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Untangling the Web of Violence:

The Network Effects of Civil Gang Injunctions

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The materials included do not represent the opinions of the OJJDP.

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EXECUTIVE SUMMARY

Purpose. Civil gang injunctions (CGIs) impose significant behavioral restrictions on individuals (i.e., setting curfews, prohibiting free movement, and restricting social activity), to reduce social interactions that may lead to conflict. Yet, despite their widespread use, we know little about the effects that CGIs have on conflict relations. This study examines how the web of violence changes at two levels—the local social neighborhood of specific gangs and the network level for a community of gangs. Comparing pre- and post-injunction networks of violence for specific gangs, as well as cumulative effects across four phases of CGI implementation, we investigate how the imposition of CGIs alters the tendency of gangs to direct serious violence at non-gang involved individuals and engage in new conflict with rival groups, while controlling for historical effects and group characteristics with quadradic assignment procedure (QAP) nodal regression and stochastic actor-oriented modeling.

Methods. Starting with 72 enjoined gangs, we use a 2-step sampling process to map the social landscape of violence within which each group is enmeshed. Drawing upon information recorded in 986 prosecuted cases (970 unique cases with 16 additional related cases involving co-defendants) we investigate violent conflict among 317 gangs and 11 community groups that are active in the City of Los Angeles (1998-2013). Linking named defendants and accomplices to victims, directed valued networks are observed for the entire period and comparisons made across phases of CGI implementation to assess cumulative impacts—baseline (1998-2001), ascent (2002-2005), maturity (2006-2009), and saturation (2010-2013). Of note, most cases involved murder or attempted murder (77%), robbery (12%), or assault (9%)—with most of these incidents being classified as gun crimes (91%) occurring within the City of Los Angeles (71%). Young people were involved in 53% of the cases examined.

Result Highlights. Investigating the association between CGIs and gang violence we find that the web of conflict is dynamic, exhibiting significant change across observations. Post-CGI conflict patterns become more complicated, and transitivity preferences tend to favor new conflict among enjoined groups. Higher levels of competitive dominance and aggression are associated with inter-group violence crossing racial/ethnic divisions; youth are embedded in adult conflict networks. Mapping conflict from adjudicated cases offers insight into the influence that criminal justice procedures have on mapped conflict relations.

Project Significance. We are among the first to explore whether CGIs are associated with observable dynamic and compound effects on the social structure of serious violence affecting gang-involved youth. In doing so, this study advances crime prevention policy in three ways.

1) Investigating the inter-group structure of violence across 16 years, we document the dynamic properties of street gang conflict, suggesting that future use of CGIs should reshape behavioral prohibitions, reducing the emphasis on "one-size-fits all" approaches. CGI stipulations should be more tailored to the set of interconnected combatants for a limited period, with a focus on the groups with the greatest competitive advantage or greatest influence in facilitating conflict. Such modifications may improve focused-deterrence measures, supporting desistence and recovery from gang involvement.

2) By including all enjoined groups and others in conflict with them, we shed light on inter-gang violence that crosses racial/ethnic divisions and investigate how young people are embedded in networks of adult violence. Our findings suggest that interagency cooperation and coordination spanning child welfare and the criminal justice system can improve case management and maximize the benefits of anti-gang efforts.

3) Using adjudicated cases, this study draws information from a different point in the criminal justice system than prior studies of gang-on-gang violence. Prior studies, using crimes known to police, are unable to contribute to our understanding of the effect that prosecutorial efforts have in suppressing gang conflict and reducing community exposure to gang violence. When compared to prior research, the findings reported here begin to expose how court processes shape the nature of conflict relations that proceed through the system.

4) This study demonstrates the utility of applying a social network science approach to investigating the ecology of gang violence.

Project Management. Project leadership completed the study within the designated timeframe. In total 35 people were associated with deliverables. In addition to generating nine unique datasets and 10 scholarly products (presentations and manuscripts), we hosted a symposium to discuss the implications of this research with community partners. The symposium was organized around two panels, the first focused on presentations spotlighting the impact of CGI's by investigating what is known about how gang violence spreads in response to CGI's, rivalries and alliances, and spatial proximity. The second panel explored intelligence-led approaches to containing networked gang violence with a moderated panel of leading experts. The 75 registered attendees represented 31 different organizations including academic institutions, law enforcement agencies, and community-based agencies.

Report Notation. Excerpts of this report were extracted from several completed manuscripts, two of which are published and one that is under peer-review. Additional publications are planned; information is available upon request.

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PROGRAM NARRATIVE

Statement of the Problem

Most social phenomena (i.e., information, disease, and emotions) are transmitted through a network, moving from person-to-person like an infection. Individuals respond to what they learn or experience, in turn, this reaction facilitates additional ripple effects back towards the origin and forward towards new people (Christakis & Fowler, 2009). Of critical importance in understanding how social pathogens like gang violence spread through a community is the structure of the local social neighborhood (Lewis & Papachristos, 2020). Formed by the aggregation of social relations among directly connected actors, local social neighborhoods influence what information individuals receive and how they react to events. When a gang member becomes embroiled in a dispute that causes injury or perceived harm to reputation or status, the individual (or group) reacts (e.g., Papachristos et al., 2013; Papachristos et al., 2015). Since the imposition of a civil gang injunction (CGI) is, without doubt, a clear public admonition of a group's behavior and may be viewed by the group, allies, and rivals, as an "attack" by the criminal justice system, CGIs are likely to trigger a shift in violent behavior. Behavioral changes could manifest in the selection of targets, direction of attack, or frequency of victimization.

Understanding the network structure of street gang violence, supports efforts to fashion focused deterrence strategies that minimize displaced aggression, reduce gang conflict, and improve public safety. The structure of gang violence has been investigated within a single gang (e.g., McCuish et al., 2015), within an identifiable neighborhood and large regions (e.g., Tita & Radil, 2011; Randle & Bichler, 2017), and across cities, i.e., Boston (Papachristos et al., 2013), Chicago (Papachristos, 2009), Montreal (Descormiers & Morselli, 2011), and Newark (McGloin, 2005). However, to the best of our knowledge, the effects of CGIs on the structure of street gang violence has not been investigated. The present study extends this line of inqury by investigating the social structure of gang violence involving 72 enjoined street gangs operating in the City of Los Angeles, California, as revealed by prosecutions over a 16-year study period (Jan. 1, 1998 – Dec. 31, 2013).[1] Our primary aim is to assess the effects of CGIs by exposing shifts in the web of violence. Before we outline how we implemented this research program, we describe CGIs as implemented in California.

[1] While individuals are not always named in the injunction, 807 people are listed, and consequently, face sanctions for violating behavioral restrictions, i.e., associating with each other in public.

Civil Gang Injunctions (CGIs)

Description

CGIs establish “safety zones” wherein members of the target gang(s) are prohibited from engaging in a predetermined list of activities, ranging from illegal behavior (e.g., drug selling) to social nuisances (e.g., hanging out in public while flashing gang signs to intimidate area residents) and general restrictions (e.g., curfews). Public behavior is a central focus of CGIs. Akin to other nuisance abatement litigation, violators face civil sanctions, such as financial penalties, for failing to abide by the behavioral orders.

Given the information requirements needed to establish that individuals or a group impose a significant nuisance to a community, prosecutors work closely with law enforcement agencies integrating gang intelligence with crime reports, testimonials, and evidence from prior criminal cases. This information identifies specific individuals/groups to sanction, defines the scope of the injunction regarding establishing the physical parameters of safety zones (mapping the area), and outlines prohibited behaviors. Although primarily a problem-oriented prosecutorial strategy to reduce violence, police are responsible for enforcing the terms of the injunction, and thus, it is critical that representatives of the agency are involved in setting the behavioral expectations that they will have to enforce.

The legal framework used in California to establish that gang behavior constitutes a public nuisance to the neighborhood is California Civil Code sections 3479 and 3480. To impose a sanction against named individuals or a group of people, the behavior in question must affect a definable group (e.g., community or neighborhood) and be considered

> *[…] injurious to health or is indecent or offensive […], or an obstruction of the free use of property, so as to interfere with the comfortable enjoyment of life or property, or unlawfully obstructs the free passage or use, in the customary manner, of any navigable lake river, bay, stream, canal, or basin, or any public park, square, street, or highway*. CCC, 3479.

CGIs have a long history in California, and nowhere are they more prevalent than in Los Angeles. Since 1987, the Los Angeles City Attorney’s Office has filed more injunctions than anywhere else in the U.S. When this project started there were 46 injunctions targeting 72 gangs. As illustrated in Table 1, most of these injunctions were imposed before 2010. Common prohibitions include refraining from drug use and sales, possession of firearms, involvement in graffiti and vandalism, associating with known gang members, or intimidating people in the neighborhood.

Table 1. Characteristics of Los Angeles civil gang injunctions

Characteristic	Percent of Injunctions (N = 46)
Implementation Phase (Year Enacted)	
Baseline (1998-2001)	15.0%
Ascent (2002-2005)	40.0%
Maturity (2006-2009)	35.0%
Saturation (2010-2013)	10.0%
Prohibited from hanging out near schools	13.0%
No alcohol	87.0%
Curfew	73.9%
Renunciation or Opt-out	34.8%

At the onset of this study, the restrictions imposed by CGIs were indefinite. For this reason, 34.8% of injunctions include a clause permitting individuals demonstrating no gang activity for a period of 3 years to be able to petition to have the injunction against them lifted. Recent California legislation established statutorily provisions for individuals to contest their inclusion (AB-2298 Criminal Gangs).[2] This legislation simplifies procedures and expands the possibility that individuals can remove their information from all gang databases (Crawford, 2009). The impact of this legislation on gang injunctions is still unclear.

Effectiveness of CGIs

It is notable that although this anti-crime strategy is used across California and in at least seven other states, their impact is not widely studied, and the results are as varied as the methodologies used (see Table 2). Some research found that injunctions led to a reduction in violent or serious crime in enjoined areas (e.g., Ridgeway, Grogger, Moyer, & MacDonald (2018); Carr, Slothower, & Parkinson (2017); LA Grand Jury, 2004). For example, Grogger (2002) found that compared to matched neighborhoods without injunctions, neighborhoods with injunctions experienced a 5-10% decline in violent crime during the first year of the imposed injunctions with no evidence of displacement to adjoining areas. While other studies found an increase in violent crimes in enjoined areas (e.g., ACLU, 1997). Goulka et al. (2009), for example, reported a significant increase in violent crimes and weapons crimes in the enjoined block groups post injunction; although, they also found a decrease in property crime during the

[2] The Governor of California approved the legislation on September 28, 2016. At present, the impact of the implementation on future court proceedings is unknown. Contested designations may reduce the number of gang enhancement penalties sought in future cases, with certain individuals being able to remove themselves from scrutiny, generating potential implications for future CGI assessments. Because the current investigation includes cases only prior to enactment of this legislation, the internal validity and reliability of our findings are not affected.

same period. Although prior research finds mixed results, a consensus exists that the effects are short lived (e.g., Maxon et al., 2005; O'Deane & Morreale, 2011). Given the heavy use of CGIs in Los Angeles, it should come as no surprise that this city is the focus of several evaluations.

One possible explanation for the mixed results is that prior studies typically use police data or calls for service to examine the effects of injunctions on violent crime rates within enjoined areas (LA Grand Jury, 2004) comparing areas with injunctions to matched control areas (Grogger, 2002) or surrounding areas without injunctions (ACLU, 1997; Goulka et al., 2009). Spatial units of analysis differ, and efforts to assess displacement typically identify physically proximate areas as opposed to neighborhoods that are socially proximate due to linkages among rival and ally gangs. Pre- and post-observations are short, ranging from 6 months to two years. Of interest to the current study are the findings of Hennigan and Sloane (2013) and Swan and Bates (2017) which suggest that much can be learned from alternative sources with the potential to uncover more information about social interactions.

Interviewing male gang-aged youth (14-21 years old), Hennigan and Sloane (2013) examined the effect of CGIs on youth within the targeted areas[3], with a specific focus on perceived risk of being caught and punished for criminal activity, the effect of gang injunctions on gang cohesion, and the effect of gang injunctions on an individual's identification with their gang in CGI areas. Even though no differences emerged between gang-involved youth in CGI areas and similarly situated gang-involved youth in the control area regarding the expectation of being caught and punished for criminal and violent activity, these authors did find that gang-involved youth in CGI areas were less likely to identify with their gang (weaker social identity) and reported spending less street time together (lower street cohesion) than gang-involved youth in the control area with no injunctions. No differences were found in general cohesion and there was no difference in how often gang-involved youth got together in general.

[3] Because safety zones varied, the researchers identified size small micro-neighborhoods within each target area and the control area in which to conduct interviews.

Table 2. Prior studies of civil gang injunctions

Citation	Focus of Study	Location	Data	Method	Main Results	Follow-up
Police Data						
ACLU (1997)	Blythe Street Injunction (1993)	Los Angeles, CA	police data (1991-1996)	19 reporting districts – target CGI area compared to surrounding areas	increased violent crime and drug trafficking in adjoined areas	n/a
Carr, Slothower, & Parkinson (2017)	4 (24 month) injunctions	Merseyside, UK	police data (2009-2016)	compared pre & post offending by 36 individuals affiliated with organized crime groups	59% group and 61% individual decline in offending and severity; victimization declined by 60% post injunction	36 months
Grogger (2002)	14 injunctions	Los Angeles County, CA	police data (1993-1998); part 1 crimes	areas with injunctions compared to matched comparisons	5-10% decline in violent crime: mostly due to a reduction in assaults; no displacement to adjoining areas	1 year
LA Grand Jury (2004)	14 injunctions	Los Angeles, CA	police data (2003-2004); part 1 crimes	areas with injunctions	6-9% decline in serious crime	1 year
Goulka et al. (2009)	Santa Nita Injunction (2006)	Santa Ana, CA	calls for service – crime & disorder (2005-2007)	6 enjoined block groups compared to 166 other blocks, pre- and post- injunction & trend analysis	sig. increase in violent (20%) and weapons crime (27%) and decrease in property crime (-17%)	18 months
Ridgeway, Grogger, Moyer, & MacDonald (2018)	46 gang injunctions	Los Angeles, CA	police data (1988-2014) - quarterly crime reports	short- and long-term effects models; analysis of interrupted injunctions	5% short term and 18% long term decline in crime (more pronounced for assault); no displacement to nearby areas	18 months
O'Deane & Morreale (2011)	25 injunctions	Ventura, Los Angeles, San Diego & San Bernardino Counties	police data (1982-2007); part I & II crimes	matched pairs; 25 gang injunctions, one year pre- and post- injunction	Part 1 crimes sig. decrease in first year post-injunction; smaller decreases in Part 2[1]	n/a
Surveys or Dyadic Interactions						
Maxson et al. (2005)	Verdugo Flats Injunction (2002)	San Bernardino, CA	resident surveys	4 areas (2 target & 2 controls); compared resident perceptions 18 months before and 6 months post-injunction	immediate change in primary target area: more police visibility, fewer gang members hanging around, less intimidation and fear	6 months
Hennigan & Sloane (2013)	3 injunctions	Los Angeles, CA	interviews gang aged youth (14-21 yrs old) police data (2004-2009)	4 areas (3 target & 1 control)	mixed results: CGIs reduce street time but have little effect on group cohesion, injunctions did not deter crime, & gang cohesion did not decline	2 years
Swan & Bates (2017)	San Diego County	San Diego County	22 in-depth interviews	purposive, snowball sampling process	disruption of family relationships and friendships; blockage of opportunities; increase in feelings of futility and injustice	n/a
Valasik (2014)	Hollenbeck Community Policing area	Los Angeles, CA	Hollenbeck LAPD Division field investigation cards and homicide case files	network and spatial analysis	changed interaction patterns; CGI reduces likelihood of gang under injunction leaving their claimed territory; homicides shift from public spaces in the more private spaces.	n/a

[1] Calculated percentage change as*: [(pre injunction – post injunction) / pre injunction] x 100 = percent change from baseline].*

Through 22 interviews and court observations conducted between 2009 and 2014, Swan and Bates (2017) examined the effects of CGIs in San Diego County. Their objective was to learn from people who experienced the effects of this gang suppression tactic. Findings suggest that CGIs inadvertently damage family ties and disrupt social relations needed to support desistence efforts. Specifically, injunctions reduced the ability to re-establish pro-social behavior and pursue opportunities for education, employment, and housing. Leading these authors to argue that

> Cumulatively, these difficulties worked against the interests of the people who were targeted by gang-related enforcement measures by increasing their experiences of social strain, frustration and humiliation (Merton, 1938). The pro-social ties that help people develop full lives and stay on conventional paths (Hirschi, 1969) were being dismantled without their consent (Swan & Bates, 2017:7).

The result was an increased feeling of injustice, which served as a motivation to transform gang activity instead of suppressing or eliminating conflict. These authors also show us how important it is to examine how CGIs change the local social interaction patterns of targeted individuals (and by extension, the groups to which they belong) with information that is not generated by law enforcement activities.

Current Study

Structured Violence

Papachristos (2013) argues that deterrent strategies must consider the social structure within which individual gang members are embedded, as well as the group's cohesion, and linkage to other groups. This argument is consistent with recent scholarship that shows that the behavior of gang members is constrained (and enabled) by the social network within which the individual and their group are emeshed (e.g., Bichler, 2019; Descormiers & Morselli, 2011; McCuish, Bouchard, & Corrado, 2015; McGloin & Rowan, 2015; Papachristos, 2009; Papachristos, Hureau, & Braga, 2013; Papachristos, Wildeman, & Roberto, 2015). Investigating the concentration of violence within predominantly black gang conflict networks, Papachristos (2009) concludes that

> Gang members do not kill because they are poor, black, or young or live in a socially disadvantaged neighborhood. They kill because they live in a structured set of social relations in which violence works its way through a series of connected individuals (p. 75).

Social networks place "adversaries in positions where each must attempt to defend, maintain, or repair their reputation" (Papachristos, 2009: 76). Building from a growing body of work examing the structure of gang violence (see for example Descormiers & Morselli, 2011; McCuish et al., 2015), Papachristos (2009) argues that patterns of networked violence emerge from the aggregation of individual-level disputes associated with historic rivalries, retaliation for perceived harms, and efforts to retain or elevate social status in accordance with street gang culture (Lewis & Papachristos, 2020). Perceived disturbances will trigger new waves of violence and conflict ends when an equillibrium is achieved. As factions jostle for social position, conflict can emerge between groups that are otherwise thought to be in allegiance (Descormiers & Morselli, 2011; Decker & Curry, 2002). Simply stated, violence spreads through social networks as individuals react to the behavior of others (Papachristos, 2009).

Analyzing street-gang behavior at the dyadic level, studies show that the local structure of social relations differentiates groups in terms of their patterns of inter-group violence, choice of co-offending partners, and group longevity (See Table 3), and these characteristics are associated with the group's social position within the gang community. For example, conflict (and co-offending) often involves conflict among groups with the same racial or ethnic description, referred to in social network terms as homophilous or intra-group conflict (e.g., Gravel, Allison, West-Fagan, McBride, & Tita, 2018; Grund & Densley, 2015; Flashman & Gambetta, 2014; Papachristos, Hureau, & Braga, 2013; Randle & Bichler, 2017), although a small subset of gangs attack across racial/ethnic lines (Papachristos, Hureau, & Braga, 2013). Spatial proximity elevates the likelihood of conflict but does not fully explain aggression among groups (e.g., Radil, Flint, & Tita, 2010; Tita & Radil, 2011; Valasik, 2014). The social dominance of a gang may be associated with its size (e.g., Brantingham, Valasik, & Tita, 2019), with larger gangs or those percieved as strong being observed as having more close like structures, and smaller gangs or those percieved as weak relying on alliances (e.g., Ouellet, Bouchard, & Charette, 2019). Moreover, examining 636 homicides among 68 Chicago gangs, Lewis and Papachristos (2020) find that structural patterns are dynamic and that reciprocity exhibits two forms – direct retaliation and generalized, potentially hierarchical patterns representing triadic complex patterns.

Table 3. Dyadic Investigations of Street-Gang Behavior

Citation	Focus of Study	Location	Data	Main Results
Bichler, Norris, Dmello, & Randle (2019)	Effects of CGIs on violence	Los Angeles, CA	Court cases prosecuted Los Angeles (n=272)	Gang violence is not centralized. CGIs correspond with attack behavior—leading to more violence and deepened inter-gang conflict. CGIs do not lessen attacks on the community.
Brantingham, Valasik, & Tita (2019)	Inter-group gang violence	Los Angeles, CA	LAPD Homicide Reports (1990-2012)	Gang size and directionality of are not good indicators of competitive rank and ability. Competitive pressures can be mitigated by occupying gaps in spatial coverage of gangs viewed as superior.
Flashman & Gambetta (2014)	Preference for deviant and non-deviant friends	USA (n=80 unspecified communities)	National Longitudinal Study of Adolescents Health (1994-95)	Homophily is greater among deviant adolescents than non-delinquents. Deviant behaviors done in secret and with more severe sanctions increase homophily among friendships.
Gravel, Allison, West-Fagan, McBride, & Tita (2018)	Gang formation and participation in violent attacks	USA	N/A. Simulation model.	Homophily in gang formation is influenced by social distance present between racial groups in a community--the more same race-based gangs in an area the more intra-racial violence there will be.
Grund & Densley (2015)	Preference for co-offending with same ethnic background.	London, United Kingdom	Arrest and conviction records (n=48 youth with gang ties)	Gang members who share the same ethnic background are two times more likely to co-offend than those who do not. Ethnic homophily is also partially associated with a shared third co-offender—this accounts for ethnic mixing patterns.
Lewis & Papachristos (2020)	Structure of violent relations	Chicago, IL	Gang homicides; 1996-2000 (4 observations: 1996-97, 1997-98, 1998-99, 1999-2000)	Direct reciprocity is a dominant pattern, however higher ordered (generalized reciprocal and structural effects) vary across observations; ethnic-racial variation exists; gang size increases involvement in conflict; density decreases.
Ouellet, Bouchard, & Charette (2019)	Network dynamics that influence life span of criminal groups	Montreal, Quebec	Police data (3 observations: 2001-03; 2004-06; 2007-09)	Survival of a gang is a function of their cohesion and embeddedness – indirectly influence by gang size. Large gangs thrive by maintaining closed structures, whereas small gangs are reliant on alliances.
Papachristos (2009)	Social order and structure of gang affiliated murders	Chicago, IL	Chicago PD Homicide Reports (1994-2002)	A gang is more likely to commit murder if it is exposed to higher levels of violence. Black gang networks are more active and denser, whereas Hispanic gang networks display star like structures of powers. Patterns of gang conflict enable and promote gang values, norms, and culture.
Papachristos, Hureau, & Braga (2013)	Effects of geographic proximity, organizational memory, and additional group processes on gang violence	Chicago, IL; Boston, MA	Chicago PD Homicide Reports (2008-09); Boston PD Gunshot Reports (2009)	Gang violence clusters around ethnic and racial enclaves, with a higher density observed among black gangs – did enable a dominance hierarchy or pecking order. Space alone does not explain gang violence. Prior conflict can enable gang violence regardless of spatial proximity.
Radil, Flint, & Tita (2010)	Rivalry criminal street gangs	Los Angeles, CA	LAPD Survey Data asking gang rivalries in Hollenbeck (2000-02)	Geographic patterns in gang violence is not fully attributed to spatial proximity between rival gangs across gang violence networks.
Randle & Bichler (2015)	Inter- and intra-gang violence	Los Angeles, CA	Court Cases prosecuted Los Angeles between 2002-2010 (n=284)	More than half of violence observed between gangs is due to intra-gang violence. A small portion of violence observed generated reciprocal violence—most common between same gang subsets. Most attacks involve individuals with no known gang affiliation. Support is found for notion that gang violence enables a sort of pecking order among groups.
Tita & Radil (2011)	Neighborhood patterns of violence (Hollenbeck)	Los Angeles, CA	LAPD Reports (May 2000-December 2002)	Gang violence stems more from social/spatial issues of gang rivalries than with just mutual borders.

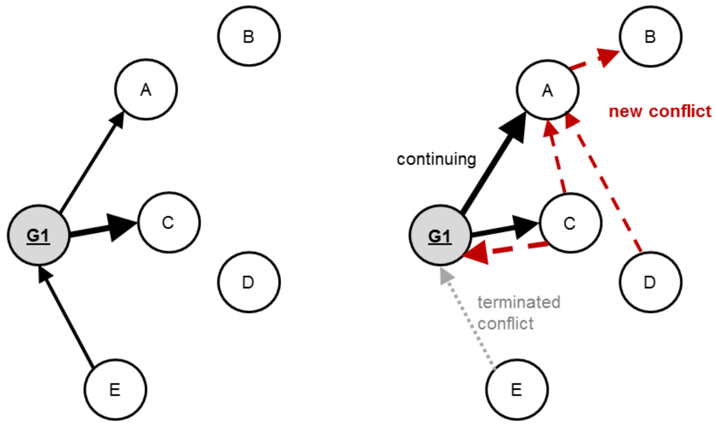
Expectations

As noted above, variability in the pattern of local conflict relations is thought to reveal something about the hierarchy of inter-gang relations that may be associated with competitive advantages (e.g., Brantingham et al., 2019) and this may offer predictive insight into the way violence spreads within a community (Papachristos et al., 2013; Lewis & Papachristos, 2020). Prior studies found that perceived harm can trigger an act of retaliatory violence as groups struggle for dominance. Represented as a network pattern of reciprocity, if the social status among actors is even, attacked gangs may react to a perceived harm by responding in kind. In Chicago, for example, reciprocal attacks accounted for 37% of gang-related homicides (Papachristos, 2009) and in a subsequent study, reciprocity was found to be a significant predictor of fatal and nonfatal gunshot injuries in Boston and Chicago (Papachristos et al., 2013). Violence could also spread to those not directly involved. In this scenario, we may see a knock-on or domino effect, where the victimized group, reacts by attacking another street-gang, those who are perceived to have a lesser status (e.g., Randle & Bichler, 2017). Additionally, groups may respond to an attack by initiating a campaign of violence, attacking many other groups in what is described as an out-star formation (e.g., Descormiers & Morselli, 2011; Papachristos et al., 2013).

At the gang-level, CGIs should materially alter the local web of violence within which groups are embedded. Figure 1 illustrates some ways gang violence may change. Panel A illustrates that during the baseline period, Gang 1 attacked two different gangs, A and C, and is targeted by a third group, gang E. The arrowhead is larger and line thicker connecting Gang 1 and C because there are multiple victimizations during the baseline. Prior to the injunction, Gang 1 played a dominant role in its local social neighborhood because it attacked more groups, with greater levels of inflicted harm (victimizations), than it received.

In this hypothetical example, a significant change occurs post-injunction. The conflict between Gang 1 and group E ends; a dotted grey line represents this decline in violence. Many new conflicts also form, shown in red: Group C launches an offensive, retaliating against Gang 1 and attacking group A; group D, perhaps in response to perceived weakness of group A, victimizes someone from this group; and, a domino effect emerges as group A, suffering from multiple attacks it is unable to counteract, subjugates a weaker group, gang B. Two existing conflicts continue, albeit in an altered form.

Figure 1. Illustration Changes in Gang Conflict



a) Baseline (prior to injunction) b) Post-Injunction

While prior research investigated networked street-gang violence (e.g., Lewis & Papachristos, 2020; Papachristos, 2009; Randle & Bichler, 2017), this study is the first comprehensive investigation of whether the imposition of civil injunctions reshape the structure of conflict networks. If CGIs work as intended, and the behavior of individual gang members is affected by the imposition of behavior restrictions, specifically a reduction in publicly visible social interactions among group members in designated safety zones, then there should be measurable change in the web of conflict at the local level. Figure 2 outlines our expectations regarding how CGIs could change the structure of street-gang violence. These expectations are tested in three distinct research components as outlined in the logic model that follows.

Figure 2. Synopsis of Expected Structural Effects

CGI triggers change (working hypothesis)	**CGI has no effect** (alternate hypothesis)
Conflict Structure Evolution (RC 1) 1. Serious violence will involve conflict with new groups, intensifying the complexity of violence resulting in more local hierarchies post-injunction. 2. Significant structural change is expected through the CGI adoption cycle-developmental baseline, ascent, maturity, and saturation for non-CGI groups adjacent to targeted gangs.	1. Serious violence will continue to involve inter-gang violence among factions previously in conflict without change in the observed structure of local relations. 2. Spatial patterns will not shift post-CGI implementation.
Competitive Advantage (RC 2) 3. Gangs with competitive advantages over rivals will exhibit greater aggression and suffer fewer attacks post-CGI implementation. 4. Gangs with claimed turf near other gangs will exhibit greater aggression and victimization post-CGI implementation.	3. Gangs with competitive advantages over rivals will not alter level of aggression and attacks exhibited. 4. Gangs with claimed turf near other gangs will exhibit less aggression and victimization.
Homophily (RC 3) 5. While most conflict relations will exhibit racial/ethnic homophily as groups compete within community enclaves, post-CGI the most aggressive groups will be involved in inter-racial/ethnic conflict (heterophily).	5. Conflict relations will exhibit homophily.

Logic Model

Enjoined gangs may react against community sanctions to exert their dominance in the local neighborhood, against other proximate gangs and the community-at-large. An upsurge in violent activity may be associated with an effort to save face in response to the negative public attention associated with the injunction. Our logic model suggests that post-injunction, highly visible attacks on non-gang citizens may also serve the group well, i.e., acts of public violence may intimidate community members and decrease interference in group activities that might affect the profits gained from illicit enterprise. Consequently, the following patterns could emerge across our research components.

Conflict Structure Evolution (RC 1). Local hierarchies will intensify and retaliation (reciprocated attacks) will increase post-injunction, leading to evolving structures across phases of CGI implementation (working hypotheses H_1 and H_2). Enjoined gangs will become more aggressive in a struggle for dominance to remedy a tarnished street reputation; observed as an increase in the knock-on or domino pattern suggesting a shift in the inter-gang social pecking order. Groups previously dominated by an enjoined gang will be emboldened, leading to greater levels of retaliatory violence. Support is found in Bichler et al. (2019), where seven of eight enjoined gangs in the City of Los Angeles were observed to engage in more violence post-CGI implementation. Similarly, Papachristos et al. (2013) found that gangs are more likely to respond to violent behavior, rather than to initiate without cause, and Lewis and Papachristos (2020) found evidence of generalized reciprocity and local hierarchy in conflict patterns over subsequent observations.

Competitive Advantage (RC 2). Gangs that have competitive advantages over rivals will exhibit greater aggression and suffer fewer attacks post-CGI implementation (working hypothesis H_3). As enjoined groups adjust routine behaviors, venturing into the territories of other spatially proximate rivals, serious violence will involve conflict with new groups (working hypothesis H_4). Brantingham et al. (2019) acknowledge that competitive pressures faced by gangs in general can be mitigated by occupying territories in which they are able to sustain a dominant status, maintaining their aggressive nature without increasing their level of victimization. Larger gangs tend to be dominant aggressors and victims (Lewis & Papachristos, 2020).

Homophily (RC 3). While most conflict relations are likely to exhibit racial/ethnic homophily as groups compete within community enclaves (density effect), several factors confound homophilous tendencies. For instance, intra-group patterns dominate when there is social distance between groups (e.g., Gravel et al, 2018) and social connectivity does not join non-adjacent groups (e.g., Radil et al., 2019). Material to this investigation, attacking rivals who are well positioned within the greater gang conflict network (e.g., greater competitive dominance) may be observed as homophilous attacks on groups with similarly high levels of successful gang-on-gang violence or heterophilous attacks on peer-rivals from different communities reflected as inter-group conflict (working hypothesis H_5). Winning these conflicts, may spark significant net gains in group reputation as per the street-gang code of conduct (Lewis & Papachristos, 2020).

Alternatively, CGI will have no effect. G*ang violence will continue unabated, with no apparent structural change between the pre- and post-injunction period.* This means that, on average, there will be no significant changes to the structure of networked violence for the enjoined street-gangs.

Methods

Identifying Incidents of Serious Gang Violence

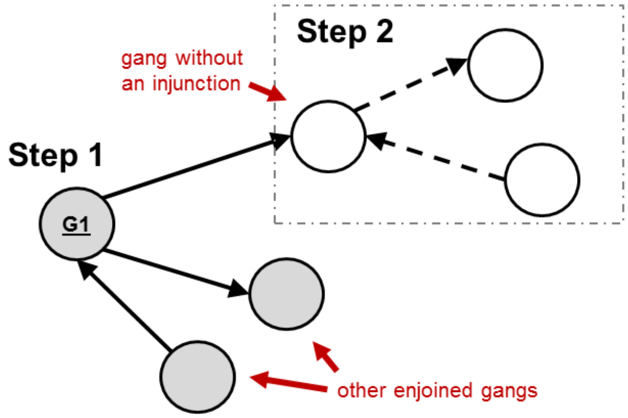
Network data stems from relational information, representing dependence among the actors under observation (Borgatti et al., 2002; Krackhardt & Stern, 1988). Our first step to generating networks mapping conflict relations identified all criminal convictions involving an individual associated with any of the gangs named in the 46 civil gang injunctions filed in the City of Los Angeles between Jan. 1, 2000 and Dec. 31, 2012.[4] These 72 gangs constitute a list of seeds (see Figure 3). In social network terms, a seed is a starting point (considered the ego) in the generation of a social network. By using the gang's name as a search term, we identify cases wherein *at least one defendant or victim was a known gang member at the time of the incident.*

To find cases, the name of each of these LA-based gangs is searched on Westlaw/Lexis-Nexis: both Westlaw and Lexis-Nexis are electronic libraries that provide information about federal and state cases. Then, we determine the gang affiliations of all named individuals—defendants, co-defendants, and victims—identified in the court documents. We apply a set of selection criteria to narrow our focus to serious violence occurring within a specified timeframe and in a predetermined study area. To be included in the study, the case must involve

1. at least one charge/conviction for assault with a deadly weapon, attempted homicide, or homicide;
2. at least one defendant was tried as an adult; and
3. the crime occurred between Jan. 1, 1997[5] and Dec. 31, 2016 somewhere within the five-county study region—Los Angeles, Orange, Ventura, Riverside and San Bernardino Counties.[6]

[4] Two injunctions, filed in 2013, are too recent to permit a complete follow-up period.
[5] The baseline period predates the target injunctions to regular gang activity with no injunctions in force.
[6] While the focus of this investigation is on gangs enjoined in LA, it is plausible that injunctions may facilitate the geographic spread of gang activity. We must also acknowledge the migratory exodus from LA that resulted from the housing crisis that occurred throughout the mid to late 2000s. Combined, these factors suggest that LA-based gangs may have committed offenses in adjacent counties. Thus, the geographic scope of this investigation could not be restricted.

Figure 3. Description of the Case Selection Protocol



The second step requires repeating the search protocol described above for gangs that are not under CGI in the City of Los Angeles. By searching all gangs involved in cases found during step 1 that are not part of the initial set of 80 groups (including the 72 targeted gangs and 6 named cliques of those gangs), we cast a wide net that reveals a deeper level of gang-on-gang embeddedness, specifically, retaliatory violence and local dominance, leading to the identification of 154 primary and 88 secondary alter gangs. Primary alters battle with focal CGI gangs and secondary alters battle with primary alters. Combined, this protocol results in 226 local conflict neighborhoods referred to in network terms as egocentric networks.

Over 4,610 appeals were screened on eligibility criteria described above. Screening reduced the potential sample to about 1,075 cases. Considering the uneven distribution of cases caused by right-hand (recent cases not yet reaching appeals) and left-hand censoring (temporal limitation of case archiving), we reduced the study period from 20 to 16 years. Since CGIs are inherently a prosecutorial crime control mechanism aimed at addressing chronic community crime problems, we considered the social-legal context of CGI implementation when adjusting the observation period (explained shortly).

Restricting the study period resulted in 970 unique cases with 16 additional related cases involving co-defendants (986 cases). These cases provided information on 1,059 incidents (in some cases defendants were charged with multiple crimes occurring on different days, sometimes with the same accomplices). Approximately 77% of the incidents involved murder or attempted murder, 12% involved robbery (this included carjacking), 9% involved assault, and 2% involved other types of violence: most incidents are gun crimes (91%).

Investigating the location of reported street-gang incidents, we found that 71% took place within the City of Los Angeles, with the remaining 29% located across 84 different cities in

California spanning from Oakland to San Diego. Focusing on violent incidents in the City of Los Angeles, 97 different neighborhoods or areas were identified. Most cases involved a social context wherein an offender did not act alone, however, only 65.8% of cases list co-offenders, with about half of these incidents (31.7% of cases) identified 2 or more co-offenders. A single victim was named in about 48.5% of cases.

In total, 4,114 actors are described in the cases. However, some actors have the same names—individuals could be involved in several incidents or cases (e.g., as a victim and a defendant) or different people may share a name (or initials if juveniles). Thus, we identified 3,697 uniquely named individuals. Actor characteristics were not always provided. We have age information for 3,004 actors. Of these individuals, 597 (20%) are known to be under 21 years of age. Considering the number of incidents with age-related information, 34.4% (young people were to be involved in 318 of the 924 incidents with some age details). Regarding youth involvement by gang, this study captured youth involvement in conflict for 168 gangs (of 317 observed): 53% of the gangs observed were linked to cases of serious violence involving young people. About 87% of individuals were described as male.

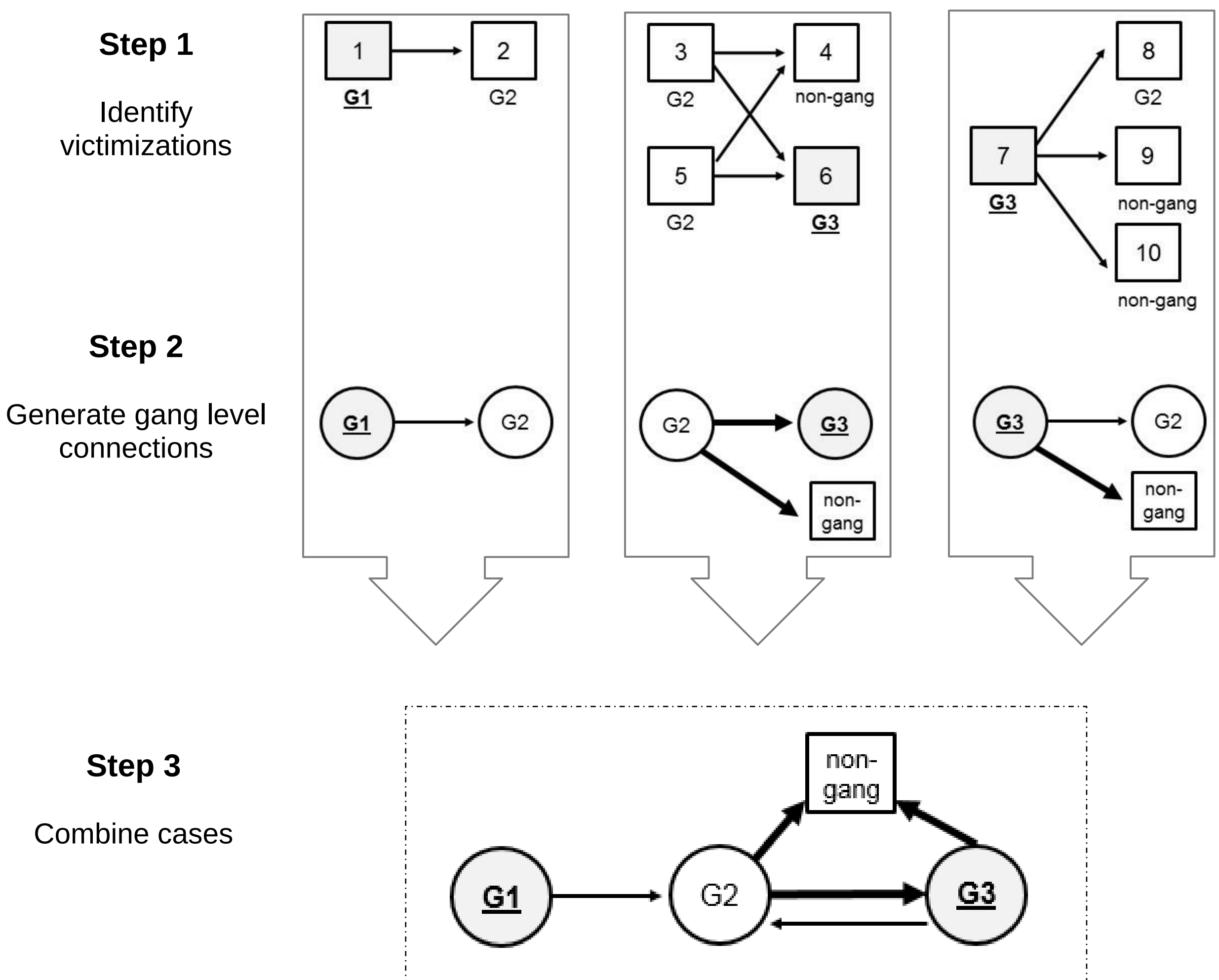
Generating Networks of Gang Violence

Multiple steps were used to generate connections among gangs identified in the case. We began at the dyad level with each offender and victim pairing. A valued and directed network was generated by linking the defendant and accomplices named in a case to each victim identified. This means that the existence of multiple co-defendants (or accomplices) and victims results in many offender-victim pairings—we coded up to ten victims and five offenders. Each offender-victim pairing constitutes a directed tie, referred to as an arc, representing an act of aggression. In instances where two co-offenders and one victim were named, two arcs are generated; two co-offenders and two victims results in four arcs; and if a single offender attacks three victims, then three arcs are generated. Amplifying the amount of violence this way allows us to create a weighted network in which the dominance of gangs is observed. When multiple gang members attack, or a lone offender victimizes a group of people, community impact is magnified as this level of aggression stands to inflict greater street terrorism.

Figure 4 illustrates this initial step (labeled step 1). In the figure, we represent individuals with squares and the lines connecting individuals illustrate aggressions. Each line indicates a single victimization: the lines linking offenders and victims represent all offender-victim permutations, or aggressions associated with the incident. The lines are directed based on case status. Arrows originate with offenders and terminate with victims.

In the second step we aggregate aggressions to groups, using the associated gang and clique information reported for each offender and victim. This generates valued links between groups. For example, in the second case, two members of gang “G2” victimized a member of the gang “G3” resulting in a thicker line, which would be valued in the network with a score of two. Finally, the third step involves generating a community violence network by integrating the group level linkages developed from all cases.

Figure 4. Converting Individual Victimizations to a Master Network of Gang Violence



Note: Circles represent gang groups and squares depict individuals. Underlining denotes seed gangs. Line thickness indicates the number of victimizations and arrowheads denote the direction of the attack.

Inter-Rater Reliability Assessment

An inter-rater reliability assessment investigated the reliability of case identification and coding protocols. Inter-rater agreement was assessed on case inclusion criteria and identification of variables capturing defendant characteristics, victim characteristics, witness characteristics, characteristics of other individuals involved in the case (e.g., gang experts, responding officers, etc.), and situational elements of the case. Coders were assessed on a training sample of cases selected from the most difficult cases involving multiple incidents, each consisting of different elements). Results of the assessment produced a Cohen's Kappa of .84, indicating substantial agreement between the ten coders (Landis & Koch, 1997). However, when just looking across defendant and victim characteristics the agreement increased (k = .96). This indicates that in capturing the defendants and victims' names, aliases, demographics, and which gangs they belong to there was almost perfect agreement. Subsequent random spot checks of coding confirmed reliable retrieval of offenders, victims, and their gang affiliation, but problems with coding the motivation, context, and location of the event. Motivation was dropped from the study, and context and location were regathered for each case by one research assistant—the person with the most consistent coding scores.

Network of Violence

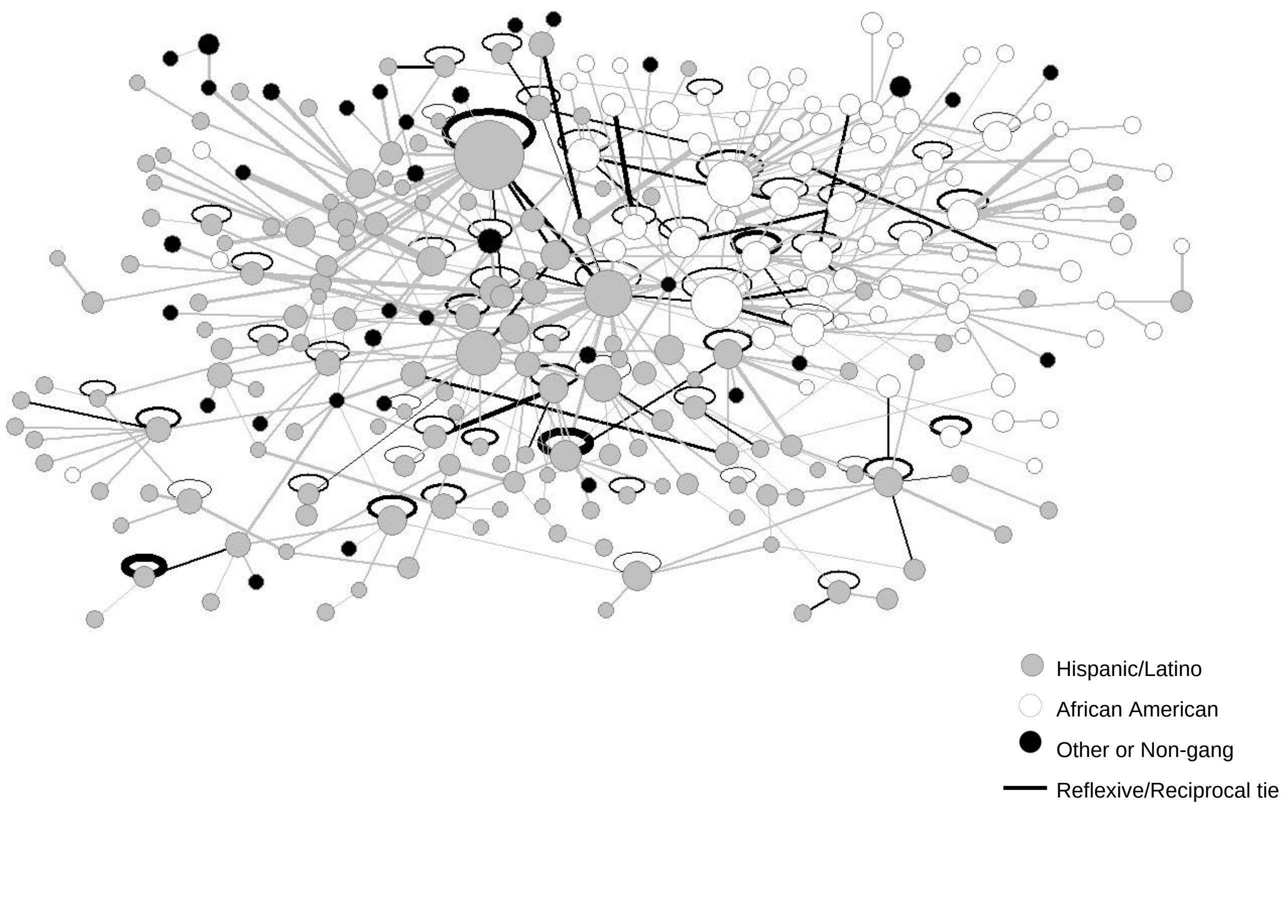
The master edge file for the full study period (1998-2013) includes 3,808 directed arcs connecting 317 gangs and 11 non-gang groups—4 community groups (community, drug dealer, drug involved, and pimps), 6 law enforcement and criminal justice agency groups, and 1 incarcerated group (inmates from correctional facilities with no designated gang affiliation reported). Of note, some arcs could not be included in the master file. A loss of 4.6% of arcs (179 offenders/victims dyads) is the byproduct of missing case details—23 ties were missing about the year when the crime occurred and the rest lacked gang affiliations (e.g., a victim or offender was described as a gang member but the gang was not named).

Despite finding a high level of connectivity in the main component of the network—96.6% of groups are linked—the global structure has low cohesion. Of all the possible conflict combinations, 3.4% of the groups are connected by violence. On average, groups engage in 10.8 aggressive behaviors (attack dyads) and are subjected to 11.6 victimizations. While groups attack or are attacked by 1.8 other groups on average, specific involvements vary greatly (0 to 20 groups attacked, and 0 to 139 groups victimized by). Out-degree centrality scores range from

0 to 163 (.4% centralization; standard deviation of 21.7) and in-degree centrality scores range from 0 to 1,930 (5.6% centralization; standard deviation of 108.1). [See the technical appendix for an explanation of these conventional network descriptive metrics.] Removing the non-crime community group from the network structure reduced the number of groups in the main component to 271 (85% of groups).

Within the network there is a clear division between Latino and African American gangs, with a small subset of gangs attacking across racial lines (see Figure 5). Of note, 20 Latino and 18 African American gangs engage in conflict that crosses ethnic/racial divisions. Second, a small group of gangs have significantly higher recorded aggression than other groups. And finally, there appears to be a substantial amount of internal violence (51 self-conflict halos in the main component) and less reciprocation of attacks between groups (43 black ties indicating conflict pairs or dyads) than reported elsewhere (e.g., Lewis & Papachristos, 2020).

Figure 5. Conflict Network (excluding community groups), Main Component



CGI Implementation Phases – Sub-networks

To investigate the cumulative impact of CGIs across the 16-year study period, we generate networks for each four-year observation— baseline (1998-2001), ascent (2002-2005), maturity (2006-2009), and saturation (2010-2013). The baseline period (1998-2001) includes two years prior to the filing of the first CGI investigated in this study to capture the violent events that precipitated political and community impetus leading to the use of this gang control strategy. Fifteen percent of CGIs were filed during the baseline period under the leadership of Los Angeles City Attorney James K Hahn. The next two phases of CGI implementation took place during City Attorney Rockard J. Delgadillo's term in office—ascent (40% of injunctions were filed 2002-2005) and maturity (35% were filed 2006-2009). The final saturation phase captures waning enactment of CGIs (10% filed 2010-2013)—this decline occurred when Carmen A. Trutanich was the City Attorney of Los Angeles.

The conflict network observed for each phase of CGI implementation varies in size and cohesion, but networks do exhibit some comparable characteristics (see Table 4). Networks exhibit low density[7], meaning that the webs of conflict are sparse, and over time, there is a slight decrease. For instance, during the baseline period, when few gangs are sanctioned with CGIs, 4.4% of potential conflict pairings are observed in the network. By the saturation phase, density decreased to 3.4%. This finding of low density is consistent with other types of criminal networks (e.g., Bright, Hughes, & Chalmers, 2012).

Table 4. Network Description by Phase

	BASELINE (1998-2001)	ASCENT (2002-2005)	MATURITY (2006-2009)	SATURATION (2010-2013)
Network Size				
Groups	113	173	197	124
Aggression (unique attack arcs / total aggressions)	152 / 599	247 / 1,315	264 / 1,242	145 / 554
Internal conflicts (% of unique conflicts)	16 (10.5%)	28 (11.3%)	22 (8.0%)	15 (10.3%)
Cohesion				
Number of components (connected structures)	10	8	15	9
Percent of groups in the largest structure	78.8%	90.2%	82.7%	83.9%
Density	4.4%	4.0%	3.0%	3.4%
Average clustering coefficient	.11	.12	.14	.08
Structural Similarity				
Jaccard coefficient of similarity (with prior period)	--	12.0%	16.1%	10.1%
Pearson correlation coefficient (with prior period)	--	.400	.393	.427

[7] Density is a measure of cohesion, which indicates what percent of the actors in a network are interconnected with each other (See: Wasserman & Faust, 1994, p. 101).

Groups are characterized as being situated in star-like networks where there is minimal conflict among alters of focal gangs. Theoretically, the average clustering coefficient[8] ranges from 0, suggesting that the pattern of conflict ties linked to each gang looks more like a star centered on the focal gang, to a 1, where there is a thickly connected mass of fighting. As reported in Table 4, the clustering coefficients range between a .08 and .14. This means that on average, gangs are not embroiled in tight dense clusters of fighting. [Note: the statistics reported are calculated on dichotomized networks.]

Networked violence evolved with each phase of CGI use. Looking at the network structure over time, the Jaccard Coefficient of similarity[9] finds that between baseline and ascent only 12% of the conflict relations involve the same pattern of violence, meaning that for 12% of dyads, the same aggressor and victim links exist. Between ascent and maturity, the most similarity is found overall in network connectivity, 16% of unique ties involve the same pair of groups in a consistent role. The least similarity is found between the maturity and saturation. Said another way, we can interpret these values to suggest that there is a great deal of change in conflict patterns over time. The Pearson correlation coefficient tells us that while the tie structure changes, the value associated with ties (number of aggressions) is moderately strong[10]. Conflict relations with a lot of aggressions in one period tend to also exhibit a lot of aggressions in the subsequent time period.

Explanatory Variables

In addition to generating a CGI variable for each gang, where 1 indicates an injunction and 0 indicates no injunction (overall and for each observation phase), several additional covariates representing potential confounding factors were developed so as to isolate CGI explanatory effects on conflict patterns.

[8] The average clustering coefficient is a measure of cohesion, based on how many triplets (grouping of three nodes) are present overall in a network (See: Watts, 1999, p. 498). Lower scores highlight that potentially important sub-groups exist within the network.
[9] Jaccard coefficient of similarity is a measure of association, based on how many shared ties are present between different networks (See: Hanneman & Riddle, 2005). The measure identifies the percentage of ties that are the same in two observations of the network.
[10] Pearson correlation coefficient is a measure of association, like Jaccard; however, networks must be valued (See: Hanneman & Riddle, 2005).

Competitive Advantage

Gangs are thought to have a competitive advantage over others if they have a stronger, more dominant position in the community relative to competitors (Brantingham et al., 2019; Papachristos 2009; Papachristos et al. 2013; Randle & Bichler, 2017). Several indicators were developed to account for competitive advantage.

- *Number of cliques*. Groups with more factions or identifiable subgroups are likely to experience more conflict overall, as internal dynamics interact with efforts to dominate neighborhoods. The number of cliques was identified by searching gang names in Unitedgangs.com and Streetgangs.com, both of which are online public sources. Supplemental data coding identified 309 gangs under observation as having one or more associated cliques. In total, the study identifies and recognizes 685 cliques as associated groups associated with gangs in the study.

- *Egonet density.* Egonets are comprised of a focal actor and all alters directly tied to each ego (Hanneman & Riddle, 2005). As used here, egonets include all groups the ego was in conflict with (as an aggressor or victim) and all interactions among alters. Groups embedded in thick networks of conflict, where all combatants interact with the ego, as well as each other, are constrained within a warring community. If found to be significant, then conflict may be better explained by group entrenchment within larger conflict neighborhoods, rather than other explanatory variables. We used egonet density, calculated on a non-directed network. Egonet density reflects the percent of alter ties that involve conflict with each other (relative to the number of ties that would exist if all alters were in conflict with all other alters that are part of the egonet).

- *Internal conflict.* Cohesive groups are better able to persist (Oullett, Bouchard, & Charette, 2019), and thus may have greater competitive advantage over other gangs, when they are able to strategically grow and maintain their social position in their communities. To capture internal conflict, we use the diagonals of the adjacency matrix calculated on a directed, valued network. Internal conflict reflects the number of aggressions wherein individuals from a gang attack fellow members or associates.

Turf Proximity

Street gangs often claim to control turf, and studies attribute the spatial distribution of gang violence to a mix of geographic factors and social proximity between gangs (e.g., Brantingham et al., 2019; Radil et al., 2010; Sierra-Arevalo & Papachristos, 2015; Tita & Radil, 2011; Valasik, 2018; Valasik, Barton, Reid, & Tita, 2017). To generate a valued, non-directed matrix recording the number of turfs each group claims in proximity to another, we observed each gang territory as identified by either using the LAPD Citywide Gang Injunctions map located on the LAPD website or identified by using online interactive Google Maps of California gang territories. Three Google Maps are used: “California Gang Territories”, “SoCal Gang Map”, and “Gangs of

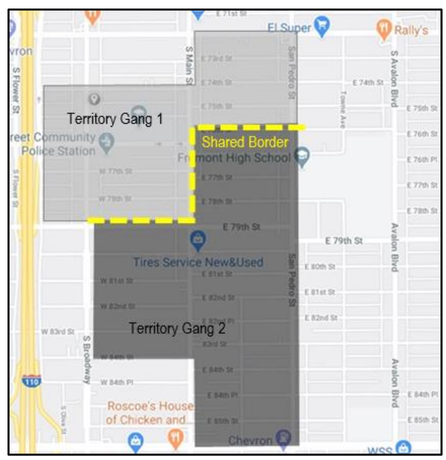
Los Angeles.”[11] Proceeding one gang at a time, each associated territory was examined, and all other gang territories surrounding the focal group recorded and described by type of connectivity. Since each territory claimed by a gang is examined, a gang could have several territories linked to another gang. Triangulating across maps ensured accuracy and completeness.

- <u>Overlap.</u> Gang territory is classed as overlapping when one gang’s territory covers (or shares) an area with another gang. A valued, non-directed matrix of overlapping territories is used to calculate degree centrality; the overlapping turf matrix contains 154 gangs with 527 symmetric, non-reflexive ties. Degree centrality is used to estimate the relative level of territorial overlap each gang has with others.

- <u>Adjacency.</u> Gang borders are classed as adjacent when they are next to each other; meaning they share a common side/edge (see Figure 6). A valued, non-directed matrix of adjacency was used to calculate degree centrality; the adjacent turf matrix contained 304 gangs.

Figure 6. Illustration of Adjacent and Overlapping Gang Territory

(a) Overlapping territory



(b) Adjacent territory due to a shared border

11 LAPD Citywide Gang Injunctions Map:
http://assets.lapdonline.org/assets/pdf/COLUMBUS%20STREET%20GI%20gang_injun_citywide_85x11.pdf
GoogleMaps, “California Gang Territories”:
https://www.google.com/maps/d/u/1/viewer?hl=en&mid=1MyoToeYPKEx54C3BPdblKZEKaRQ&ll=33.959581016719206%2C-118.20239699422388&z=13
GoogleMaps- “SoCal Gang Map”:
https://www.google.com/maps/d/u/1/viewer?hl=en&mid=14tC5b2hV2ai6GwO4A16FB_dyAhY&ll=33.954472876768264%2C-118.09194370066871&z=12
GoogleMaps- “Gangs of Los Angeles”:
https://www.google.com/maps/d/u/0/viewer?mid=1ul5yqMj7_JgM5xpfOn5gtlO-bTk&ll=33.990303182210106%2C-118.27076720146954&z=12

Conflict Homophily-Heterophily

Research shows that gang violence tends not to cross ethnic/racial lines (e.g., Papachristos et al., 2013), thus, when gangs exhibit conflict heterophily they play an unusual role within the social landscape of violence. Bridging communities, these groups may play a pivotal role linking different groups and may be more likely to exhibit greater levels of violence, victimization, or imbalance (difference between attacks and victimizations). Conflict homophily is measured with the E-I index. The E-I index represents correlations between selected egos and alters based on observable attributes (Krackhardt & Stern, 1988). Scores are calculated by subtracting out-group ties from the number of in-group ties, and then dividing by the total number of ties. Since most gangs in this sample are either African American or Latino, a partition was generated along this categorization. This means that for African American gangs, the E-I index was calculated by counting the number Latino or other gangs the group was in conflict with and subtracting the number of within group conflict relations (with other African American gangs), then this figure was divided by the total number of groups in the egonet. This calculation does not consider the number of aggressions or victimizations, meaning the E-I index is generated on a dichotomized network. The E-I index ranges from -1 to 1, with negative scores indicating more within group conflict (homophily) and positive scores indicate more conflict that crosses ethnic/racial lines (heterophily). When calculating the E-I index we did not include attacks on non-gang community groups because there was no way to consistently determine whether the violence crossed ethnic/racial lines. On average, gangs exhibit a tendency to attack other groups like themselves: the average score on the E-I index was -.562 indicating homophily is more typically observed.

Efficiency

Burt’s (1992) measure of efficiency is used to account for the structure of local social neighborhoods. Having more unique conflict partners may increase the focal group’s influence within the gang violence network. In other words, being involved in larger local social neighborhood characterized by a pattern of non-redundant violence increases the likelihood that a focal group fights with other gangs of different descriptions; thereby increasing the possibility of being involved in inter-ethnic/racial conflict. Efficiency was calculated on a transformed conflict network—dichotomized and non-directed. On average gangs were observed to have two internal conflicts. Efficiency ranges from .563 to 1, with a mean of .966, indicating that on average, egos exhibit a relatively high level of efficiency.

FINDINGS

Conflict Structure (Research Component 1)

Violent encounters involving gang members do not occur in isolation. Gang members are embedded within an intricate web of social relations that aggregate to form a complex network of inter-linkages binding groups within a larger community of violence. At the individual-level, individuals respond to what they learn or experience, and in turn, this reaction facilitates additional ripple effects, often spreading in a hyper-dyadic process towards new people (*See*: Christakis & Fowler, 2009). Individuals involved in the initial act of violence may not be the actors who retaliate to the harm: other members of the gang may react, suggesting that group-level analysis may be more informative regarding the structure of conflict than individual-level analysis.

At the group-level, structural hierarchies are likely to exist that reflect local patterns of social dominance. Local social neighborhoods are important because they influence what information groups receive and how they react to events, providing a glimpse into the social context within which a focal gang is embedded, revealing their conflict network structure. And, understanding network change requires being able to model how the structure evolves rather than what it may be observed to look like at any given time.[12] The working hypotheses under investigation state that:

> **Study H_1. Serious violence will involve conflict with new groups, intensifying the complexity of violence resulting in more local hierarchies in the post-injunction period.**
>
> **Study H_2. Significant structural change is expected through the CGI adoption cycle-developmental baseline, ascent, maturity, and saturation for non-CGI groups adjacent to targeted gangs.**

Triad Census

Exploring the structure of conflict through a triad census we investigate the level of complexity interweaving groups. Selection of specific conflict patterns and tallying the number observed for each configuration provides an opportunity to calculate a ratio; where simple structures[13]

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[12] The analyses presented here are adapted from: Bichler, G., Norris, A., & Ibarra, C. (2020). Evolving Patterns of Aggression: Investigating the Structure of Gang Violence During the Era of Civil Gang Injunctions. *Social Sciences*, 9(11):203-221. DOI: 10.3390/socsci9110203.

[13] Percentage distributions for simple structures are based on arc patterns for retaliatory conflict rather than permutations. For instance, the denominator in the start-up phase was 145 (14 reciprocal arcs+ 79 domino patterns, and 52 multi-target attacks).

dominate, violence suppression efforts could independently target select aggressors, and where complex patterns emerge, actions require a coordinated approach focused on a set of interlinked combatants.[14] While it is conventional to count many lower order simple structures, a shift in the ratio between types of structures over time can reveal important changes in the topography of conflict.

General Complexity. Across observations, we find simple structures reflecting a domino pattern of aggression where one group attacks another, who in turn attacks a third group (see the percentages reported in Table 5). This pattern is interpreted to suggest that groups are not of equal status or resources, and thus, groups are unable to retaliate for attacks. Instead they prey upon other groups, perhaps those perceived as weaker than themselves (e.g., Papachristos, 2009). Of course, without detailed information about the specific groups involved, this interpretation is speculative. We also observe a relatively high level of multi-target attack behavior where one gang victimizes two other groups.

Table 5. Triad Census by Observation Period

TYPE	STRUCTURE	BASELINE (1998-2001)	ASCENT (2002-2005)	MATURITY (2006-2009)	SATURATION (2010-2013)
SIMPLE	RETALIATION*	661 (14 arcs; 9.6%)	1,262 (16 arcs; 5.8%)	1,271 (16 arcs; 5.5%)	142 (4 arcs; 4.3%)
	DOMINO	79 (54.5%)	121 (43.8%)	162 (55.9%)	47 (50.5%)
	MULTIPLE TARGETS	52 (35.8%)	139 (50.3%)	112 (38.6%)	42 (45.2%)
COMPLEX	3-WAY INTEGRATED CONFLICT	16	33	44	12
RATIO OF SIMPLE TO COMPLEX		50:1	46:1	35:1	19:1

*Retaliation sets counted in a triad census include situations where actors A and B have a mutual conflict, but no one is in conflict with C. Internal conflict is ignored in this calculation. Since every permutation is counted, the reciprocity scores do not reflect the true count of reciprocated violence. Investigating actual situations where violence is reciprocated and is not linked to internal conflict we count the following: 14 reciprocated ties during the start-up period), 16 reciprocal ties in the building period, 16 reciprocal ties in the peak period, and 4 reciprocal ties in the decline period.

[14] Complex ties include seven configurations: triad sets 9-10 and12-16 as listed by UCInet. Specifically, this includes A->B<-C, A->C; A<-B<-C, A->C; A<-B->C, A<->C; A->B<-C, A<->C; A->B->C, A<->C; A->B<->C, A<->C; and, A<->B<->C, A<->C.

The dramatic change in the ratio between simple and complex structures is a prominent result of this inquiry. While the baseline period, when civil gang injunctions are first introduced, exhibits many simple structures (50:1), the violence network observed during the saturation period exhibits a major structural change. As more gangs face injunctions, the complexity of conflict patterns as indicated by the ratio increases (as reflected in smaller ratios). This suggests that gang violence becomes more integrated. The direct implication is that as the CGI strategy takes effect, new or additional coordinated actions are needed to quell the conflict among sets of gangs.

CGI gangs compared to non-CGI gangs. A community-level analysis offers insight into macro-level changes, but is there a differential effect on enjoined gangs compared to non-enjoined gangs? Table 6 reports on the patterns of conflict observed for enjoined gangs compared to primary alters with no injunction. All groups with egocentric networks containing at least two alters are selected for this analysis. A triad census is then conducted for each phase. Since some gangs did not have sufficiently large egonets for each phase, the sample size varies. Overall, simple structures are more prevalent irrespective of injunction status. We find that there are low levels of direct retaliation and a higher proportion of domino patterns (directed chains), with one notable exception. During the ascent phase (2002-2005), when CGIs are being used more frequently, there is an appreciable shift to multiple targets (out-star formations) among enjoined groups. Of note, the ratio of simple to complex structures declines for enjoined gangs until the final observation—suggesting an increase in complex interactions as more groups are sanctioned. The pattern is different for non-enjoined groups, although, by the final phase there is no appreciable difference in ratios.

Table 6. Triad Census Comparing Egonet Structure of Enjoined Gangs to Focal Alter Gangs

SAMPLE	STRUCTURE	BASELINE (1998-2001)	ASCENT (2002-2005)	MATURITY (2006-2009)	SATURATION (2010-2013)
74 ENJOINED GANGS	**SIMPLE** RETALIATION DOMINO MULTIPLE TARGETS	**99** 9 (9%) 57 (58%) 33 (33%)	**218** 12 (5%) 97 (45%) 109 (50%)	**183** 12 (7%) 101 (55%) 70 (38%)	**56** 3 (5%) 28 (50%) 25 (45%)
	COMPLEX (3-WAY INTEGRATED CONFLICT)	**23**	**51**	**61**	**16**
	RATIO	**4 : 1**	**4 : 1**	**3 : 1**	**4 : 1**
	AVG. RATIO	**5 : 1** (n = 43)	**4 : 1** (n = 60)	**3 : 1** (n = 56)	**4 : 1** (n = 41)
74 FOCAL ALTERS	**SIMPLE** RETALIATION DOMINO MULTIPLE TARGETS	**44** 2 (5%) 21 (48%) 21 (48%)	**52** 3 (6%) 25 (48%) 24 (46%)	**95** 7 (7%) 54 (57%) 34 (36%)	**32** 1 (3%) 19 (59%) 12 (38%)
	COMPLEX (3-WAY INTEGRATED CONFLICT)	**9**	**18**	**26**	**9**
	RATIO	**5 : 1**	**3 : 1**	**4 : 1**	**4 : 1**
	AVG. RATIO	**6 : 1** (n = 41)	**3 : 1** (n = 55)	**4 : 1** (n = 52)	**4 : 1** (n = 43)

Note. The values reported sum the number of structures observed for all egos.

Highly Aggressive Gangs. Aggregate analysis on whole networks is useful for thinking about how violence plays out across a community of actors, but these results obscure important variation at the local level. Gang-level analysis of aggression is key to unlocking the effects of CGIs on specific groups. It is plausible that the preceding aggregate results obscured phase-level fluctuation for specific groups. Table 7 reports on a triad census of simple to complex structures found in the egocentric network of each of the most violent gangs. The ratio listed in each corresponding cell indicates the number of simple structures to complex patterns. Zeros are present due to a failure to observe certain types of structures in the web of violence. The asterisk indicates when specific CGIs were enacted. Exclamation marks identify the most violent gang in each observation period. Overall, eight of these gangs (73%) are enmeshed in more complex patterns of violence at the end of the observation period compared to the initial baseline period. Three Bloods affiliated gangs—the Black P Stones, Denver Lane Bloods and Bounty Hunter Bloods—exhibit variable patterns across the four observations. These findings offer some support for our working hypotheses.

Table 7. Triad Census for the Eleven Most Violent Groups

GANG	BASELINE (1998-2001)	ASCENT (2002-2005)	MATURITY (2006-2009)	SATURATION (2010-2013)
MARA SALVATRUCHA	4:1	20:1*	8:1(!)	5:1
HOOVER CRIMINALS GANG	9:1 (!)	4:1*	3:1	3:1
EAST COAST CRIPS	4:1	4:1	4:1	0:2 (!)
VARRIO NUEVO ESTRADA	3:0	8:1*(!)	2:0	1:0
BLACK P STONES BLOODS	0:0	1:1	1:2*	2:1
DENVER LANE BLOODS	1:0	3:0	2:1	2:1
GRAPE STREET CRIPS	0:0	9:1*	2:1	1:1
LANGDON STREET GANG	3:0*	3:0	4:1	0:0
18TH STREET LATINO	5:1	8:1*	1:6	2:1
BOUNTY HUNTER BLOODS	1:1	0:2*	2:1	6:1
ROLLIN 40S NEIGHBORHOOD CRIPS	1:1*	1:1	1:2	0:1
FULL NETWORK STATISTICS				
Mean Aggressions (Std Dev.)	5.3 (6.9)	7.6 (12.6)	6.3 (10.6)	4.5 (6.5)
Min. to Max.	0 - 47	0 - 94	0 - 87	0 - 41
Aggression Centralization	1.3%	1.1%	0.7%	0.7%

Note. Exclamation marks indicate most violent gang in the network for the phase; the asterisk notes the period when a civil gang injunction was enacted; simple to complex structure reported following analytic protocol used to generate results for Tables 2 and 3. Grey highlights gangs not subject to an injunction during the study period.

Stochastic Actor-Oriented Models

We used stochastic actor-oriented modeling (SAOM) to conduct a more precise investigation into the evolution of network structure over time and to test hypotheses about how CGI status directly corresponds with observed change in conflict patterns. Using a method of moments maximum likelihood estimation process, the model runs a logistic regression to explain change in ties (formation or dissolution) across successive time periods. These models generate parameter estimates with an initial value of gain set at 0.2. Deviation values were calculated from 1,000 iterations. Estimates are stable if convergence occurs and t-ratios are near a value of 0.1. SAOM are useful in that they allow us to explore the relative impact of different change elements and interaction effects (e.g., CGI status indicating a tendency to attack other enjoined gangs), and we can do this while modeling communal effects of multiple CGIs.[15]

[15] For an explanation of this application see: R. Ripley, T. Snijders, & P. Preciado Lopez, *Manual for RSiena*, (University of Oxford, Department of Statistics and Nuffield College, 2011); T. Snijders, 'Network dynamics', in *The SAGE Handbook of Social Network Analysis*, ed. J. Scott and P.J. Carrington (Thousand Oaks, CA: SAGE, 2011),

Table 8 reports several SAOMs disentangling how patterns of violence changed across phases of CGI implementation. The baseline model estimates the tendency of gangs to reciprocate violence and for conflict to thicken (become transitive) when no other factors are considered. Of note, the interaction effect, *CGI transitive triplets*, reveals if enjoined gangs are more likely to battle with other enjoined gangs in a subsequent observation (e.g., T_1 compared to T_2). Negative values indicate a tendency for the network not to change in the prescribed way and positive coefficients indicate a tendency for change to exhibit the characteristics being tested. Bolded estimates are significant. Next, we present models dissecting transitivity and investigating the effect of actor attributes. Selecting significant estimates, a full model is generated, and from this model emerges our final, parsimonious model. According to the T ratios, the parameter estimates for the final models are stable, reaching an acceptable threshold for model convergence. While change is significant across all models, the rate of change from assent (T_2) to maturity (T_3) is the greatest.

Several findings are worthy of comment. First, gangs may have a long memory as new attacks are more likely to involve reciprocated violence. (Recall that each observation captures 4 years of conflict: this means that a gang member's murder in T_1 could be reciprocated with a murderous attack on the aggressor up to four years later). The baseline model also shows that tie changes are not likely to form *transitive triplets* (significant negative effect for transitive triplets), except among gangs with CGIs. This means that we observe a tendency among gangs with CGIs to attack in a manner that generates a transitive triplet with another CGI restricted gang (the effect remains significant across subsequent models). And, although initially important, the probability that a new attack generates *balance* (where gangs exhibit a tendency to attack others that they are structurally similar to, meaning they also attack the same alters) weakens with the introduction of gang attributes. Interestingly, whether a focal gang or its combatant has a CGI does not account for tie formation or dissolution, instead, popularity is the most significant factor. Gangs suffering a lot of attacks in an initial observation will suffer more in subsequent observation. Gangs who attack a lot, are less likely to be attacked in a subsequent observation (*outdegree popularity*), suggesting that overt aggression may ward off attack. Taken together these findings support our working hypotheses.

501-513; and, T. Snijders, G. Van De Bunt, & G. Steglich, 'Introduction to stochastic actor-based models for network dynamics', *Social Networks*, 32 (2010), 44-60.

Table 8. SAOM Investigation of Structural Complexity (*p <.05)

	Baseline		Transitivity Dissection		Actor Attributes		Full Model		Parsimony	
Factors	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Structural										
Reciprocity	**-1.849***	0.761	-0.355	0.445	**5.997***	1.182	**3.827***	0.369	**5.540***	1.836
Trans. triplets	**-2.917***	0.819								
CGI Trans. triplets	**2.212***	0.872	**0.737**	0.361	**4.491***	0.836	**2.478***	0.664	**4.079***	0.997
Trans. mediated triplets			-0.94	1.086			1.032	0.618		
Trans. reciprocated triplets			1.682	2.684			-0.798	2.492		
3-cycles			1.120	1.222			2.346	1.621		
Balance			**0.488***	0.065			**0.214***	0.099	0.118	0.168
Betweenness (control)			**-2.488***	0.310			-0.187	0.334		
Actor Attributes										
Indegree - popularity					**0.045***	0.017	**0.025***	0.009	**0.045***	0.019
Outdegree - popularity					**-4.734***	1.078	**-2.839***	0.328	**-4.328***	1.506
CGI alter					-0.229	0.480				
CGI ego					-0.5036	0.664				
CGI similarity					-0.7984	0.488				
Rate of Change										
Period 1, T_1 to T_2	**0.881***	0.054	**1.128***	0.075	**0.952***	0.0605	**0.945***	0.058	**0.955***	0.061
Period 2, T_2 to T_3	**1.056***	0.059	**1.534***	0.105	**1.168***	0.0718	**1.183***	0.071	**1.176***	0.077
Period 3, T_3 to T_4	**0.961***	0.054	**1.291***	0.089	**1.036***	0.0628	**1.036***	0.066	**1.043***	0.064
Estimate Performance										
T Ratio (model convergence)	2 under .1		all under .1		all under .1		all under .1		all under .1	

Competitive Advantage (Research Component 2)

Competitive advantage refers to the position an individual or group could have within a community of actors. As used here, gangs are thought to have a competitive advantage over others if they have a stronger, more dominant position in the community relative to competitors (Brantingham et al., 2019; Papachristos 2009; Papachristos et al. 2013; Randle & Bichler, 2017). Several indicators were developed to account for competitive advantage—*number of cliques, egonet density*, and *internal conflict.*

We use the multivariate version of quadradic assignment procedure (QAP) nodal regression models to investigate which indicators of competitive advantage best account for aggression, victimization, and imbalance (between attacking and victimization) while controlling for turf proximity.[16] QAP models account for interdependence within the sample by using a nonparametric test based on simulations. QAP compares observed parameters with a set of estimates (standard errors and significance) generated using a random permutation method (simulation) (Krackhardt & Stern, 1988). Significance is determined by the proportion of random results which are equal or more extreme to the observed correlation. A finding that 5% of random results are as extreme as the observed estimates is equivalent to the p-value of 0.05 and are unlikely to be due to chance (e.g., Borgatti et al., 2002; Dekker, Krackhardt, & Snijders, 2003; Krackhardt & Stern, 1988). Only standardized coefficients are reported. The multivariate version of QAP implemented in Ucinet 6 is frequently used to investigate criminal networks (*See*: Campana & Varese, 2013; Campana, 2016; Diviák, 2015; Lantz & Ruback, 2017). Three sets of results are presented in Table 9. All results are generated from MR-QAP node-level procedures running 20,000 permutations; we used a random seed start.[17] The working hypotheses under investigation state that:

> **Study H_3. Gangs with competitive advantages over rivals will exhibit greater aggression and suffer fewer attacks post-CGI implementation.**

> **Study H_4. Gangs with claimed turf near other gangs will exhibit greater aggression and victimization post-CGI implementation.**

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[16] Multicollinearity was assessed using bootstrapping methods available in UCINET 6.620 (Borgatti et al., 2002). Moderately strong relationships were observed between cliques and turf adjacency, cliques and turf overlap, and turf overlap and turf adjacency; however, no variables included in the study were found to highly correlate with one another.

[17] These analyses are adapted from: Bichler, G., Norris, A., and ***Ibarra, C*** (forthcoming). Explaining the Directionality of Gang Violence with Court Records. *Journal of Aggression, Conflict and Peace Research.* 10.1108/JACPR-11-2020-0558

Aggression, Victimization, and Imbalance

The dependent variable of the first model is out-degree centrality (see the Technical Appendix for an explanation of these metrics). As it is used here, out-degree centrality captures the number of aggressions committed by each group. Several findings are notable. First, gangs with injunctions are expected to instigate significantly more aggression than non-enjoined gangs. Correcting for variability in measurement, the standardized coefficient indicates that although this association is significant, its relative explanatory influence is substantive but not as important as other factors. Second, we find that two measures of competitive advantage—number of cliques and the amount of internal conflict—are also significant. Between these two metrics, internal conflict has the strongest effect, suggesting that with every increase in the number of internal conflicts there is an expectation that the gang is involved in more aggressions with other gangs. The third substantive result pertains to physical proximity. Between the two proximity indicators, turf adjacency is associated with aggression—with each increase in the degree of adjacent gang territories, there is an expectation that the group instigates significantly more aggressive actions. Turf adjacency indicates the relative connectivity that a gang's turf has with other groups. The standardized coefficient reveals that it has the most substantive effect in the model. Taken together, these results paint an interesting picture about the most aggressive gangs. Supporting our working hypotheses, these findings suggest that enjoined gangs, with many cliques and internal conflict, have high levels of aggression when their turf is situated adjacent to many other gangs.

Table 9. MR-QAP Nodal Regression Models

VARIABLES	AGGRESSION	VICTIMIZATION	IMBALANCE
Civil Gang Injunction	0.197*	0.052	0.206*
No. of Cliques	0.123	0.392*	-0.021
Egonet Density	0.011	-0.055	0.037
Internal Conflict	0.261*	0.188*	0.224*
Turf Adjacency	0.431*	0.282*	0.382*
Turf Overlap	-0.094	-0.012	-0.104
Model Fit			
N	305	305	305
Adj R-square	0.452	0.476	0.266
F	42.779	46.99	19.385
Sig.	0.000	0.001	0.000

Note: ** p<.001; *p<.05.

Table 9 also reports the results of our investigation of victimization. Apart from the dependent variable, all model parameters are the same as described above. The dependent variable is in-degree centrality—being on the receiving end of an attack is classed as victimization for the purposes of this study. This model accounts for about 47% of the variance in victimization (F 46.99, p<.001). Two differences emerge when comparing victimization to aggression. First, with one exception, the explanatory variables are the same. While CGIs do not account for victimization levels, the previously identified measures of competitive dominance—number of cliques and amount of internal conflict—and turf adjacency are significant predictors. Second, as indicated by the standardized coefficients, the substantive importance of explanatory factors shifts. A greater amount of the variability observed in victimization is accounted for by the number of cliques a gang has; turf adjacency, though still a significant factor, is second; and, internal conflict exhibits about half the influence of the number of cliques.

Turning to the issue of imbalance between observed levels of aggression and victimization, the final set of models presented in Table 9 accounts for about 27% of the variance (F 19.385, p<.001)—this is the weakest performing model. Consistent with prior models, internal conflict and turf adjacency are identified as significant explanatory variables: we observed higher imbalance for gangs as their rate of internal conflict increases; moreover, gangs with territory situated adjacent to many other gangs are also predicted to have higher levels of imbalance. CGIs have a significant effect—consistent with the aggression model, enjoined gangs are predicted to launch more attacks than they are victimized, and this effect, is substantively greater than any other variable in the model. Reviewing the standardized coefficients, we find that once again, turf adjacency has the greatest explanatory value, holding all other factors constant.

Most Combative Gangs

To contextualize these findings, Table 10 presents aggression and victimization for select groups. For all but the last three of the most violent gangs listed, aggression is higher than victimization. Looking at the ratios, Langdon Street Gang and Varrio Nuevo Estrada are the most dominant as their aggression far outweighs their victimization. All but two of the most aggressive groups are enjoined. Mara Salvatrucha attacks the most groups, with Hoover Criminals, East Coast Crips and Varrio Nuevo Estrada trailing behind. Among these highly aggressive gangs, Hoover Criminals Gang and 18th Street appear to be targeted by the most groups. However, these groups are not heavily victimized relative to other groups.

As a point of comparison, the average number of aggressive behaviors (attacks) across the network is 10.8 and groups are subjected to an average of 11.6 victimizations; whereas among the most violent groups named in the table, the average number of aggressive behaviors is 109 and the groups experience about 30 victimizations. In addition, across the network, groups attack or are attacked by 1.8 other groups, whereas the most violent groups attack about 9 others. Specific involvements vary among the most violent gangs—the number of groups attacking another gang range from 5-20.

Table 10. Most Aggressive and Most Victimized Groups 1998-2013[1]

GANG (INJUNCTION)	AGGRESSION			VICTIMIZATION		RATIO[2]
	COUNT	GROUPS ATTACKED	% INTERNAL CONFLICT	COUNT	GROUPS VICTIMIZED BY	
MOST AGGRESSIVE GROUPS						
MARA SALVATRUCHA (2004)	186	20	12.4	53	7	3.5
HOOVER CRIMINALS GANG (2002)	**166**	**12**	**5.4**	**42**	**14**	**4.0**
EAST COAST CRIPS	**155**	**13**	**2.6**	**28**	**9**	**5.5**
VARRIO NUEVO ESTRADA (2004)	115	11	0	12	4	9.6
BLACK P STONES BLOODS (2006)	**106**	**6**	**2.8**	**20**	**4**	**5**
DENVER LANE BLOODS	**104**	**6**	**5.8**	**16**	**4**	**6**
GRAPE STREET CRIPS (2005)	**83**	**7**	**1.2**	**15**	**5**	**5.5**
LANGDON STREET GANG (2000)	80	5	0	0	0	--
18TH STREET LATINO (2002-05)	**78**	**12**	**6.4**	**86**	**16**	**0.9**
BOUNTY HUNTER BLOODS (2003)	**70**	**5**	**21.4**	**40**	**10**	**1.8**
ROLLIN 40S NEIGHBORHOOD CRIPS (2000)	64	5	3.1	25	6	2.5
MOST VICTIMIZED						
KRAZY ASS MEXICANS (2003)	45	6	53.3	38	6	1.2
FLORENCIA 13 SURENOS (2009)	**41**	**5**	**17.8**	**34**	**7**	**1.2**
COMMUNITY DRUG DEAL	0	0	0	32	9	--
COMMUNITY DRUG DEALER	0	0	0	38	10	--
SANTA MONICA 13 SURENOS	2	1	0	40	3	--

[1] Grey shading highlights groups without CGIs and bold text identifies gangs initiating violence across racial lines.
[2] Ratio shown as attacks to one victimization.

Groups other than non-crime involved community[18] that are victimized the most are also reported in Table 10. Three gangs, two with CGIs and one without, are named in the table. Santa Monica 13 (Surenos) and the Krazy Ass Mexicans are observed to be the most victimized

[18] Note, the general community category is victimized the most (1,930 victimizations and 14 aggressions).

gangs, followed by Florencia 13 (Surenos). Individuals who are involved in illicit drug market activity suffer relatively high levels of victimization. Victimization is high for known dealers (e.g. targeted robbery of supply) or non-gang affiliated individuals while they are involved in a drug transaction.

This analysis reveals something interesting about inter-racial violence. Note the bold text identifying gangs initiating violence across racial lines. Seven of the most aggressive groups (64%) and one of the most victimized gangs (33%) directed violence toward another racial group as indicated by defendant or accomplice status in the cases investigated. As this assessment includes all incidents, we are unable to comment on whether these actions involved one off events or sustained conflicts. In the next section, we explore this issue in greater detail.

Homophily (Research Component 3)

Patterns of homophilous relationships, where people interact with others like themselves, are found among individuals with prosocial connections, as well as among deviant and criminal actors (e.g., Lee & Butts, 2020; Malm, Nash & Vickovic, 2011). Studies investigating the structure of criminal and deviant relations typically explore homophily using identifiable characteristics that pertain both to the individuals involved and to the group's composition. Race and ethnicity figure prominently, in accounting for the selection of co-offending partners and patterns of violence. While gang research consistently finds that intra-group violence is most likely to fall along racial or ethnic divisions (Hipp et al., 2009, 2010; Maxon et al.,1985; Messner & South, 1992; Papachristos et al., 2010; Wadsworth & Kubin, 2004), emerging evidence suggests that some gangs exhibit a tendency to cross these social cleavages (Bichler et al., 2019; Lewis & Papachristos, 2020; Papachristos et al., 2013).

We use a MR-QAP nodal regression model to investigate whether observed variability in E-I index scores, are significantly associated with the structure of gang-on-gang conflict (infighting, group divisions, turf proximity) while controlling for a street gang-suppression strategy that has been used in Los Angles for nearly two decades (civil gang injunctions). Estimates are based on 30,000 permutations with a random seed start using the QAP legacy procedure available in UCINET 6 (Borgatti, Everett, & Freeman, 2002).[19] The working hypothesis under investigation states that

[19] These analyses are adapted from: Bichler, G., Norris, A., & Ibarra, C. (unpublished manuscript), "Crossing Lines: Investigating the Markers of Homophily-Heterophily in Street Gang Violence."

Study H_5. While most conflict relations will exhibit racial/ethnic homophily as groups compete within community enclaves, post-CGI the most aggressive groups will be involved in inter-racial/ethnic conflict (heterophily).

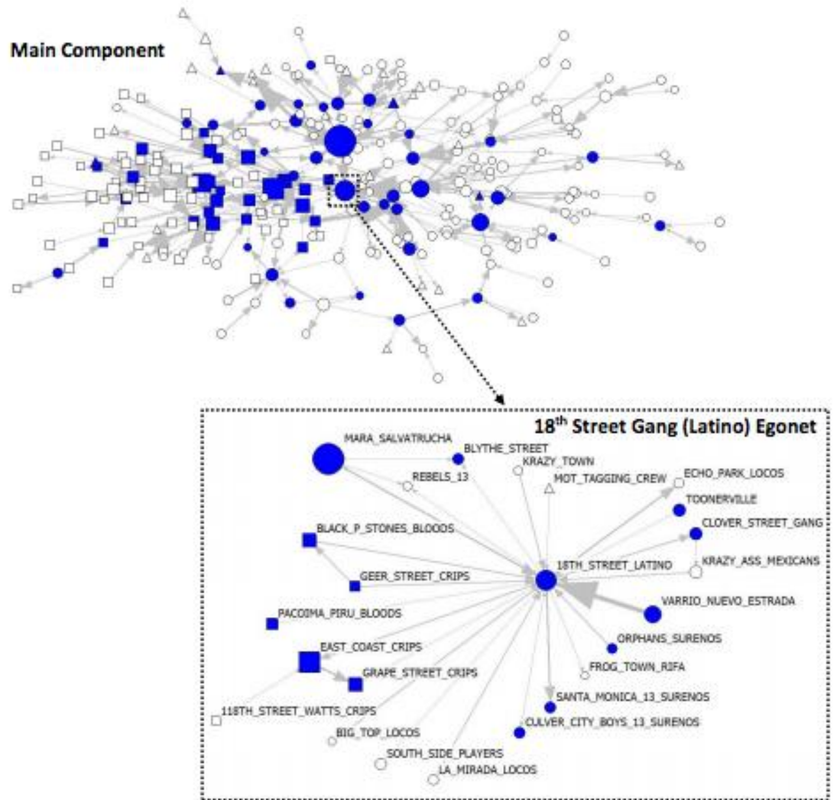
Sub-sample

To investigate homophily, we extracted a subset of conflict relations from the master data file to focus on gang-on-gang conflict. Removing edges due to a lack of information about the gang affiliation (e.g., 12 arcs did not have an offender/accomplice gang affiliation and 36 arcs did not have victim gang affiliation), not including gang-on-community conflict, and removing all gang-criminal justice agency conflict, resulted in a final set of 1,682 gang-on-gang conflict arcs among 291 groups. The network includes 11 components and 3 isolates (gangs that were only observed to attack non-gang involved people). Note, internal conflict (diagonal of the conflict matrix) was not included: as previously explained, this information was used to generate an independent variable—*internal conflict*.

Only gangs with egocentric networks that included 2 or more groups were selected. By applying this inclusion criterion, all gangs with only one alter are removed, resulting in a sample of 136 gangs (46.7% of gangs). Our justification is that a single recorded gang-on-gang pairing was insufficient to identify homophilous targeting patterns. We also discovered that it was not possible to compensate for this limitation by including homophilous attacks on non-gang groups (such as conflict with members of the community with no gang affiliation) because ethnic and racial descriptors were rarely provided for victims listed in these cases.

Figure 7 maps the main component of the gang-on-gang conflict network [MC = 258 gangs, or 89% of gangs, linked through 378 unique dyads (counted dichotomously) representing 94.5% of conflict pairings]. Blue symbols denote gangs that cross ethnic/racial social boundaries and have egocentric networks that are large enough that the group was included in our analysis. Line width indicates number of offender-victim dyads with arrows pointing to victimized gangs. Symbol size varies by outdegree centrality calculated on the main component. Circle symbols denote Latino Gangs, square symbols are African American gangs, and gangs of other description are represented with triangles. The insert shows conflict patterns for one of the most violent gangs using the symbology previously described to provide an illustrative case study that encapsulates the inter-group conflict which is the subject of this investigation.

Figure 7. Gang-on-Gang Conflict Network with Extracted Focal Group Insert



Inter-Group Violence

Table 11 reports two models. The full model included all control and explanatory variables, and given the limited sample size, the second set of results accounted for the limited power of this investigation and describes a parsimonious model which included only significant predictors found in the full model. Of note, the inter-item correlations are reasonable, with only one pairing (turf adjacency and turf overlap) approaching a .60 threshold.[20]

Overall, we found that two factors have positive associations with the E-I Index. Higher levels of efficiency and having more recognized cliques is predictive of a positive score, indicating more conflict that crosses ethnic/racial lines. Efficiency is a standardized metric accounting the size and non-redundancy of the local social neighborhood for each gang. A higher score on the efficiency metric suggests that the gang is involved in conflict with more groups relative to all other groups in the whole network and that these conflict relations have low

[20] Available upon request.

redundancy. This suggests that being involved in larger local conflict neighborhood characterized by non-redundant aggression increases the likelihood of becoming embroiled in inter-ethnic or inter-racial violence. Similarly, gangs with greater divisions, meaning more recognized cliques, are more apt to engage in aggression that crosses ethnic/racial lines. These findings partially support the working hypothesis that conflict heterophily is more associated with dominant groups. Turf adjacency significantly depressed inter-group conflict. Gangs that are spatially located with gang turf or set space that is adjacent to many other gangs, are more apt to attack other gangs described as being of the same ethnic/racial description: this finding supports prior research finding a homophilous tendency in patterns of gang violence (a somewhat contradictory finding to Gravel et al., 2018). And, contrary to our expectations and the results of the prior two research components, CGIs are shown to have no significant effects. Thus, once we account for competitive dominance (measured as number of cliques) and turf adjacency (measured as degree centrality), the effect of CGIs dissipates.

Table 11. MR-QAP Regression Models for E-I Index

	Full Model			**Parsimonious Model**		
Variables	St'dized Coefficient	Prop. as Extreme (sig.)	Distribution Mean (SE)	St'dized Coefficient	Prop. as Extreme (sig.)	Distribution Mean (SE)
Efficiency	0.206	0.022	0.007 (0.353)	0.196	0.025	0.001 (0.343)
Internal Conflict (count)	-0.108	0.309	0.000 (0.014)	--	--	--
Cliques (count)	0.341	0.015	0.000 (0.009)	0.355	0.002	0.000 (0.008)
Turf Adjacency (degree centrality)	-0.277	0.052	0.000 (0.014)	-0.252	0.018	0.000 (0.011)
Turf Overlap (degree centrality)	0.103	0.500	0.000 (0.020)	--	--	--
Enjoined Gang (0/1)	-0.042	0.737	0.001 (0.153)	--	--	--
Model Fit						
R^2 (adjusted)	0.166 (0.128)			0.150 (0.131)		
F (sig.)	4.292 (.037)			7.766 (.004)		

While these models were significant, the adjusted R^2 value is low. Given that MR-QAP procedures are non-parametric, we would have expected a higher proportion of explained variance. One possibility for the low explanatory value of the model is that the E-I index is sensitive to egonetwork size. Considering the data limitations discussed above, the number of conflict relations recorded for each gang may not accurately reflect gang aggression, in that groups could be embroiled in conflict with more gangs than was observed. If they are involved in more conflict, there is a possibility that some of the unrecorded conflict crosses a social barrier (inter-group).

Using ANOVA we explored whether gangs involved in inter-group conflict are more aggressive on three measures—number of aggressions (outdegree centrality capturing number of attack dyads), imbalance (number of attacking dyads minus the number of victimization dyads, or outdegree centrality minus indegree centrality), and the total number of conflict involvements (degree centrality for a non-directed network). Bootstrapping procedures were used, generating 1000 samples with 95% confidence intervals with equal variances not assumed. The results reported in Table 12 suggest that on average, gangs involved in inter-group violence were significantly more centrally positioned in the overall gang-on-gang conflict network as measured by aggressive behavior (outdegree centrality) and total conflict (degree centrality calculated on a non-directed, valued network). There was a direct association between engaging in more aggression and the likelihood of attacking across racial or ethnic social boundaries. These findings offer additional support for the working hypothesis.

Table 12. Independent Samples Mean Test for Inter-Racial/Ethnic Conflict and Measures of Aggression

	Inter- R/E Violence	**Bootstrap Estimates**		**95% Confidence Interval**	
	Mean (SD)	Bias (SD)	Std. Error (SD)	Lower (SD)	Upper (SD)
Aggression					
F Test 17.233; p<.001					
No (n=65)	4.60 (4.88)	-0.04 (-0.12)	0.59 (0.65)	3.49 (3.58)	5.82 (6.06)
Yes (n=71)	11.97 (13.53)	0.12 (0.09)	1.63 (1.90)	9.09 (9.48)	15.33 (17.05)
Imbalance					
F Test 0.169; p = 0.681					
No (n=65)	-0.09 (7.04)	-0.04 (-0.13)	0.85 (0.79)	-1.79 (5.44)	1.48 (8.49)
Yes (n=71)	0.73 (14.69)	0.03 (-0.14)	1.76 (1.89)	-2.52 (10.96)	4.25 (18.49)
Total Conflict					
F Test 24.21; p<.001					
No (n=65)	9.29 (6.89)	-0.03 (-0.16)	0.86 (0.97)	7.75 (4.93)	11.09 (8.70)
Yes (n=71)	23.21 (21.83)	0.22 (-0.21)	2.66 (3.42)	18.31 (15.13)	28.78 (28.35)

LIMITATIONS

Despite offering novel insight into the structured network of gang violence, this study is not without its limitations. Four main limitations are worth highlighting—the first two issues pertain to the data source and the second set address analytic decisions.

Adjudicated Cases. We mapped the structure of violence using information extracted from court cases generating appeals, as trial transcripts offer a viable alternative to investigate social networks that avoids some of the inherent biases of police data (see: Bright, Hughes, & Chalmers, 2012; Calderoni, 2012; Campana & Varese, 2012; Campana, 2016; Klein, 2009). However, court cases have their own limitations. For example, in many of the conflicts, the designation of aggressor and victim is arbitrary, related more to the outcome of the incident—surviving combatants were defendants and individuals who perished were victims. Thus, the directionality of conflict could be misconstrued. Additionally, not all violent conflict results in an arrest, let alone a successful prosecution or appeal. As such, the findings are most reflective of networks of violence involving murder—recall that 77% of the cases investigated in this study involve murder or attempted murder.

While future research is needed to establish the effect court processes have on the recorded directionality of violence and sample representativeness, we conservatively estimate that our sample captures about 34% of gang-homicides. During the study period, the LAPD reported 3,390 gang-related homicides associated with about 450 active street gangs (LAPD, 2020). Applying published homicide clearance rates—between 1996-2016 about 50.7% of homicides occurring in the City of Los Angeles were cleared by arrest (Snibbe, 2018; LAPD, 2017)—we estimate that our study includes at least 34% of all cleared gang-related homicides. Additionally, the present study investigated 317 active gangs (most of which were based in the City of Los Angeles)—about 68% of gangs active in LA.

Though limited in scope, the types of incidents captured in these cases are the forms of violence CGIs are meant to deter. Understanding the structure emerging from these cases provides a glimpse into how CGIs are impacting behaviors stemming from the most serious forms of gang violence. As CGIs are rooted in problem-based prosecutorial strategies, compiling information from 226 case studies is a reasonable effort to generate direction for continued exploration and development of court-based crime control strategies. In addition, this study offers a point of comparison to Lewis and Papachristos (2020) who used violence known to police—incidents known to police constitute a measure of crime situated at the opposite end of the criminal justice information continuum to what we investigated. Comparing our results to their study identifies which kinds of cases filter out as cases move through the system. For instance, are direct acts of retaliation less likely to result in a successful prosecution? And, to what extent does victim or witness cooperation impact case movement through the system? To date, network science has yet to explore how criminal procedures and case characteristics filter cases, affecting the nature of relations identified at the dyadic level, as well as the network structures that emerge when conflict is mapped as a social network. The insight gained from such investigation could inform prosecutorial efforts to enhance social justice.

Gang Affiliation. Gang identities were not always well-documented in the data; thereby generating a coding issue. For example, individuals may have been listed as gang members without identifying the specific gang they belonged to. Also, naming conventions were not consistent across cases. For instance, 83 Gangster Crips were identified as Eight Tray Crips, Westside Eight Tray, and 8 Tray Gangsters. This inconsistency in naming made it harder to identify which gang defendants and victims belonged to. In addition, while individual association with the larger parent gang may have been recorded, clique or subset information was missing. Since some gangs are reported to have upwards of a thousand members, understanding violent interactions may be better served by exploring the structure of clique-to-clique interactions. The extensive, labor intensive cleaning protocol developed to deal with these issues lead us to strongly suggest that a greater effort should be made to be consistent when describing gangs and gang associations during investigations and trials. This is a particularly salient point given that Californian courts can impose gang enhancement penalties that significantly increasing sentence severity. Clear evidence should be presented at trial documenting gang (and clique) involvement. Meanwhile, these issues with naming conventions affect all gang research, and thus, our results are comparable to the literature.

Mapping Evolutionary Conflict. While it is possible to capture the stochastic effects of CGI implementation with stochastic actor-oriented models (SAOM), network-based regression models of change are feasible only when there is a reasonable level of stability. Using the Jaccard coefficient, we can examine two networks (pre- and post-injunction for the gang-level analysis or two observation periods at a time for the dynamic model) to calculate the proportion of the two networks that remained the same. Generally, scores below .2 suggest the networks are not the same (as networks changed significantly between observations) and values above .6 are indicative of a high level of similarity (or stability); when scores fall between this range the network exhibits substantive evolution worthy of change analysis (for an explanation of SAOM modeling see: Ripley, Snijders, & Lopez, 2011; Snijders, 2011; Snijders, Van De Bunt, & Steglich, 2010). The Jaccard coefficients reported here were under .2 despite using smoothing techniques, i.e., combine several years of observations into meaningful timeframes. Additional investigation is needed to identify appropriate time windows to improve model stability. For instance, Lewis and Papachristos (2020) use rolling 2-year windows to increase stability but no justification was provided for this decision.

Gang Attributes. Some gangs investigated here have reached local infamy, and as such, information about group characteristics was easy to acquire, however, this is not the case for all groups. Gang size, number of cliques, and group demographics may suffer measurement issues that affect our investigation of competitive advantage and inter-group violence. However, the effect is unlikely to nullify our findings. Having a competitive advantage over other gangs in the region does not necessarily depend on formal membership or group size. Appearances can be deceiving because gang membership is fluid, in that individuals join and leave gangs; greater turnover can extend a group's presence within a defined area; and, by spending a lot of time hanging out with known associated individuals, though not officially gang members, inflate the perceived dominance of the group. To compensate for missing information, we coded gang affiliates as "perceived members" and we avoided using group size as an indicator of competitive advantage.

Research shows that gang violence tends not to cross ethnic/racial lines (e.g., Papachristos et al., 2013), thus, when gangs exhibit conflict heterogeneity they play an unusual role within the social landscape of violence. In fact, the LAPD (2017) reports that only 9.8% of gang-related homicides cross racial boundaries. Bridging communities, the groups involved in inter-racial violence may be exposed to more gangs, and thus, exhibit greater violence, victimization, or imbalance. Since most gangs in this sample are either African American or Latino, a partition was generated along this categorization. This oversimplification of ethnic/racial identity may mask important group-level variation, obscuring the nuances of conflict within diverse communities. However, knowledge building must proceed using a measured approach, and this study builds incrementally on foundation work in this area (e.g., Lewis & Papachristos, 2020).

IMPLICATIONS

Despite the limitations noted above, the findings presented suggest that the datasets generated will serve to improve our understanding of how CGIs influence gang conflict relations. The effects of gang violence extend deep into the heart of communities. Faced with the challenge of stemming entrenched gang violence, the City of Los Angeles implemented 46 civil injunctions against gangs and their members. The intention behind these legal restraints on individual movement and association is to prevent conflict. Despite 33 years of use in Los Angeles,[21] the effects of injunctions on the gang-on-gang structure of violent conflict have yet to be fully investigated. The present study contributes to addressing this deficiency.

CGIs impose significant restrictions on individuals. Despite their use in cities across California and beyond, there are few scientific evaluations of the effect that CGIs have on those facing sanctions, the community CGIs are meant to protect, and on the ability of law enforcement to keep the peace in troubled communities. Factoring for the significant costs associated with implementing and enforcing injunctions,[22] scholars are beginning to question whether the limits placed on personal mobility, ability to congregate, and freedom of expression are justified, perhaps, there are other focused-deterrence strategies that are more effective and cheaper. Alternatively, is there a way to modify CGIs to strengthen their impact without adding to the social and financial costs they pose?

Building on emerging research about the interconnected nature of gang-related violence, the findings of the current study stands to advance crime prevention policy in three ways.

Policy Implication No. 1. CGIs aim to restrict social interactions among gang members, with the intent of reducing violent conflict. However, gangs can perceive these sanctions as admonishments or attacks by the community, and, as such, they may trigger significant change in the nature of gang violence, i.e., CGIs may increase the likelihood that gangs target citizens from the neighborhood in retaliation. Investigating inter-group violence across 16 years, we are among the first to document how local social networks aggregate to form a larger network of violent relations. Such a mixed level investigation helps to improve focused-deterrence efforts. *Investigating the inter-group structure of violence, we document the dynamic properties of street gang conflict, suggesting that future use of CGIs should reshape behavioral prohibitions, reducing the emphasis on "one-size-fits all" approach. CGI stipulations should be more tailored to the set of interconnected combatants for a designated period, with a focus on the groups with*

[21] The first injunction was filed in Los Angeles by the City Attorney in 1987 (Maxson, Hennigan, & Sloane, 2005).
[22] Few assessments are available of the financial burden posed by CGIs. However, this anti-crime policy does incur considerable costs as they involve effort over and above conventional criminal justice system activity. For instance, Grogger (2005) estimates that the 14 injunctions he studied in Los Angeles (1993 – 1998) cost upwards of 1.4 - 2.1 million dollars to prosecute, and possibly an equal amount for enforcement; however, given the possible reduction in crime, this may be warranted if we factor in the social and economic costs of crime prevented. Goulka et al. (2009) documented that the enforcement and prosecution costs associated with *one injunction* in Santa Ana, CA was $99,985 (this includes overtime billed by the Santa Ana Police Department and paralegal costs to the Orange County District Attorney's Office).

the greatest competitive advantage or greatest influence in facilitating conflict. Such modifications may stand to be less detrimental to wrap-around services aimed at supporting desistence and recovery from gang involvement.

Policy Implication No. 2. By including all enjoined groups and others in conflict with them, we shed light on inter-gang violence that crosses racial-ethnic divisions and investigate how young people are embedded in networks of adult violence. Our findings suggest that interagency cooperation and coordination spanning child welfare and the criminal justice system can improve case management and maximize the benefits of anti-gang efforts.

Policy Implication No. 3. Using adjudicated cases, this study draws information from a different point in the criminal justice system than prior studies of gang-on-gang violence. Prior studies, using crimes known to police, are unable to contribute to our understanding of the effect that prosecutorial efforts have in suppressing gang conflict. When compared to prior research, the findings reported here begin to expose how court processes shape the nature of conflict relations that proceed through they system (e.g., can be successfully prosecuted).

Policy Implication No. 4. *Social network science extends our capacity to understand and respond to gang violence.* While, CGIs were found to be associated with patterns of gang violence, the level of internal conflict and turf proximity (proximity to many other gangs), significantly accounted for crossing ethnic/racial boundaries, as well as for higher levels of aggression measured with degree centrality. Taken together, these factors support recent arguments in favor of using a network approach to theorizing and testing hypotheses that will advance our understanding the socio-spatial ecology of gang conflict and alliances (e.g., Brantingham et al., 2012; Brantingham et al., 2019; Radil et al., 2010; Valasik, 2014) that enhance group dominance (Gravel et al., 2018), transmit risk (Papachristos et al., 2012; Green, Horel, & Papachristos, 2017), and account for community patterns of violence (e.g., Lewis & Papachristos, 2020). This study also contributes to a growing body of work advocating that social network analysis can be used to support targeted crime prevention efforts (e.g., McGloin & Rowan, 2015;) such as those aimed at using deterrent strategies to pressure central actors into behavioral changes that will reduce gun violence (e.g., Brag 2008; Braga et al., 2019; Boston Police Department 1998; Melde, 2013).

PROJECT MANAGEMENT

Project Personnel

Three people led this project—Dr. Gisela Bichler, Dr. Alexis Norris, and Ms. Citlalik Ibarra. Their roles and involvement were consistent throughout the duration of the study. As principal architects of the project, these individuals are named as originators of the data.

- ***Gisela Bichler, Ph.D., Principal Investigator.*** Dr. Gisela Bichler led the study. Dr. Bichler is a senior faculty member in the Department of Criminal Justice and director of the Center for Criminal Justice Research (CCJR) at CSUSB. She routinely engages in network research, having investigated communications among terrorist groups with stochastic actor-oriented models, organized crime groups involved in narcotics trafficking using exponential random graph modeling, and weapons trafficking with agent-based simulation models. Recent publications have appeared in *Crime and Delinquency*, *Global Crime*, *Journal of Criminal Justice*, the *Journal of Research in Crime and Delinquency*, *Policing: An International Journal of Police Strategies and Management*, and *Trends in Organized Crime*.

- ***Alexis Norris, Ph.D., Co-Principal Investigator.*** Dr. Norris is a subject matter expert in drug-related issues, domestic violence, and the effectiveness of gang intervention programs. Recent publications appear in the *Journal of Drug Issues*, *Journal of Interpersonal Violence, Evaluation Review*, and the *International Criminal Justice Review*.

- ***Citlalik Ibarra, M.A., Data Manager.*** Citlalik Ibarra is a research associate of the Center for Criminal Justice Research. She obtained her Master of Arts in Criminal Justice at California State University, San Bernardino. Her work focuses on social network analysis, gangs, and program evaluation.

In addition, 32 other people were directly involved in generating products and deliverables, bringing the total number of people involved to 35. Six staff were paid employees for part of or for the duration of the project, 21 people volunteered their services (mostly data coding for course credit), and 8 non-CSUSB affiliated persons involved with developing deliverables. Responsibilities and term of involvement are described in Table 13.

Table 13. Project Personnel

Name	Title	Duties	Term+	Coding Note
Staff				
Gisela Bichler, Ph.D.	PI	Oversee project, symposium organization and presenter	Full project	Coded pilot cases
Alexis Norris, Ph.D.	Co-PI	Oversee volunteers and data collection, symposium organization and presenter	Full project	Coded pilot cases
Citlalik Ibarra, M.A.	Project Manager	Train volunteers, supervise data collection, data coding and cleaning, maintain the gang name reference file, symposium planning, and lead on supplemental gang file and case files	Full project	Primary coder (PC)
Britney Boyd	Graduate Research Assistant	Data coding and cleaning, built gang connectivity file	Pilot, Phase 1 & 2	PC
*Ashley Valiente (volunteer & staff)	Research Assistant	Data coding and symposium planning	Phase 1 & 2	PC
*Jennifer Perretti (volunteer & staff)	Graduate Research Assistant	Data coding and symposium planning	Phase 1 & 2	PC
Volunteers				
Jared Dmello, Ph.D.	Graduate Research Assistant	Sample identification and data coding	Pilot project	PC pilot only
*Emily Ibarra	Research Assistant	Data coding	Pilot project	PC
*Adriana Ornelas	Research Assistant	Data coding	Pilot project	Minor involvement
Jasmin Randle, M.A.	Graduate Research Assistant	Data coding	Pilot project	PC pilot only
*Torey Arlotti	Research Assistant	Data coding	Phase 1	Secondary coder (SC)
Nicholas Chavez, M.A.	Graduate Research Assistant	Data coding	Phase 1	Minor involvement
*Adriana Leyva	Research Assistant	Data coding	Phase 1	SC
*Tristan Quiambao	Research Assistant	Data coding	Phase 1	Minor involvement
*Cheyenne Rogers	Research Assistant	Data coding	Phase 1	SC
*Yessica Medrano	Research Assistant	Data coding	Phase 2	Minor involvement
*Melvina Johnson	Research Assistant	Data coding	Phase 3	Minor involvement
*Doris Lorenzana	Research Assistant	Data coding	Phase 3	Minor involvement
*Marcus Pudilo	Research Assistant	Data coding	Phase 3	Minor involvement
Christine Famega, Ph.D.	Consultant	Symposium planning		
Shuryo Fujita, Ph.D.	GIS Research Supervisor	GIS analysis- displacement pilot	Report writing	n/a

Ivette Jimenez	Graduate Research Assistant	GIS analysis- displacement pilot	Report writing	n/a
***Samantha Scodellaro**	Research Assistant	GIS analysis- displacement pilot	Report writing	n/a
Consultants (non-CSUSB)				
Christopher J. Bates, Ph.D. candidate, University of California, Irvine	Presenter	Topic: Social and Economic Impact of CGIs	Symposium	n/a
Stacy Bush, M.A., San Bernardino Probation Department	Report editor	Advising and editing of the final report; cross-check of final files/codebooks	Deliverables	
Jason Gravel, Ph.D. University of Pennsylvania	Presenter	Topic: Information Diffusion within Gang Networks	Symposium	n/a
Michelle Mioduszewski, Ph.D. candidate, University of California, Irvine	Presenter	Topic: Social and Economic Impact of CGIs	Symposium	n/a
LAPD Commander Robert López (ret)	Discussant	Topic: CGIs in Los Angeles	Symposium	n/a
DJJ Sgt. Steven Valencia	Discussant	Topic: Juvenile Gangs in Correctional Facilities	Symposium	n/a
Emily G. Owens, Ph.D. University of California, Irvine	Co-author	Topic: Social and Economic Impact of CGIs	Symposium	n/a
Jerry Ratcliffe, Ph.D., Temple University	Moderator	Topic: Intelligence-Led Approaches to Containing Networked Violence	Symposium	n/a
Volunteers Terminated				
Monze Ortiz	Research Assistant	Data coding	Phase 1	Stopped post training
Silvia Lozano	Research Assistant	Data coding	Phase 1	Stopped post training
David Barreto	Research Assistant	Data coding	Phase 1	Did not complete training
Naveen Madahar	Graduate Research Assistant	Data coding	Phase 1	Did not complete training

*Undergraduate students received course credit, either CJUS 575 (internship) or CJUS 595 (independent study), for completing 120 to 200 hours of volunteer work on this project. Primarily recruited from the crime analysis degree program, these students have advanced data management skills. Crime analysis majors must complete an independent study or internship to graduate. With about 100 majors, recruitment and selection was a competitive process.

[+]Data collection was divided into three phases: Phase 1 included cases for seed gangs and step 2 gangs associated with pilot seed gangs; Phase 2 included step 2 cases for gangs in conflict with seed gangs identified in phase 1; Phase 3 included a subset of Mexican Mafia cases.

Deliverables

Project deliverables include data files, a symposium, and academic products. Notably, COVID-19 restrictions significantly constrained our initial efforts to disseminate research products. As travel and work restrictions lift, we anticipate extending additional efforts to extend the impact of this work.

Data. The information gathered for this study are recorded in nine Excel files.

1. Case details can be found in the *WOV_case_details* file.
2. Gang-on-gang conflict edges are recorded in the *WOV_offender_to_victim_group_edgefile*: this file can be used to generate networks of violence.
3. Location edge file (place-to-place connectivity) is recorded in the *WOV_CITY_TO_CITY_EDGEFILE*. These data can be used to explore the inter-city exportation/importation of gang violence.
4. Actor demographics, such as age and gender, are recorded in the *WOV_ACTOR_ATTRIBUTES* file.
5. Gang attributes recorded in the *WOV_GANG_ATTRIBUTES* file.
6. Gang territory proximity edge file is named *WOV_GANG_PROXIMITY_EDGEFILE*.
7. Gang cliques are recorded in the *WOV_CLIQUES_EDGEFILE*.
8. Rivalries are recorded in the *WOV_GANG_RIVALRIES_EDGEFILE*.
9. Alliances are recorded in the *WOV_GANG_ALLIANCES_EDGEFILE.*

Symposium. Research reports authored by academics and published in scholarly outlets or presented at academic meetings rarely capture the attention of practitioners working at the operational level. To ensure that the results of our efforts reach these important stakeholders, we hosted a discussion with district and city attorneys, law enforcement agencies, and probation departments from across the region. Hosting a local symposium, inviting a wide array of community stakeholders, facilitated an open dialogue about CGIs and alternatives, to weaken the web of violence and improve community safety across the greater L.A. metropolitan region. The symposium occurred on September 11, 2019. There were 75 registered attendees (74 in-person involvements and one zoom) representing 31 different institutions/agencies. The program included two panels. The first panel presented current research and the second was a moderated discussion of the research findings within an operational context—law enforcement and correctional settings. See Appendix 1 for the event brief.

Academic Products. To expand the reach of this project, findings were presented at scholarly conferences and submitted for publication in peer-reviewed scholarly journals. We believe these venues will encourage other researchers to undertake replication studies, further informing practitioners seeking to address gang violence around the country. Notably, as a result of these efforts a subsequent study was just funded by the U.S. Department of Justice, Office of Justice Programs, National Institute of Justice, Award # 2020-75-CX-0009:

> Gun Wars and Community Terrorization: Investigating Longitudinal Gang Violence in New Jersey from a Networked Perspective. Partnership: Principal Investigator: Jared Romeo Dmello, Ph.D. (Texas A&M International University) and Co-Principal Investigators: Gisela Bichler, Ph.D. (California State University, San Bernardino); Arie Perliger, Ph.D. (University of Massachusetts Lowell).

Presentations. COVID-19 travel restrictions constrained efforts to present preliminary findings; however, six presentations occurred within the funding period (two presentations were given at the symposium described above). Name in bold italic font are graduate students involved as co-presenters or co-authors.

2019 Bichler, G., Norris, A., & ***Ibarra, C***. "Mapping the Evolving Structure of Gang Violence in Los Angeles—A question of observation periods", Illicit Networks Workshop (Montreal, Canada: June 27-28).

2019 Bichler, G., Norris, A., ***Ibarra, C.*** & ***Boyd, B.*** "Finding the Trigger Modeling Change in Networked Gang Violence." Western Society of Criminology (Honolulu, HI: Feb. 7– 9).

2019 Bichler, G., Norris, A., ***Ibarra, C.*** & ***Boyd, B.*** "Mapping the Evolving Structure of Gang Violence in Los Angeles—Preliminary Results," American Society of Criminology (San Francisco, CA: November 13-16).

2019 Bichler, G., "Adding a Network Orientation to Intelligence-Led Approaches to Gang Violence," Gang Violence Symposium, San Bernardino CA (September 11).

2019 Bichler, G., and Norris, A. "Mapping the Long-term Impacts of CGI on Gang Violence," Gang Violence Symposium, San Bernardino CA (September 11).

2018 ***Boyd, B., Ibarra, C.*** & Bichler, B. "Hunting for Combatants: Methods to Generate More Complete Network Maps of Gang Violence." Western Society of criminology (Long Beach, CA: Feb. 1 – 3).

Academic Publications. Three manuscripts written from this data-two are published and one is currently under peer-review. One manuscript is in development. Details follow.

Bichler, G., Norris, A., and Ibarra, C (forthcoming). Explaining the Directionality of Gang Violence with Court Records. *Journal of Aggression, Conflict and Peace Research.* 10.1108/JACPR-11-2020-0558

Bichler, G., Norris, A., & Ibarra, C. (2020). Evolving Patterns of Aggression: Investigating the Structure of Gang Violence During the Era of Civil Gang Injunctions. *Social Sciences*, 9(11):203-221. DOI: 10.3390/socsci9110203.

Bichler, G., Norris, A., & Ibarra, C. "Crossing Lines: Investigating the Markers of Homophily-Heterophily in Street Gang Violence" Status: under review.

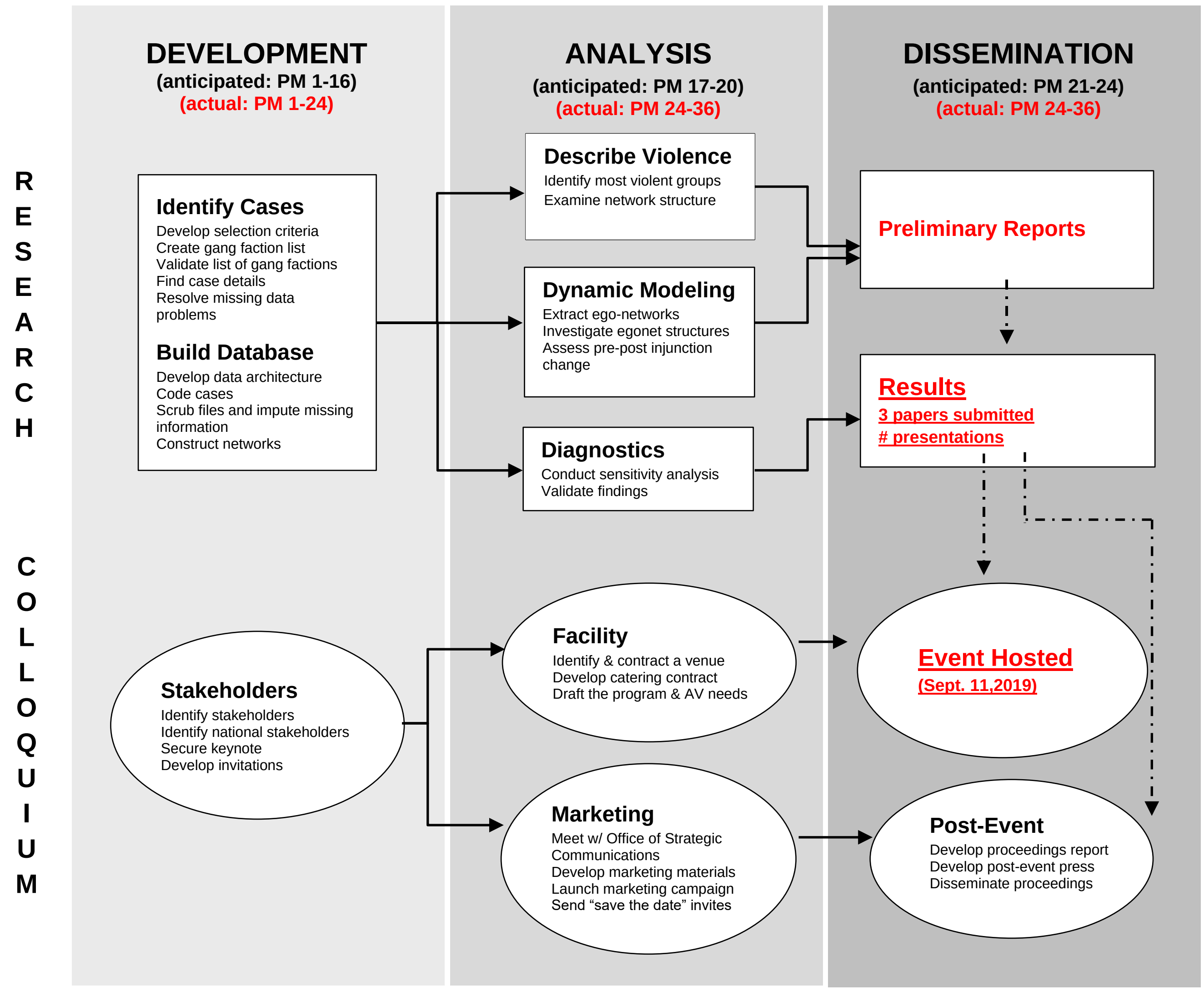
Fujita, S., Bichler, G., Norris, A. & Ibarra, C., "Spatial Proximity: Turf Borders and the Dispersion of Networked Conflict Post-CGI." Target completion date: Oct. 2020

Moving forward, we will continue data exploration, co-authoring additional presentations and papers. Several additional papers are currently in development.

Timeline

Figure 8 outlines the project timeline. Since there are two parallel streams of activity, rectangles denote research activity and ovals describe tasks associated with hosting a symposium to facilitate a public dialogue about anti-gang policy. As noted by the dotted lines, the two activity streams join in the last four months of the project. Comparing anticipated and actual project months (PM) reveals that data collection, collection and initial dissemination took longer than expected due to the data limitations previously described.

Figure 8. Timeline of Activity by Project stage by Project Month (PM)



APPENDIX 1. GANG VIOLENCE SYMPOSIUM EVENT BRIEF

Gang Violence Symposium
September 11, 2019

CCJR
CALIFORNIA STATE UNIVERSITY
SAN BERNARDINO

Event Brief

Symposium Recap

The symposium opened with remarks from Dr. Gisela Bichler. She drew attention to the importance of adding a network focus to intelligence led practices relating to gang violence. Organized around two panels, the first panel focused on spotlighting CGI's by investigating what is known about how gang violence spreads in response to CGI's, rivalries and alliances, and spatial proximity. The second panel focused on intelligence-led approaches to containing networked gang violence with a moderated panel of leading experts.

Panel I consisted of three research-based presentations:

- *Information Diffusion within Gang Networks* – presented by Jason Gravel, Postdoctoral Fellow, Penn Injury Science Center, University of Pennsylvania
- *Mapping the Long-term Impacts of CGI's on Gang Conflict* – presented by Dr. Gisela Bichler and Dr. Alexis Norris, California State University, San Bernardino
- *Social and Economic Impacts of CGI's* – presented by Michelle Mioduszewski and Christopher J. Bates, Ph.D. Candidates, University of California, Irvine

Panel II consisted of an open discussion moderated by Dr. Jerry Ratcliffe, from Temple University, including:

- Commander Robert Lopez (retired), Los Angeles Police Department, 40 plus years of field experience
- Sergeant Steven Valencia, California Youth Authority, 15 years of field experience

Symposium ran for the entire allotted time.

Registered Attendees

In total 75 individuals registered for the symposium across four different categories: Academic Institutions (n=29), Law Enforcement Agencies (n=32), Community Organizations (n=2), and Other (n=11).

Registered attendees represented 31 different organizations across four categories:

- Academic Institutions included:
  CSU San Bernardino, CSU Los Angeles, CSU Long Beach, UC Irvine, and Temple University.

- Law Enforcement Agencies included:
  California Department of Justice, Cathedral City PD, Department of Homeland Security, Hemet Police, Hemet Gang Task Force, Los Angeles County Probation, Los Angeles PD, Palm Springs PD, Riverside County Probation, Riverside County Sheriff, San Bernardino County Probation, San Bernardino County Sheriff, and San Bernardino PD.

- Community included: Operation New Hope and Young Visionaries Youth Leadership.

- Other included: California State Assembly, Central Square Technologies, Inland Empire News, Law Office of James McGee, Los Angeles City Attorney's Office, Ross, and Target.

Registered attendees came from four different Southern California counties, including one out of state (see Figure 1 for break down), spanning across 21 different cities: Los Angeles County (n=4), Orange County (n=1), Riverside County (n=8), and San Bernardino County (n=7). In addition to one out of state city (Philadelphia, PA).

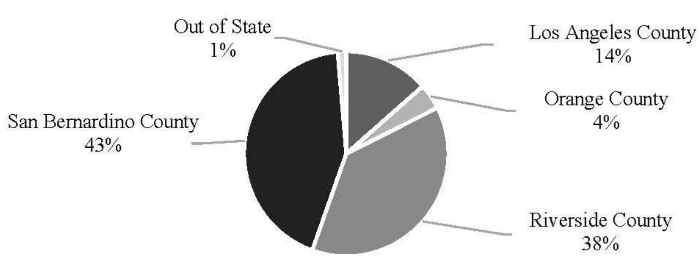


Figure 1. Where Registered Attendees Came From

Attendee Feedback

An anonymous survey was distributed online to gather feedback from registered attendees. Of the 74 registered attendees, 14 completed the survey. Of the 14 surveys, only 12 were completed fully. The following is based on the responses provided by the 12 registered attendees that fully completed the survey.

Key Responses

Survey feedback indicates that registered attendees would have liked more time for discussion with practitioners, discussion of materials presented, small group conversations, and more case studies or examples. See Figure 2 for break down.

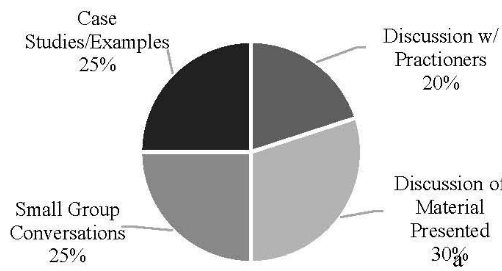


Figure 2. What Participants Wanted More of

Registered attendees asked that more of law enforcement focus be integrated into symposiums. Particularly, attendees would benefit from more direct discussion about they could use the research findings to in the field. Attending the symposium allowed attendees to expand their network by getting reacquainted and/or meeting new professionals in their field (50% of attendees expanded their network). All in all survey participants indicated that they left the Gang Violence Symposium with new information that would be useful in their line of profession (79% indicated that the meeting was beneficial).

Of note, all survey participants indicated that they would be interested in attending another symposium hosted by the Center for Criminal Justice Research. When asked what topics registered attendees would like to see covered in future symposiums the following was reported:

- International and Domestic gangs
- Gun Violence within Law Enforcement
- Evaluation of new California laws meant to curb crime
- Local crime trends and information
- Juvenile offenders and detention centers
- Criminal networks pertaining to drugs
- Homicide trends and investigation
- Internet crime prevention

APPENDIX 2. REFERENCES

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APPENDIX 3. TECHNICAL APPENDIX

1. Density

Density is a measure of cohesion, based on how interconnected nodes within a network are to one another. This statistic measures the number ties observed among nodes in a network, relative to the number of potential ties within the same network. Highlighting if nodes within a network are well connected. Density in general form is expressed as:

$$\Delta = \frac{l}{g(g-1)/2}$$

For details, refer to (Wasserman & Faust, 1994, p. 101).

2. Average Clustering Coefficient

The average clustering coefficient is a measure of cohesion, based on how many triplets (grouping of three nodes) are present overall in a network. This statistic measures the number of closed triplets (grouping of three interconnected nodes), relative to the number of all triplets within the same network. Highlighting potentially important sub-groups within the network. Average clustering coefficient is expressed as:

$$C = \frac{number\ of\ closed\ triplets}{number\ of\ all\ triplets\ (open\ and\ closed)}$$

For details, refer to (Watts, 1999, p. 498).

3. Jaccard

Jaccard is a measure of association, based on how many shared ties are present between different networks. Networks must be binary and include the same number of nodes. This statistic measures the number of ties shared between similar nodes across different networks, identifying the percentage at which ties are shared. Highlighting rate at which two different networks are similar. Jaccard is expressed as:

$$J = \frac{number\ of\ shared\ nodes}{number\ of\ total\ nodes} \times 100$$

For details, refer to (Hanneman & Riddle, 2005).

4. Pearson

Pearson is a measure of association, like Jaccard; however, networks must be valued. Highlighting rate at which two different networks are similar. Pearson is expressed as:

$$r = \frac{N\Sigma xy - (\mathrm{E}x)(\Sigma y)}{\sqrt{[N\Sigma x^2 - (\Sigma x)^2][N\Sigma y^2 - (\Sigma y)^2]}}$$

For details, refer to (Hanneman & Riddle, 2005).

5. Degree Centrality

Degree centrality is a measure of centrality for binary networks, based on the number of ties a node has. Two modes of degree centrality exist when a network is valued:

> 5a. In-Degree Centrality—based on the number of incoming ties for a single node. This statistic measures the number of ties received by a particular node. Highlighting nodes that function as recipients. In-degree centrality is expressed as:
>
> $$C'_D(n_i) = \frac{x_{+i}}{g-1}$$
>
> 5b. Out-Degree Centrality—based on the number of outgoing ties for a single node. This statistic measures the number of ties initiated by a particular node. Highlighting nodes that function as initiators. Out-degree centrality is expressed as:
>
> $$C'_D(n_i) = \frac{x_{i+}}{g-1}$$

For details, refer to (Wasserman & Faust, 1994, p. 199, 203).

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