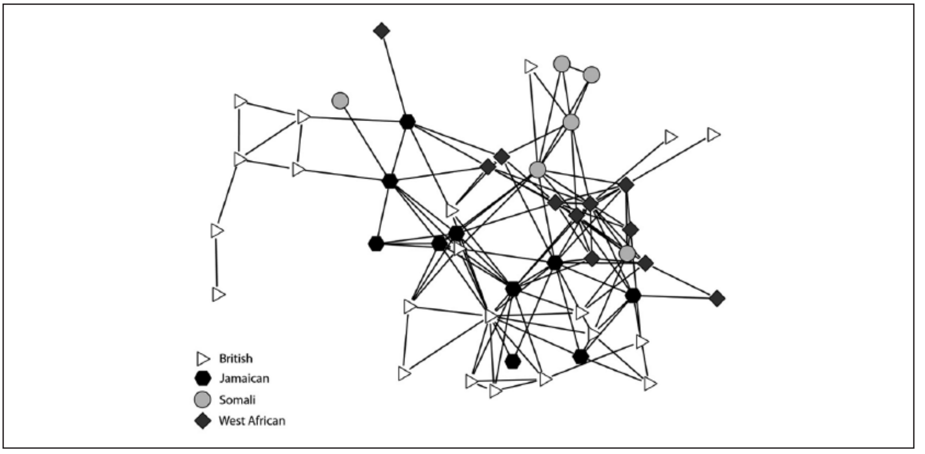


Figure 1. Co-offending network of youth gang.

where $g_A(y)$ represent network statistics for the local patterns A (e.g., number of triad closures) in a network y; η_A s are parameters to be estimated.

A simplified way to understand ERG models is to think of them along the lines of logistic regression. We can reformulate the above equation in such a way that it represents the likelihood ratio between two hypothetical networks that only differ on a single dyad value Y_{ij}. We can then estimate the probability that gang members i and j co-offend with each other conditional on the rest of the network Y_{ij}^c.

$$\text{logit}\left[prob\left(Y_{ij}=1|Y_{ij}^c\right)\right]=\sum_A \eta_A \delta g_A\left(y\right).$$

Here, $\delta g_A\left(y\right)$ stands for the amount by which a potential co-offending tie between gang members i and j changes an underlying network statistic (e.g., number of co-offending triads)—the independent variables. The parameter η_A is interpreted straightforwardly as the increase in the log-odds that a particular co-offending tie will be formed if the formation of this tie increases the corresponding network statistic by one (Goodreau et al., 2009)—the interpretation is analogous to logistic regression.[3]

Independent Variables

Homophily—the tendency for ties to form between individuals who are similar on attribute k—is parameterized straightforwardly. One simply counts the number of ties between similar individuals in a potential network. In our data, there are 63 homophilous ties between gang members with the same ethnicity.

$$g_{\text{MATCH}}\left(y\right)=\sum_{i=1}^{n}\sum_{j=1}^{n} y_{ij},$$

with $k_i = k_j$.

Concerning triad closure, this becomes a little more complicated because each co-offending tie between gang members i and j can "close" multiple triads at the same time (see Table 1).[4] More recently, a network statistic based on the geometrically weighted edgewise-shared partner distribution (GWESP) received attention instead (Goodreau, 2007; Hunter, Handcock, Butts, Goodreau, & Morris, 2008; Robins et al., 2007a). This network statistic corresponds to the number of triangles a potential tie between gang members i and j would "close," but discounts higher numbers with a factor τ. The GWESP statistic for a whole network is calculated as follows:

$$g_{\text{GWESP}}\left(y\right) = e^{\tau}\sum_{z=1}^{n-2}\left\{1-\left(1-e^{-\tau}\right)^{z}\right\}p_z,$$

where p_z equals the number of gang members who co-offend with each other and who have exactly z other co-offending partners in common. For example, in Table 1 (Graph A), there are four actor pairs who have exactly one other network neighbor in common and one actor pair who has two network neighbors in common. When the constant τ is set to zero, all edges that have *at least* one shared partner are counted exactly the same (see Table 1).

In our theoretical considerations, we proposed that co-offending might be even more likely when two gang members are similar and share another co-offender partner. Accounting for such an interaction effect in ERG models is more complex than in standard regression models. One cannot simply multiply the scores for GWESP and homophily. Instead, one must incorporate a new configuration in the model, which captures the underlying idea that substructures where three nodes are connected with each other and all three (or only two) have the same value on attribute k are over- or underrepresented in the network.

We propose an extension of the GWESP statistic, which explicitly accounts for such an interaction. In our novel statistic, only triads are considered where all three nodes have the same attribute:

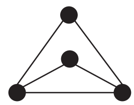
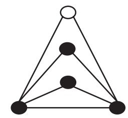
$$g_{\text{GWESP\_MATCH}}\left(y\right) = e^{\tau}\sum_{z=1}^{n-2}\left\{1-\left(1-e^{-\tau}\right)^{z}\right\}q_z,$$

where q_z equals the number of actor pairs who are (a) connected, (b) have the same value on attribute k, and (c) who have exactly z shared partners, who also have the same value on attribute k. In Table 1 (Graph B), we illustrate the calculation of this network statistic. We implemented this novel effect in statnet using the ergm.userterms R-package (Hunter, Goodreau, & Handcock, 2013).

Results

ERG model results are presented in Table 2. The parameters can be interpreted similar to logistic regression coefficients. They indicate by how much the log-odds for a tie to

Table 1. GWESP and GWESP_Match Statistics.

	Graph A	Graph B
		
Basic triangle count	2	3
Edgewise-shared partners		
p_0	0	0
p_1	4	6
p_2	1	0
p_3	0	1
GWESP, $\tau = 0$	5	7
GWESP, $\tau = 0.25$	5.22	7.27
GWESP, $\tau = 0.5$	5.39	7.55
Match	5	5
Homophilous edgewise-shared partners		
q_0	0	2
q_1	4	4
q_2	1	1
q_3	0	0
GWESP × Match, $\tau = 0$	5	5
GWESP × Match, $\tau = 0.25$	5.22	5.22
GWESP × Match, $\tau = 0.5$	5.39	5.39

Note. GWESP = geometrically weighted edgewise-shared partner.

exist change when the presence of this tie increases the corresponding network statistic (e.g., Match(ethnicity) standing for the total number of ties between similar gang members) by one (conditional on the rest of the network). The edge parameter can be interpreted like an intercept.

In Model 1 (see Table 2), we find clear evidence for ethnic homophily, which confirms the results from our previous study (Grund & Densley, 2012). The odds for a tie between two gang members who are from the same ethnicity are 2.51 times higher than for a tie between gang members from different ethnic groups. In Model 2, we include an effect for triad closure (GWESP). For reasons of simplicity we fix $\tau = 0$, which means we do not distinguish whether a tie "closes" one or more triads, but rather whether a tie closes one triad at least. As expected, we find the homophily estimate (Match(ethnicity)) decreases after including GWESP in the model. Substantively, this means that not all ethnic homogeneity (63 ties between gang members from the same ethnicity) is explained by ethnic homophily. Some of the ties between similar gang members are the result of gang members co-offending with others with whom they have another co-offending partner in common. A non-ERGM analysis of the network would not detect this.

Table 2. ERG Model Results, Homophily.

	Model 1	Model 2	Model 3	Model 4
Edges	−2.35 (0.13)***	−3.67 (0.26)***	−4.36 (0.28)***	−4.06 (0.30)***
Match(ethnicity)	0.92 (0.19)***	0.78 (0.17)***	1.12 (0.18)***	0.39 (0.40)
Ethnicity				
British			r.c.	r.c.
Jamaican			0.61 (0.13)***	0.57 (0.14)***
Somali			0.50 (0.18)**	0.48 (0.16)***
West African			0.49 (0.13)***	0.45 (0.13)**
GWESP, τ = 0		1.20 (0.23)***	1.16 (0.23)***	0.99 (0.24)***
GWESP_Match(ethnicity), τ = 0				0.59 (0.30)*

Note. ERG = Exponential Random Graph; GWESP = geometrically weighted edgewise-shared partner.
*p = .05. **p = .01. ***p = .001.

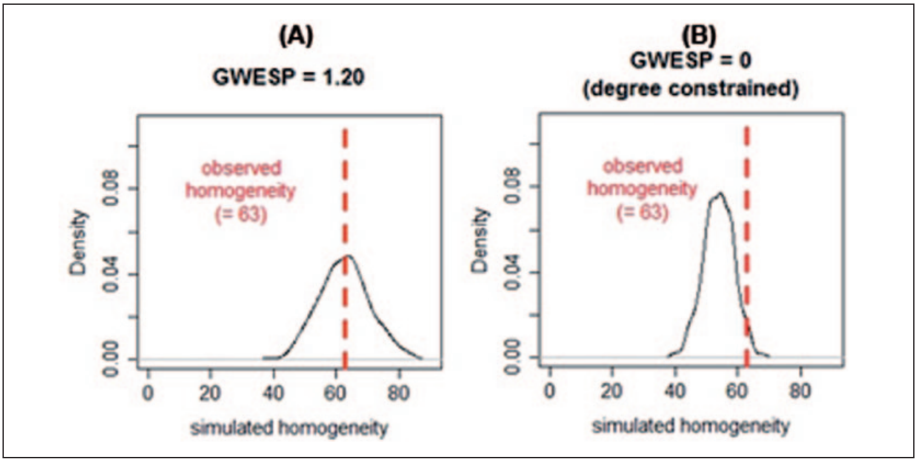


Figure 2. Simulated homogeneity with and without triad closure.
Note. Based on simulated networks using the parameter estimates from Model 2. GWESP = geometrically weighted edgewise-shared partner.

To assess the impact of triad closure on homogeneity (i.e., absolute number of ties between similar individuals), we apply a novel technique that draws on simulations. We use the parameter estimates from Model 2 (which includes triad closure) to simulate 500 networks. Simulations are performed with the simulate.ergm command in the ergm R-package (Hunter et al., 2013). For each of the simulated networks, we calculate the number of ties between similar individuals (homogeneity) and illustrate the distribution of simulated homogeneity in Figure 2(A). In a next step, we simulate another 500 networks with the same parameters where we fix the parameter for

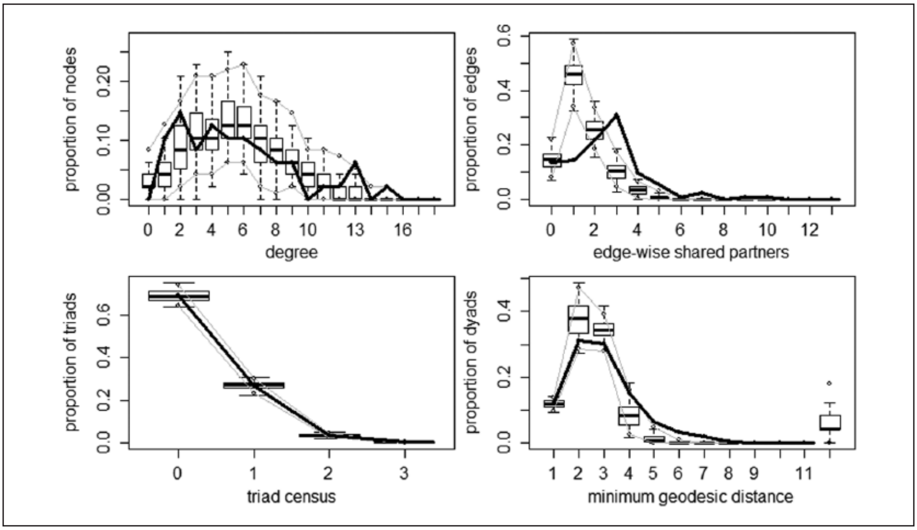


Figure 3. Goodness-of-fit assessment for Model 7.

GWESP = 0. Again, we calculate the homogeneity for the simulated networks and show the distribution of these scores in Figure 2(B). Thus, Figure 2(B) illustrates how much homogeneity one would produce with the parameters from Model 2 if the effect of triad closure would be blended out. To avoid changes simply due to density, we fix the degree distribution.

The simulated networks in Figure 2(B) exhibit a fair amount of homogeneity even without triad closure. But the remaining mechanism, ethnic homophily, falls short in explaining all observed ethnic homogeneity. One can interpret the deviation of the simulated homogeneity in Figure 2(B) from the observed homogeneity (dashed line) as the contribution of triad closure for the production of ethnic homogeneity.

Moving on to our next conjecture, we suggested there is an interaction effect for homophily and triad closure—ethnic homophily is even more pronounced when it is embedded in a triad. In Model 3 (Table 2), we include overall ethnic homophily, triad closure and a general ethnicity effect. The last one captures the idea that some ethnic groups might co-offend more or less in general. In Model 4 (Table 2), we add our novel GWEP_Match statistic.

The estimate for GWESP_Match(ethnicity) is 0.59 and significant. This suggests that homophilous triads are overrepresented in the network compared with the number of homophilous triads one would expect to find by chance based on the main effects alone. There is a positive interaction effect of homophily and triad closure—ethnic homophily is more pronounced when it is embedded in a triadic configuration.

A crucial element in ERG analyses is goodness of fit. For Model 4, it is depicted in Figure 3. The boxplots stand for the simulated networks; the black solid line for the observed network. An acceptable goodness of fit is achieved when the network features in the simulated network do not deviate too much from the observed network. Figure 3 shows an excellent fit; the simulated networks (boxplots) tend to capture the features of the observed network (black solid line) well.

Discussion and Conclusion

Recent years have seen growth in the study of the group interactions and processes that make gangs unique (Melde & Esbensen, 2013; Papachristos, 2009), but our understanding of the mechanisms underlying processes such as gang cohesion remains limited (Papachristos, 2013). One reason is although scholars increasingly draw on the "network" paradigm to recreate the structure of criminal groups like gangs, the statistical modeling of co-offending networks remains surprisingly rare (for a discussion, see Carrington, 2011; McGloin & Kirk, 2010; Papachristos, 2011). This research breaks from tradition, using statistical modeling to explore two candidate explanations for gang cohesion—homophily and triad closure. Recent research has shown that ethnicity matters for who co-offends with whom (Grund & Densley, 2012). Using ERG models rarely seen in criminology to recreate the internal structure of a London-based street gang (cf. Malm et al., 2010; Papachristos et al., 2013; Schaefer, 2012; Young, 2011), this research refines the role of ethnicity within gangs and offers a blueprint for further investigation of within-group co-offending processes.

Our analyses find support for all three hypotheses we postulate. First, we do find that gang members are more likely to co-offend with each other when they are both from the same ethnic group (Hypothesis 1). This confirms previous results on within-gang structure (Grund & Densley, 2012) and is in line with the general literature on homophily in social networks (McPherson et al., 2001). Second, we also find that triad closure—the tendency for co-offending to occur among three gang members—accounts for parts of the ethnic mixing pattern we observe (Hypothesis 2). Not considering the effect of closing triads makes us believe there is more homophily than there actually is. Finally, our findings indicate that ethnic homophily is even more pronounced when it is embedded in a triad co-offending configuration (Hypothesis 3). One possible explanation is aggregation effects in the recruiting pattern of the gang over time with consolidation reflecting "selectivity" in gang recruitment (see Densley, 2012). Having friends in a gang is a "risk factor" for gang membership (Klein & Maxson, 2006), but also a mechanism to secure acceptance within the group (Densley, 2012). More generally, homophily in triads—as shown in our study—requires reassessing the mechanisms driving network formation and change. The existing literature, mostly originating in the statistical modeling of networks, underemphasizes how contexts (such as embeddedment in triads) moderate lower level mechanisms, such as homophily. Some recent work on friendship dynamics (Block & Grund, 2014) illustrates this more and shows that homophily effects should be contextualized.

From a policy point of view, our consideration of multiple mechanisms at once (homophily and triad closure), calls for caution in interpreting ethnic mixing patterns in gangs. Overall homogeneity (gang members from the same ethnic group co-offending with each other) is also driven by structural effects and not only by deliberate choices of gang members to co-offend with similar others. Almost by definition, gangs involve multiple individuals, typically of a similar age, race and/or ethnicity, and shared experience, who may or may not co-offend (Klein & Maxson, 2006). Arbitrary and capricious labeling of Black and minority ethnic males both within and without gangs has serious criminal justice consequences (Tapia, 2011).

Of course, this study also has its limitations. We focus on data from one street gang in London, which, given no two gangs are alike, limits the scope for generalizations. Additional research should investigate within-gang structure elsewhere with multiple gangs for comparison. Nevertheless, this study contributes to a growing literature on ethnic heterogeneity within gangs. So far, most research considered youth gangs as ethnically "monolithic" blocks and hardly investigates the complex ways gang members from different ethnic backgrounds interact (see Freng & Esbensen, 2007).

Furthermore, we acknowledge that not every offense leads to an arrest and that constructing the social network of the gang through police information may introduce police decision-making bias (Black, 1970). Moreover, police contact can *ipso facto* increase gang cohesion (Decker, 1996; Klein, 1995), thus altering the composition of the network (see Papachristos, 2013). Nevertheless, police records remain an important source for gang researchers. They exhibit strong internal reliability and external validity for both gang and nongang youth and offenses (Katz, 2003; Katz, Webb, & Schaefer, 2000). The validity of police-reported gang measures is also shown to be higher in cities like London with specialized gang units (Pyrooz, Fox, & Decker, 2010).

Finally, we only investigate a temporal aggregation and one-mode projection of the co-offending network. Our study leaves unanswered whether gang members from the same ethnic group tend to offend in larger groups or whether previous offenses create conditions for subsequent offense relationships to form. More detailed and temporally disaggregated data are needed to address this issue.

Authors' Note

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Notes

1. Confirmed gang members, according to police data, met at least two of the following criteria: admitted gang membership, been vouched for by another gang member, been arrested with a

gang member, displays a gang tattoo or brand, wears clothing or symbols intended to identify with a gang, appeared in a photograph or image with a gang member engaging in gang-related activity or displaying gang signs or symbols, communicates with a gang member in furtherance or support of gang-related activity.

2. We acknowledge that a two-mode analysis would be preferable. Anecdotally, most offenses occur in groups of two, which limits the bias introduced by the one-mode projection. In addition, the current framework does not allow distinguishing between different tie strengths.
3. In contrast to simple logistic regression, exponential random graph (ERG) models account for "dyadic dependence." That is, the presence of one tie (dependent variable) is allowed to affect the independent variables for another tie.
4. Simply counting the number of triangles often brings the problem of "degeneracy" in the estimation of ERG models (see Hunter, 2007; Hunter & Handcock, 2006).

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