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An Analysis of the Relationship Between Gang Membership, Social Networks, and Crime

presented by Alexandra Marie Ciomek

candidate for the degree of Doctor of Philosophy and hereby certify that it is worthy of acceptance.

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Date: June 29, 2021

An Analysis of the Relationship between Gang Membership, Social Networks, and Crime

A dissertation presented by

Alexandra Marie Ciomek

to the

Department of Sociology

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in the subject of

Sociology

Harvard University

Cambridge, Massachusetts

June 2021

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An Analysis of the Relationship between Gang Membership, Social Networks, and Crime

Abstract

Criminal activity not only affects the criminal justice system and those in contact with the system, but also is a public health concern for those at risk of victimization, especially gang members. My dissertation research examines the structure of the network of street gang members in Boston and how to use it to improve understanding of the meaning and implications of gang membership. Boston is an archetypical field site because the characteristics of its gangs are more similar to typical gangs in the US: they are generally geographically concentrated and smaller in size. To study the network of gang members, I use administrative data on arrests and contacts with law enforcement over the eight-year period from 2007-2014. Individuals involved in the same event have a co-offending tie connecting them, which creates a network of individuals connected through shared police contact events. I then identify gang members using the Boston Police Department's gang database. Co-offending, especially violent, is a particularly relevant interaction in the gang context, given that a defining quality of a street gang is that criminal involvement is part of the group's identity.

In the first chapter of my dissertation, I use the co-offending network of gang members to study how members of different gangs participate in different types of joint activity, including property, drug, and violent crime. Understanding co-offending between gang members at the individual level has implications for crime prevention and the life course outcomes of members,

including employment opportunities and mortality. Much of the work on gang networks focuses on the gang as the unit of analysis, relating them to one another based on organizational level rivalries and alliances. Furthermore, work at the individual level often examines the risk of victimization based on network exposure. Because of the gap in the literature concerning the individual-level relationships between members of different gangs, I examine whether contacts between gangs are primarily violence-based and through what other forms of behavior they manifest. I find evidence for strong similarity, though at different magnitudes, between co-offending within and between gangs, suggesting a lack of cohesion for Boston gangs.

The second chapter answers the question: are gangs, as defined by law enforcement, substantially different from other groups that commit crime together and in what ways? Given the impact of criminal justice system involvement on the life course, as well as the added interest from law enforcement that comes with being a gang member, we must understand how current policing practices capture the nature of offending at the individual level. I utilize community detection, a social network analysis technique, to determine densely connected groups based on the co-offending network of all individuals with police contact. I find that gang members commit more crime overall, including solo crime, compared to individuals in other co-offending groups, though the differences in co-offenses are minimal. These findings suggest that current gang classifications may not capture all criminal groups, at least in the context of co-offending, suggesting that other key individuals are at risk of engaging in crime and becoming victims.

The third chapter of my dissertation is based on a research project in collaboration with Anthony Braga and Andrew Papachristos, extending the literature on network firearms exposure to include an analysis of the characteristics of firearms, especially markers of illegal trafficking. We model the risk of gunshot victimization on the social distance to someone with firearm

access, controlling for the distance to a gang member, among other factors. We find that individuals socially closer to firearms (and those closer to gang members) are more likely to be victims and that being close to a firearm with characteristics of illegal trafficking is particularly dangerous. The danger of network exposure to firearms supports the need for interventions aimed at curtailing illegal transfers of firearms, reducing their availability for gun violence.

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INTRODUCTION

Street gangs are important subjects of study in sociology because of their role in criminal activity as well as their ability to give insight into group processes. Understandably, gangs garner academic and practitioner attention primarily for their disproportionate involvement in crime. There are approximately 2000 gang-related homicides every year nationally, about 13% of all homicides, though gang members make up only about one-fifth of 1 percent of the population (National Gang Center, 2012). For this reason, they are the focus of criminal justice intervention and policy. Additionally, studying street gangs informs theories of group processes, peer effects, and social capital dynamics in the criminal context.

The overarching themes that my dissertation addresses are the social structure of gangs, especially the role of criminal social capital, and the meaning and experience of gang membership. I examine how the network context elucidates gang dynamics, boundaries, and the far-reaching effects and implications of gang membership. A key concept throughout my dissertation is criminal social capital, which is social capital applied to the criminal context (McCarthy and Hagan, 1995). Social capital has developed as a concept with multiple definitions aimed at describing the advantages gained from social relationships. An individual's criminal social capital increases with more contacts and weak ties to individuals involved in crime. Individuals may utilize the criminal social capital that they acquire from more connections to such individuals in order to gain advantages, be they more potential co-offenders or access to firearms.

Previous work supports this relationship between co-offending and criminal social capital, showing that having accomplices provides resources including broadened knowledge of criminal opportunities, criminal network expansion, and greater potential for illegal earnings

(Andresen and Felson, 2012; McGloin and Piquero, 2010; Rowan et al., 2018),. Throughout prior work, criminal social capital has been operationalized in multiple ways, with measures based on an individual's social network being the most common (Loughran et al., 2013; McCarthy and Hagan, 2001; Morselli and Tremblay, 2004).

Gang membership also provides social capital resources. At the gang level, connections to other gangs often take the form of an alliance. Alliances can provide assistance when targeted by a rival gang as well as expanded drug markets expanded drug markets. Allied gangs may agree to use violence to defend one another, to specialize in different drugs across their joint territory, or to sell one another's drugs. At the individual level, gangs expand a member's network, which can then provide broader knowledge of criminal opportunities and has been shown to provide greater illegal earnings and access to guns (Ciomek et al., 2020; Roberto et al., 2018).

This dissertation uses social network analysis to better understand the social structure of gangs and its implications. In the first chapter, I examine how criminal social capital informs gang dynamics. The second chapter is a study of how law enforcement and networks differ in capturing gang structure and arrest patterns. Finally, in the third chapter, I assess the role of gang-related criminal social capital in gun access and test its relationship to gunshot victimization. Throughout my dissertation, I use Klein and Maxson's definition of a street gang, which is commonly cited in network studies of gangs. A street gang is "any durable, street-oriented youth group whose involvement in illegal activities is part of its group identity" (Klein and Maxson, 2006, p. 4). Given their definition, using law enforcement data can be particularly fruitful in the study of gang networks.

Boston is exemplary of many U.S. cities because of its moderate population size and crime rate. Its gang landscape is also typical of cities because they are disorganized, small in size, and geographically concentrated, the last of which is a characteristic feature of most street gangs. Boston gangs are also responsible for a disproportionately large share of arrests. In Boston from 2007-2014, identified gang members made up 4.5% of arrestees, though they accounted for 26% of arrests for homicide, and 10% of arrests for violent offenses. Additionally, gang members made up less than 0.6% of the population, while accounting for 30% of fatal and non-fatal shooting victims. Thus, Boston is an effective study site for the examination of the social networks of gang members and others in contact with the criminal justice system.

The data for the co-offending network come from two main sources provided by the Boston Police Department covering 2007-2014: Arrests and Field Interrogation and Observation reports, which are also called FIOs. FIOs record non-arrest contacts or intelligence observations made by the police. Throughout this study, I refer to the network of these joint police contacts using the term: "co-offending network," a naming convention based on previous network studies of official data. The data for the gang members in this study is from the Boston Police Department gang database. Based on the database, there were 125 gangs in Boston during the study period.

Research on gangs and gang violence in Boston is robust, inspiring and evaluating programs that address gang violence issues. However, it does not provide a rich account of criminal social capital as related to gang dynamics, one mechanism through which these strategies likely operated. Previous work has shown the importance of links between, and within, Boston gangs, and the effectiveness of strategies aimed at youth and gang violence reduction. Though not focused on all gang members, the effects of interventions such as Operation

Ceasefire potentially reverberated through the criminal networks of the main targets (Braga et al., 2001; Kennedy et al., 1996). Therefore, while gang membership has been shown to provide criminal social capital benefits, evidence on criminal social capital in the structure of relationships between members is limited, a gap filled by the first chapter. Understanding such Boston gang dynamics can elucidate mechanisms involved in not only violence reduction but also gang group processes.

The relationship between gang membership and criminal social capital bolsters the importance of understanding the boundaries of gangs in an urban area. The criminal social capital benefits of gang membership, including more knowledge of opportunities and a larger pool of co-offenders, often translate into more involvement in criminal networks and criminal activity. The criminal social capital patterns within and across gangs shown in Chapter 1 call for examination of the definition and meaning of gang boundaries. Thus, the second chapter is an investigation of how law enforcement-defined gang boundaries compare to empirical delineations of gangs, especially with respect to capturing involvement in arrests.

Criminal social capital within, between, and beyond gangs also allows for efficient and far-reaching information and resources, the most deadly of which is firearm access.
The third chapter builds on prior work on criminal social capital by expanding the understanding of resources that can serve the purpose of both enabling violent offending and protecting an individual from victimization. The primary research question in this chapter is what are the consequences and implications of connections between gang members as well as connections between gang members and those outside of gangs, especially as related to firearm access and gunshot victimization?

Overall, my dissertation provides evidence for the role of criminal social capital in gang dynamics and associated implications for gang boundaries, gun access, and the probability of victimization beyond gangs. Understanding Boston gang dynamics elucidates mechanisms involved in both violence reduction strategies and criminal group processes. The interconnectedness of gang members within and beyond gang boundaries not only has clear consequences, such as gun victimization, but also general impacts on involvement in criminal justice system contacts. Policy implications include policing changes regarding gang databases and policies targeting the supply side of the illegal firearm market.

CHAPTER 1

Many people do not commit crime alone. Scholars studying different contexts, time periods, and geographic regions concur that many crime incidents, especially those involving younger offenders, involve more than one individual, known as co-offending (Carrington, 2002; Sarnecki, 2001; Shaw and McKay, 1942; van Mastrigt and Farrington, 2009; Warr, 2002). Furthermore, offenders in groups commit more violent offenses than single offenders (McGloin and Piquero, 2009). Research also suggests peers can influence participation in crime (Warr, 1993). Given the importance of co-offenders and peers to the study of crime, the network of individuals involved in crime is key to understanding criminal activity. To this end, sociologists and criminologists have applied the concept of social capital to the criminal context, arriving at the concept of criminal social capital. Potential criminal social capital increases with more contacts and weak ties involved in crime. Since formal institutions for offenders to acquire skills and extend their networks do not exist (McCarthy and Hagan, 2001), these benefits are typically incurred through relationships with individuals involved in crime. Previous work supports the relationship between co-offending and criminal social capital, showing that having accomplices provides social capital resources including broadened knowledge of criminal opportunities, criminal network expansion, potential for illegal earnings, and increased criminal awareness space (Andresen and Felson, 2012; McGloin and Piquero, 2010; Rowan et al., 2018), enriching our insights into the nature of co-offending.

Greater criminal social capital is also a key benefit of gang membership, as gangs increase their members' criminal network and pool of potential co-offenders. This intertwined relationship between gangs and criminal social capital begs understanding, as both are important factors that affect involvement in crime. Though there is no definitional consensus, gangs have been characterized as “any durable, street-oriented youth group whose involvement in illegal activities is part of its group identity” in many studies of gang networks (Klein and Maxson, 2006, p. 4). Gangs are a small segment of the population in contact with the criminal justice system responsible for a disproportionately large share of violence and crime (Pyrooz et al., 2016). There are approximately 2000 gang-related homicides every year nationally, about 13% of all homicides, while gang members make up about one-fifth of 1 percent of the population (National Gang Center, 2012). Previous research suggests that criminal social capital, gang membership, and co-offending are related to increased illegal earnings (Augustyn et al., 2019; Loughran et al., 2013; Rowan et al., 2018), though their interrelationship has not been directly studied. Understanding criminal social capital in the context of gangs, especially the social connections between members of different gangs, can better develop the understanding of gang dynamics. It will advance the theory on the unique social capital dynamics and group processes of gangs and give important insight into key relationships that influence criminal involvement and its perceived benefits, providing insight into practical strategies for crime prevention.

To better understand the relationship of criminal social capital, co-offending, and gang membership, I examine a network of gang members in Boston, Massachusetts. Boston is an archetypical field site because the characteristics of its gangs are more similar to typical gangs in the US in that they are generally less organized and smaller in size in comparison to the larger, more organized and often-national gangs of larger cities. In Boston from 2007-2014, identified gang members made up 4.5% of arrestees, though they accounted for 26% of arrests for homicide, and 10% of arrests for violent offenses. Additionally, gang members made up less than 0.6% of the population, while accounting for 30% of fatal and non-fatal shooting victims.

Research on gangs and gang violence in Boston is robust, inspiring and evaluating programs that address gang violence issues, including those that focus on understanding networks at the gang level (Braga et al., 2013, 2008, 2001; Kennedy et al., 1997, 1996; Piehl et al., 2000). Though previous work has shown the importance of links between, and within, Boston gangs and the effectiveness of strategies aimed at youth and gang violence reduction, it has not developed a rich account of criminal social capital dynamics amongst Boston gang members, one mechanism through which these strategies likely operated. For example, though Operation Ceasefire primarily focused on the gang-involved youth most central to the city's homicide problem (Braga et al., 2001; Kennedy et al., 1996), the effects of the intervention potentially reverberated through the criminal networks of the main targets. Understanding Boston gang dynamics could therefore be a key to elucidate mechanisms involved in not only violence reduction but also gang group processes.

Although studies have examined criminal social capital in the context of gangs, its analysis has not extended to its relationship to gang network structure. This study fills the gap in the literature on the criminal social capital dynamics of Boston gangs. I use a social network analysis approach to generate new insights into gangs by studying the co-offending network of individuals with criminal justice system contact in Boston from 2007-2014. First, I analyze administrative data on arrests and Field Interrogation and Observation reports (FIOs) to construct and describe the network of the individuals involved in them. Second, I limit the co-offending network to gang members and examine the connections between individuals in the same gang (within-gang ties) and in different gangs (between-gang ties) to understand the network dynamics within and across gangs. Finally, I use a regression analysis to study the individual and incident factors that explain the propensity for ties to cross gang boundaries. The results of my analyses show that not only are connections across gangs common, but also the propensity to form such connections cannot be explained by individual and incident factors alone. This work shows that the criminal social capital associated with gang members go beyond one gang and that the network of all gang members reveals key features of their dynamics. This work provides important insight into gang membership beyond the gang itself and associated behavior. In particular, understanding criminal social capital in the context of co-offending between gang members has theoretical implications for gang studies and practical implications for crime prevention and the life course outcomes of members, including employment opportunities and mortality.

Gangs, Co-Offending, and Criminal Social Capital

From Bourdieu to Coleman to Granovetter, social capital has developed as a concept with multiple definitions aimed at describing the advantage gained from social relations, either as an individual or as a group or community (Bourdieu, 1985; Coleman, 1988; Granovetter, 1992; Putnam, 2000). In particular, Granovetter emphasizes the importance of social networks, particularly weak ties, as an effective form of social capital in job searches and other contexts (1973). Moving from the legal economy to the illegal economy, McCarthy and Hagan applied the construct to the criminal setting, introducing the term "criminal capital," (1995) and later implying the need to delineate "the social and human dimensions of the [an individual's] criminal capital" (2001, p. 1043). Further conceptualization has emphasized the multidimensionality of criminal capital and differentiated criminal social capital from criminal human capital (for a review, Nguyen, 2020). Potential criminal social capital increases with more contacts and weak ties with individuals involved in crime; criminal human capital increases with more criminal knowledge, information, and skills. Throughout prior work, criminal social capital has been operationalized in multiple ways, with measures based on an individual's social network being the most common (Loughran et al., 2013; McCarthy and Hagan, 2001; Morselli and Tremblay, 2004). While typical studies of social capital examine outcomes ranging from the labor market to migration (Boxman et al., 1991; Garip, 2008; Granovetter, 1973), studies of criminal social capital focus on the illegal economy, showing that increased criminal social capital, or more connections with other offenders, has a positive relationship with illegal earnings (Loughran et al., 2013; McCarthy and Hagan, 2001; Morselli and Tremblay, 2004; Nguyen et al., 2016; Uggen and Thompson, 2003). While relatively few people achieve substantial earnings from their crimes (Levitt and Venkatesh, 2000), individuals involved in crime typically exploit access to the small set of resources of criminal human capital and criminal social capital associated with success in the illegal sphere (McCarthy and Hagan, 2001). Criminal social capital is therefore inherent to co-offending, as involvement in deviant street networks increases willingness and opportunity to collaborate (McCarthy et al., 1998).

Previous work supports the link between criminal social capital and co-offending. Having accomplices provides criminal social capital resources such as broadened knowledge of criminal opportunities, criminal network expansion, potential for illegal earnings, and increased criminal awareness space (Andresen and Felson, 2012; McGloin and Piquero, 2010; Rowan et al., 2018). Criminal enterprises often require co-offenders, but trusting others can be considerably risky (McCarthy et al., 1998). The inherent concealment of criminal activity and threat of getting caught means that groups of offenders are often unknown to one another (Morselli et al., 2006). This interplay between protection from arrest and criminal success exemplifies the need for both strong and weak ties in a co-offending network. Each individual is surrounded by both realized and potential sources of information and other resources. The role of criminal social capital to criminal relationships and actions has critical implications, given that increasing the number of co-offenders has been found to increase the likelihood of a violent crime occurring (McGloin and Piquero, 2009).

The increased risk of criminal involvement as well as victimization that accompanies gang membership make the small groups important subjects of study as well as common foci of policy interventions (Peterson et al., 2004). Gang-involved youth are more criminally active than non-gang delinquent youth (Thornberry et al., 1993). As a small population, gangs are responsible for a disproportionately large share of crime. For example, 70% of the youth shootings in Boston in 2006 involved a gang member as a victim or perpetrator, though they represent only 1.3% of the youth population (ages 15-24) at the time (Braga et al., 2008).

Gangs are an important example of co-offending and criminal social capital. It is common for research on co-offending to focus on the effects of gangs and gang membership (Lantz, 2020; Papachristos et al., 2015; Sarnecki, 2001). According to Warr, "applied to criminal conduct, the notion of collective behavior implies that something about the presence of others during an event provides the inspiration (and perhaps the means) to engage in crime" (2002, p. 59). Collective behavior has been found to be a robust predictor of gang-related homicide (Pizarro and McGloin, 2006). Co-offending, especially violent, can be considered a key interaction in the gang context, given that according to Klein and Maxson's definition, a defining quality of a street gang is that "involvement in criminal activity is part of its group identity" (Klein and Maxson, 2006, p. 4). Gang-involved co-offending incidents, excluding homicide, are more likely to result in serious injury, controlling for co-offender characteristics, offense characteristics, and victim characteristics (Lantz, 2020). Not only is co-offending likely between members of the same gang, members of different gangs may participate in criminal behavior together, be it violence against a mutually rivaled gang or shared drug trade. Gang members are more likely to co-offend with individuals in the same gang more than once and, more generally, they are more likely to continue a co-offending relationship with a member of any gang (Charette and Papachristos, 2017).

Gangs are a source of criminal social capital, providing members access to criminal benefits including an expanded network of gang and delinquent peers, additional acquaintances, and opportunities for crime (Moule et al., 2013; Putnam, 2000). Decker and Curry interviewed current, associate, and former gang members in middle schools to better understand gang membership, finding that many current and former gang members joined the gang to meet new friends (Decker and Curry, 2000). In addition, at the individual level, street gangs encourage high levels of offending beyond exposure to deviant peers (Battin et al., 1998), showing that gang membership provides a unique type of criminal social capital beyond having a network of delinquent peers.

In addition to criminal social capital benefits for individual members, prior studies has shown that gangs as a whole benefit from criminal social capital. Underlying gang relationships and interactions are the individuals involved in each group and the group processes that translate membership into group cohesion, or the level of solidarity within a gang (Papachristos, 2013). Though earlier work found that gang cohesion and delinquency were positively related (Klein, 1971), Hughes more recently found no evidence of a relationship, though members of less cohesive groups were more likely to commit violent crime, possibly because of higher levels of conflict within gangs with weaker ties (2013).

The enhanced criminality associated with lower cohesion implies that criminal social capital may extend beyond the gang itself. Recent work has found that cohesion within gangs has a positive relationship with group survival for large gangs and a negative relationship for smaller groups, likely because criminal social capital in the form of relationships outside of the smaller groups enable recruitment, allowing them to survive over time (Ouellet et al., 2019). In addition, gangs may share clients or drug areas in their participation in the illegal drug trade (Descormiers and Morselli, 2011; Taniguchi et al., 2011) or engage in retaliatory violence on behalf of an allied gang (Kennedy et al., 1997; Knox, 2000; Papachristos, 2009).

Still, gang relationships that provide potential social capital are not unconditionally beneficial, as gangs are often subject to particular focus from law enforcement. More gang relationships subject those who have them to greater surveillance. In addition, the closer an individual is to a gang member, the more likely they are to be a victim of violence (Ciomek et al., 2020; Papachristos et al., 2015). However, these risks are typically considered worthwhile, given that the perceived benefits of gang membership beyond expanded social capital include protection from victimization, status in the community and among friends, and ability to defend one's neighborhood (Decker and Curry, 2000).

Understanding criminal social capital between gang members, especially of different gangs, at the microsociological level has implications for crime prevention and life course outcomes of members, including employment opportunities and even mortality (Pager, 2003; Pettit and Western, 2004). In particular, the network structure represented by this behavior can inspire more strategic identification by law enforcement of individuals and groups driving crime (Sierra-Arévalo and Papachristos, 2017), which may vary by crime type.

Criminal Social Capital Benefits in Gangs

In the non-criminal context, social capital resources offer benefits to those who have access to them. Greater social capital allows for individuals to gain access to more job prospect information through contacts (Granovetter, 1973) and is associated with higher income, independent of human capital and position level (Boxman et al., 1991). In addition to economic benefits, when social capital resources are greater and more accessible, the likelihood that an individual migrates increases (Garip, 2008). Just as the benefits of social capital are diverse in the non-criminal context, the same applies for the criminal context, especially for gang members.

At the individual level, entering a gang is associated with increased illegal earnings, attributable to changes in the number of delinquent peers (Augustyn et al., 2019). Similarly, leaving a gang has a direct relationship with decreased illegal earnings. In fact, gang leaders and officers, though not lower ranking gang members, make more than they would in the legitimate sector based on education and work experience (Levitt and Venkatesh, 2000). As with non-criminal social capital, benefits extend to other resources, especially guns. In a study of the sources of guns confiscated by law enforcement, the majority of guns that gang members possessed were acquired through at least one intermediary, a third person in the middle of the interaction between the licensed firearm seller and gang member (Cook et al., 2015a). Furthermore, in a survey of incarcerated individuals in Chicago, respondents provided accounts of gangs playing a role in organizing gun buys and distributing guns to members as needed (Cook et al., 2015b).

In a study of the role of street gangs in facilitating gun access, Roberto, Braga, and Papachristos (2018) found that, in a co-offending network of individuals arrested in Chicago, gang members had considerably higher average degree, the average number of individuals to which each gang member was directly connected. This shows that in the Chicago co-offending network, gang members had more potential criminal social capital resources. Moreover, gang members were twice as likely as non-gang members to be linked to recovered guns and were considerably closer to individuals linked to guns. In addition, the study found that gang members that are closer to individuals with gun access have a statistically significant greater probability of victimization in a fatal or non-fatal shooting, controlling for gang size and ethnicity. Not only did gang membership increase the potential for criminal social capital in the form of more direct associates, but also it was associated with a shorter distance to accessing the resource of a gun. As mentioned before, criminal social capital is not solely beneficial. This study provides evidence that greater criminal social capital within a co-offending network, and greater related gun access, can have negative results, including gunshot victimization.

At the gang level, criminal social capital in the form of alliances between gangs can offer a partner in retaliation after an aggravating incident (Knox, 2000; Papachristos, 2009). Gangs may also form alliances to allow for a more lucrative market for drug sales for both parties involved, although concrete data on this possibility is limited (Descormiers and Morselli, 2011; Venkatesh, 2008). If gangs specialize in the sale of certain drugs, they may share customers when demand for other drugs that another gang sells increases. In a qualitative study of 20 incarcerated gang members, respondents constructed a social network of the gangs in Montreal and elaborated on the nature of interactions between gangs, especially as related to the Bloods-Crips rivalry that is well-known throughout North America (Descormiers and Morselli, 2011). Respondents confirmed that, within alliances, gangs share the drug market; specifically, a gang will buy a drug from an allied gang to sell to their customers, if they do not have a supply. The sharing of resources across gangs shows the benefits of criminal social capital extend beyond gang members to gangs as a whole.

As related to gang dynamics, these benefits of criminal social capital are accompanied by caveats. The respondents from the Montreal study stated that members of allied gangs were to uphold the same code of conduct; if it were violated, violence by other alliance members would not be unexpected (Descormiers and Morselli, 2011). Therefore, the study is one of few that examine dynamics within gang alliances beyond participating in retaliatory violence together. However, respondents did not explain the activities, criminal or otherwise, that constituted a gang alliance or other forms of between-gang activity that would give insight into the criminal social capital involved in gang dynamics. Furthermore, a study of gang murders in St. Louis demonstrated that homicide within gangs was more common than that between gangs (Decker and Curry, 2002). This finding highlights the importance of studying individuals rather than just whole gangs, so as not to obscure interactions within groups as well.

The Networked Relationship between Gang Membership and Criminal Social Capital

More recent research has applied the network lens to the understanding of criminal social capital and co-offending, especially their processes, consequences, and dynamics (e.g., Ciomek et al., 2020; Grund and Densley, 2015; McGloin and Nguyen, 2014; McGloin and Piquero, 2009; Papachristos, 2011; Papachristos et al., 2015). Social network analysis has the ability to capture the criminal social capital of gang membership and social context of gang activity within a region.

The structure of gang relationships, especially rivalries, has profound effects on gang violence. Scholars have found that both rivalries and alliances matter for gang violence in Boston and Chicago (Kennedy et al., 1997; Papachristos, 2009). Murders between gangs result in a network of group conflict, largely due to retaliation and a history of rivalry, that goes beyond any one person's motives or participation in homicide (Papachristos, 2009). Violent acts against a particular gang provoke retaliation not only from the victimized gang, but also its allies, which require law enforcement responses to go beyond the two gangs involved in the primary conflict in order to adequately prevent future crime (Kennedy et al., 1997).

Some scholars have used co-offending networks to understand aspects of between-gang relationships. Based on a co-offending network gathered from interviews with law enforcement officials, McGloin finds that Newark gangs are less cohesive than is normally attributed to gang relations (2005). Though the street gangs are disconnected from one another, there are cut-points between groups of gang-members, or brokers between groups. These cut-points are of particular interest because, if one of their ties were broken, it would sever relations entirely between two groups. What remains unclear based on the interview method is the nature of the ties between brokers and the groups. Are brokers active participants in co-offending? Do they also "hang out" with members of both groups?

Beyond the structure of co-offending and gang membership, individual-level factors that are affected by social network have also been influential subjects of study. A widely known fact in criminology is that those involved in crime are also particularly susceptible to becoming victims. Social networks further illuminate this relationship by relating previous victimization of people in a social network to later victimization within the network. Studies in Chicago and Boston find that network exposure to victimization, including homicide and gunshot injury, predicts later victimization, net of individual and network variables (Papachristos et al., 2012; Papachristos and Wildeman, 2014).

What is clear in previous research on co-offending is that it has implications for victimization and policy intervention. Social networks not only are structured by criminal relationships, but also are disproportionately affected by risk of victimization. What is unclear from previous work on co-offending and gangs is the relationship between individuals within and between gangs. Understanding co-offending and criminal social capital between gang members at the micro level has implications for crime prevention and life course outcomes of members, including employment opportunities and even mortality (Pager, 2003; Pettit and Western, 2004). In particular, the network structure represented by these feature can inspire more strategic identification by law enforcement of individuals and groups driving crime (Sierra-Arévalo and Papachristos, 2017), which may vary by type and spatial distribution. In addition, we can learn more about the meaning and reach of gang membership as well as the interplay between gang membership, criminal social capital, and co-offending by studying gang co-offending in the network context.

Criminal social capital, co-offending, and gang membership are all positively related to criminal activity, though their interrelation and how different crime types may be involved is not understood. In particular, understanding network relationships between gangs gives important nuances to the concept of gang membership. Broadening the concept of gang membership to the contours of the urban gang network will bridge the gap between the importance of criminal social capital and gang membership to criminal involvement and contact with the criminal justice system.

Data Collection Approaches to Studying Gang Networks

Studies on gang networks use a variety of methods for data collection, though often some form law enforcement data is involved. Kennedy, Braga, and Piehl used interview sessions with groups of police officers, probation officers, and streetworkers to assess gang conflicts and alliances, as well as their territories (1997). To distill the network of homicide within and between gangs, Papachristos used official homicide data that included gang information on both the offender and victim, as recorded by homicide detectives (2009). The data were supplemented with gang turf maps from gang intelligence officers and ethnographic fieldwork for the analysis of the structure of the network. These studies are focused on the gang level, so while the methods are effective for the gang network, they would likely be ineffective for individual-level analyses as it is difficult for law enforcement and practitioners to know detailed information about interactions between gang members, regardless of whether they are in the same gang. Studies that focus on gang networks with members as nodes are more suitable to understand the relationship between individual criminal social capital and gang dynamics.

Some research has explored gang networks from an egocentric friendship networks perspective (Fleisher, 2006, 2005). This research finds that participant observation and name generators in surveys provide complementary views of the social networks of gang members. Though these methods provide valuable information on relationships within groups described as gangs, the information generated provides insight into sub-sections of the gang network, rather than a whole network view. A more global view is important to understanding how co-offending relationships and criminal social capital present across a more complete network of gang members. A survey of all gang members in Boston and their connections, over 3,000 people according to official data, would require funding, access, and trust between researchers and members, all of which are not accessible without more resources.

Although gangs are a part of a broader social dynamic relating crime, neighborhoods, group processes, inequality, and the life course (Sampson and Wilson, 1995; Schaefer, 2012; Schaefer et al., 2013; Short and Strodtbeck, 1974; Thrasher and Short, 1963), they are often particularly of interest because of their involvement in criminal activity. For this reason, networks using criminal justice system data are especially important in the study of gangs (e.g., Bouchard and Konarski, 2014; Campana and Varese, 2020; Grund and Densley, 2015;

Papachristos et al., 2015; Roberto et al., 2018). The two types of data used in broad gang networks studies are (1) court files containing transcripts of phone conversations (phone wiretaps) and (2) police-generated events, i.e. arrests or more informal contacts (Campana and Varese, 2020).

Wiretaps generate rich data on the relationships between people, including between lower-level and upper-level actors (Campana and Varese, 2020). As they are often used as evidence in trials, scholars may use court records to access the data from particular cases (Campana, 2016). Although they provide more detail as to the nature of the relationships between individuals involved in each conversation, wiretap data suffer from issues of self-censorship by actors in the conversations, group coverage, assuming conversation is directly related to behavior, and sampling bias based on agency decision-making concerning targets. Understanding a network of gang members across a city using court records likely would exclude any gangs not directly connected to the targets and could be misleading concerning behavior between individuals, especially if the recording were suspected by the actors involved.

Police-generated events include arrest records, incident records, and contact cards, more informal interviews or intelligence gathering events involving law enforcement. This police-filtered view of a gang may not offer a complete representation, as it depends on actors coming to the attention of law enforcement, having some form of contact with the police, and being designated a gang member. However, it shows the top-down view of gang activity from the perspective of an organization most interested in identifying, ceasing, and preventing its operations. A "gang member" label from law enforcement results in greater surveillance by the police, which increases the chances of contact with the criminal justice system, and can carry higher punishments when a member is convicted of a crime. Using arrest and FIO data provides an understanding of the whole gang network as perceived by law enforcement and focuses on activity that exposes members to the criminal justice system, which has implications for their life course outcomes (Pager, 2003; Pettit and Western, 2004).

This Study

While theories of criminal social capital support the importance of connections in gang network, there is a gap in the literature regarding how criminal social capital operates in the context of gang dynamics. Evidence on criminal social capital in the gang context concerns only the benefits of criminal social capital in the gang context, not its structure and characteristics. Therefore, I will examine a co-offending network of gang members in Boston. Understanding the breadth of gang membership and dynamics requires going beyond one gang. By examining gang ties, we can learn more about the interplay between gang membership, criminal social capital, and co-offending and therefore more about the meaning and reach of gang membership. How does criminal social capital in the form of co-offending ties differ within and between gangs? Are individual and incident factors predictive of the propensity for individuals to form between-gang ties?

Gang membership can increase criminal social capital at the individual level by expanding individuals' networks (Moule et al., 2013). In addition, previous literature shows there are various benefits of social capital across gangs, especially with regards to retaliation on behalf of allied gangs. In this investigation, I hypothesize the following:

(H1) Between-gang ties are significantly prevalent, though within-gang ties are most prevalent overall.

(H2) Between-gang ties from co-arrests result primarily from violence.

(H3) Following from (H2), the likelihood of forming between-gang arrest ties is associated with the type of charge involved.

The results of exploring these hypotheses will show how criminal social capital can improve our understanding of gang dynamics, which has theoretical and practical implications for the study of criminal social capital, the facets of gang membership, and the formulation of crime prevention strategies aimed at reducing criminal gang activity.

Data and Methods

Co-Offending Network

To construct the co-offending network, I use official data from the Boston Police Department of all arrests and all Field Interrogation and Observation (FIO) reports from 2007 through 2014, based on methodologies in previous work (e.g., Papachristos et al., 2012). Field Interrogation and Observation (FIO) reports record when officers stop, question, and frisk an individual or group, "engage in a consensual encounter with an individual" or group (FIO Study Results, 2015), or observe individuals for intelligence purposes. In order for multiple people to have a co-FIO, they must be observed and/or approached by the police for the same reason and because they seem to be together. Because FIOs represent spending time together visibly on the street, between-gang ties from co-FIOs would indicate a propensity to "hang out" with gang members from other gangs on the street.

Hanging out contrasts the typical violent, retaliatory depiction of gang alliances. Hunt, Joe-Laidler and Waldorf find that "kicking back" (their term for hanging out) is more than gang members doing nothing together (1996). It is an intense period of spending time together that includes talking, keeping the police at bay, discussing business, among other activities. If gang members hang out across gang boundaries, there is a need to include the possibility of such activity in their definition. Not only is hanging out a form of bonding, but it can also be dangerous in the sense that it allows for the possibility of being intentionally or unintentionally targeted by the rivals of the allied gangs, i.e. being caught in the middle. Even if co-FIOs do not indicate as strong of a relationship as co-offending or “hanging out,” they still indicate that members of different gangs spent at least a brief period in close proximity, which can still attract both police attention as well as increase the chances of getting caught in the middle of another gang’s rivalry.

The arrest data contain information on arrests and the individuals mutually involved in events (co-arrestees). I excluded events, and corresponding individuals, that resulted from co-arrests for a mutually antagonistic crime (e.g. a bar fight where the arrested individuals were combatants).[1] On the other hand, FIOs are instances in which police officers have reasonable suspicion that an individual is involved in some sort of illegal activity and thus stop and question the person or record observing a person or group for intelligence purposes. When the person of interest is around other people, the information of these associates is also recorded. Therefore, FIOs also contain individuals on FIO events and the individuals involved in them.

Throughout this study, I use the naming convention of “co-offending network” from network studies of police data to refer to the network of joint police contacts (co-arrests and co-FIOs). Regardless of culpability, the arrest and FIO data provide official records of relationships between individuals in the data. To be clear, this issue of culpability extends to all of the analyses—I make no judgments as to anyone’s involvement in a crime. Rather, because my

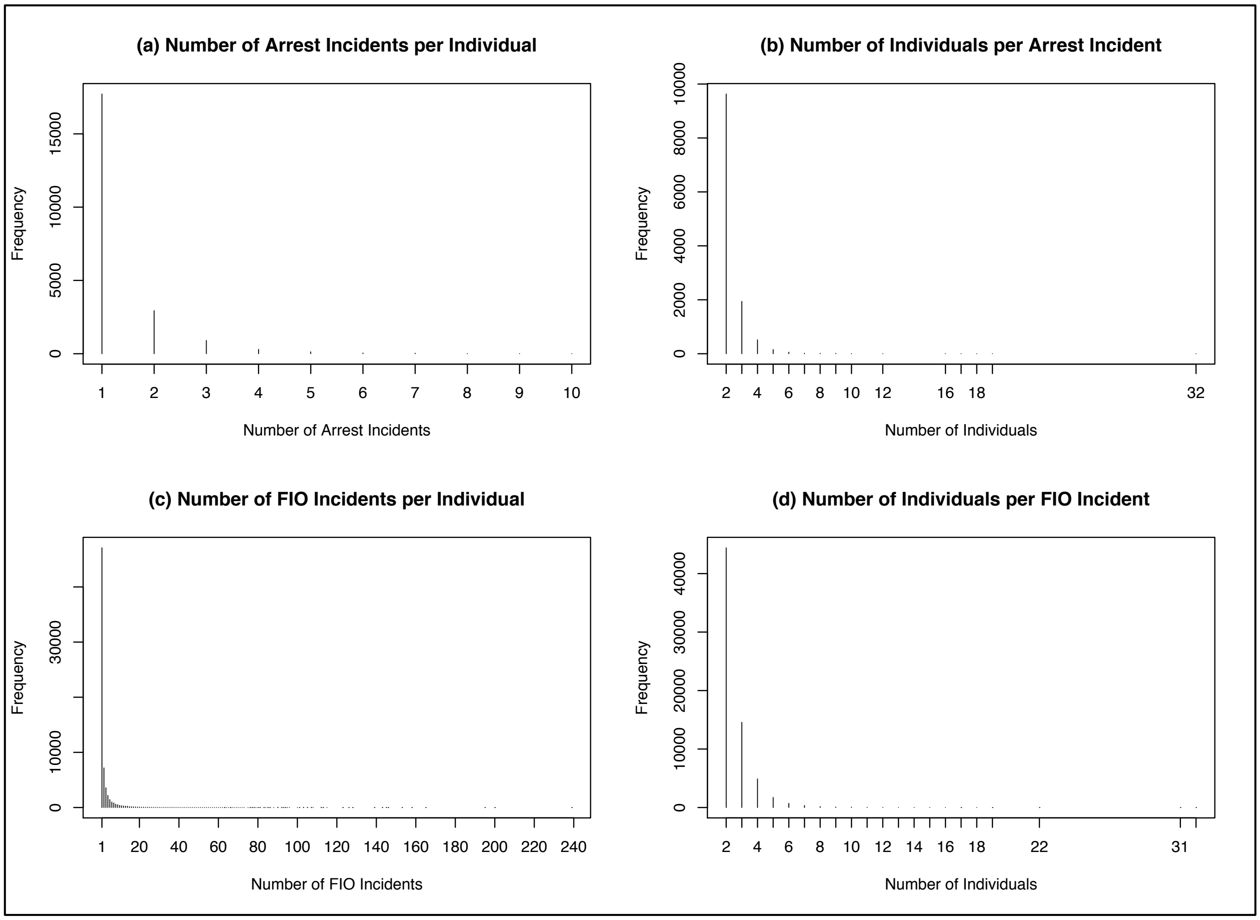
[1] The exclusion was based on the charge associated with the arrest. Conservatively, I excluded arrests with a charge for affray, simple assault, or assault and battery. The exclusion reduced the network by 1.4% ($N = 4$) individuals and 2.6% ($N = 44$) ties.

analysis is focused on the relationships between gang members, I use both arrest and FIO data to determine recorded co-behavior.

Using the individuals involved in the events in conjunction with the events themselves creates two two-mode data arrays, one for FIOs and one for arrests. Two-mode networks consists of two sets of units, in this case people and events, and their relation connects the two sets, in this case people's participation in the events. In addition, the arrest and FIO data include attribute data for each individual (date of birth, sex, and race) and each arrest event (charge). Gang affiliation and number of prior arrests are attributes of individuals from the gang database and historical arrests, respectively.

There were 121,047 arrests and 346,767 FIO records from 2007 through 2014. The arrest and FIO data were used to create the two-mode arrays connecting individuals to events. I summarize their degree distributions in Figure 1 below, limiting the data to only events (and corresponding individuals) with at least two people involved, for illustrative clarity. In the final network, such events will lead to the creation of the focal network as they allow for a connection between the individuals involved in the event.

Figure 1: Two-Mode Degree Distributions



Note: Degree distributions above represent the two-mode data arrays for arrests and FIOs, limited to incidents with at least two people involved for clarity. (a) The frequency of the number of arrest incidents per individual (*N* = 22,095); (b) The frequency of the number of individuals for each arrest incident (*N* = 12,358); (c) The frequency of the number of FIO incidents per individual (*N* = 67,413); (d) The frequency of the number of individuals for each FIO incident (*N* = 67,051).

Figure 1 illustrates the degree distributions for the two-mode arrest and FIO arrays, limited to incidents with at least two people involved for clarity. In (a) and (b), the arrest data are described: (a) shows the frequency of the number of arrest incidents per individual with a range of 1 to 10 and a mean of 1.3 incidents, while (b) illustrates the frequency of the number of individuals for each arrest incident, ranging from 2 to 32 with a mean of 2.3 individuals. For the FIO data, (c) shows the frequency of the number of FIO incidents per individual, ranging from 1 to 239, with a mean of 2.4 incidents and (d) shows the frequency of the number of individuals for each FIO incident, which ranges from 2 to 32, with a mean of 2.5 individuals. As expected, all of the distributions are right-skewed, where many individuals are involved in few events and few individuals are involved in many events. Similarly, most events involved two individuals, while few involve more than that. The degree distributions also show that FIO incidents are not only more common than arrest incidents overall, but also have a wider range of incidents per individual, while the range and shape of the plots for individuals per incident are much more similar. FIOs represent a different interaction between individuals than arrest, depicting events in which individuals gather together and hang out, rather than participate overtly in a criminal act. Individuals involved in co-FIOs may be more likely to be acquaintances given than those co-arrested, showing a potentially different facet of activity.

Table 1: Network Statistics for Arrest and FIO Two-Mode Networks

	Arrest	FIO
Number of Individuals	64,863	117,471
Number of Incidents	107,077	250,673
Number of Nodes	171,940	368,144
Number of Edges (Ties)	123,532	354,695
Density	1.8×10^{-5}	1.2×10^{-5}

As seen in Table 1, the two-mode arrest network contains 64,863 individuals, who participated in 107,077 events. Therefore, there are 171,940 nodes in the network and there are 123,532 edges between the individuals and events. The density of the network, that is, the proportion of existing edges to potential edges, is 1.8×10^{-5}, meaning that only a small share of potential ties are realized, which is expected in a two-mode network. In the two-mode FIO network, there are 117,471 individuals that participated in 250,673 events, resulting in 368,144 nodes in the network (see Table 1). There are 354,695 edges between these events and individuals, resulting in a density of 1.2×10^{-5}, again showing that the network is far from dense.

My analyses focus on the projection of the two-mode data arrays into two matrices (for arrests and FIOs) that I combine into one network, in which all arrests and FIOs are merged for each individual. When two people are involved in the same event, there is a tie between them, creating a co-offending network that directly connects individuals by co-arrests and co-FIOs. Each connection (tie) between individuals is valued; that is, its weight represents the number of unique events a pair of individuals has participated in. This network is less conservative than using arrests alone because it accounts for instances of observation and questioning on the street in addition to instances when there is probable cause of a crime occurring, the burden of proof needed for an arrest.

Table 2: Network Statistics for One-Mode Arrest, FIO, and Combined Networks

	Arrest	FIO	Combined
Number of Nodes	64,863	117,471	146,835
Number of Edges (Ties)	23,704	139,324	158,699
Number of Isolates	42,768	50,058	69,634
Density	1.1×10^{-5}	2.1×10^{-5}	1.4×10^{-5}
Non-Isolate Density	9.7×10^{-5}	6.1×10^{-5}	5.3×10^{-5}
Transitivity	0.75	0.26	0.26
Mean Non-Zero Degree	2.15	4.13	4.11
Mean Edge Weight	1.02	1.22	1.22

Table 2 shows the network statistics for the one-mode arrest, FIO, and combined networks, showing a total of 146,835 nodes (individuals) and 158,699 connections or ties between them. The reduction in edges from the two-mode networks to the one-mode networks is due to three factors, which I will explain using the arrest network. First, as seen in Table 2, 42,768 of the 64,863 individual nodes in the arrest network are isolates, meaning they have not been arrested with another person. Those 42,768 individuals participated in 64,047 arrests, thereby accounting for 64,067 of the total 123,532 edges in the two-mode network, leaving 59,485 edges in the two-mode network. Second, as each edge in the two-mode network connects an individual to an event, an event with two individuals accounts for two edges. On the other hand, in the one-mode projection, these edges are collapsed into one edge between two individuals. For events with more participants, the number of edges is the combination of each pair of total co-arrestees, which is larger than or equal to the number of edges in the two-mode network. However, events involving more than two individuals account for less than 23% of co-arrests and 34% of co-FIOs. Third, as seen by the average edge weights in Table 2 (note: I will add these as Peter suggests), individuals are often connected to others in more than one events, though the connection results in just one edge with an associated weight. For these reasons, the large drop in the number of edges from Table 1 to Table 2 is expected based on the data.

Gang Member Identification

I further limit the network to gang members, meaning that events involving less than two gang members are not represented in the network of analysis. In order to identify gang members, I use data from the Boston Police Department (BPD) concerning the gang affiliation of people in the co-offending network. The BPD gang database is maintained by officers and analysts and involves a verification point system to assign gang member and associate statuses to individuals. Individuals are assigned various numbers of points based on their activities and self-identification as members of a certain gang, be it through interaction with law enforcement, social media representation, or otherwise. Only individuals who surpass a minimum point value are entered into the gang database. After a period of inactivity or incarceration, individuals are deemed inactive. There are 3,534 active gang members in Boston representing 125 gangs. Membership by gang ranges from 4 to 132, with a mean of 47.0 members per gang. In particular, 2,908 of them, representing 123 different gangs, participated in a co-arrest or co-FIO between

2007 and 2014. Using this data, I create a historical co-offending network of Boston gang members who are active in 2015 and identify the relationships between gangs in the network.

Criminal Behavior

The arrest data have information concerning the crime for which an individual is arrested. Using this data in conjunction with the dyads in the network, I identify what kinds of crimes are common both between gangs and within them. The most frequent crimes associated with both between-gang and within-gang co-arrests are related to trespassing, assault and battery, weapons, and armed robbery, while resisting arrest is more common within gangs and affray is more common between gangs. The crime types from the data were categorized into broader groups that have been the focus of previous work: violent crime (i.e. murder, weapon possession, and robbery), property crime (i.e. breaking and entering), and drug crime (i.e. possession of drugs) (Taniguchi et al., 2011). These crime categories indicate the most prevalent and probable activities that gang members engage in, both between and within gangs.

Methods

This study aims to identify the nature of between-gang co-arrests and co-FIOs and how these cut across the whole gang network. After building the co-offending network, I describe the relationships in the network by the nature of gang ties, between vs. within, and what data source the tie is from, arrest vs. FIO. If there are few between-gang ties from co-arrests, this may mean that they are important relationships across gang boundaries, but their members do not participate in violent or drug-related activities together, as previous research suggests. This, in itself, is an interesting finding because it may indicate the relationship is largely behind the scenes. For example, allied gangs may be there to support each other if rivals act against them, but do not do so in the form of co-offending between members of different gangs. Instead, each is involved in its own form of retaliation. In addition, one gang may send an ally customers interested in a drug that it does not sell, which would mean there is a smaller chance of co-arrest because the gangs sell different drugs and probably do so in different geographic territories. On the other hand, if there are many between-gang ties from co-arrests, there is evidence for co-offending. Furthermore, if the nature of these incidents is not just violence, between-gang relationships are more than mutual aid in the face of violent rivalries. This is an aspect of between-gang relationships not previously discussed that help us understand more about gang-related crime and how to prevent it.

By characterizing relationships within and across gangs by the types of crimes or the reasons for police suspicion, I identify how criminal behavior is distributed across the network. Because individual demographic characteristics are related to gang desistance and continuity (Pyrooz et al., 2013), they may similarly be related to forming ties across gang boundaries and are therefore included in the analysis. It is more informative and concrete to use arrests alone for this analysis, because the burden of proof (probable cause in the case of arrests) is higher and indicates a greater likelihood of actual criminal activity. Using a categorization of crimes as violent, property-related, and drug-related, I determine what kinds of crimes are more common between compared to within gangs.

In addition, using FIOs, which represent events in which police gather intelligence on subjects or have reasonable suspicion to question them, I describe the larger social network of gang relationships. FIOs are a form of spending time with other gang members to the extent that an encounter is then observed and recorded by the police. In this way, they provide a broader view of the social network of gang members that can show whether between-gang relationships are not only solely related to violent crime in particular, but also related to committing crime in general.

Results – Gang Network

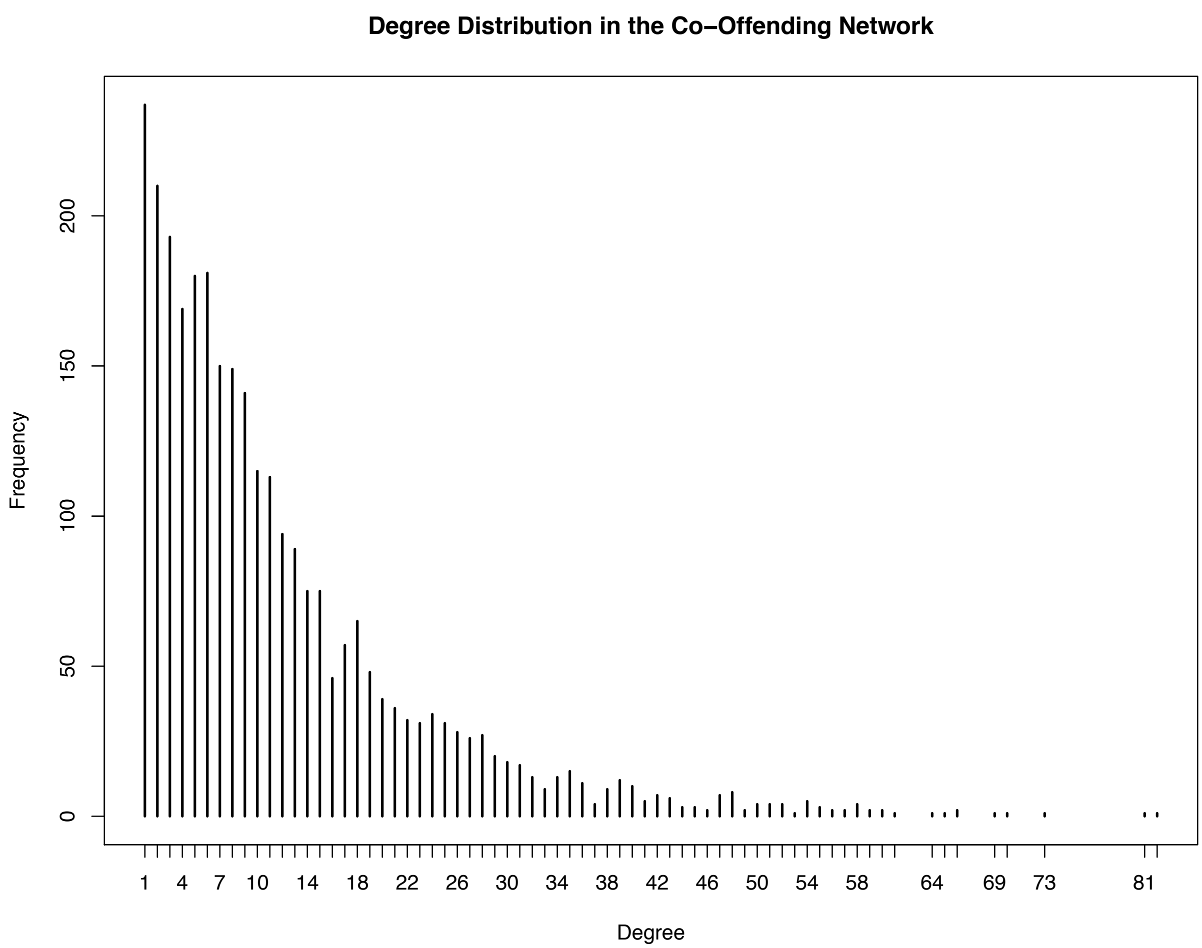
The social network of gang members was constructed from 1,091 co-arrests and 14,529 co-FIOs involving 1,603 and 2,817 gang members, respectively. Using just the co-arrests creates an arrest co-offending network of 1,603 people and the 1,809 ties between them; on the other hand, the FIO network consists of 2,817 people with 16,360 ties between them. Given the informal nature of FIOs and that they require only reasonable suspicion or intelligence gathering to occur, it is expected for the FIO network to involve more individual and, relatedly, more connections. Thus, 1,512 people and 1,030 ties are in both networks. Using all of the data, the full co-offending network contains 2,908 nodes and 17,139 edges as seen in Table 3. The density of the non-isolate network is 0.41%, which is expected given the size of the network. This is not surprising given that the network includes all gang members and any strong rivalries preclude the chance of a tie between certain nodes. Such low cohesion has also been observed in other gang studies using law enforcement data (McGloin, 2005; Papachristos, 2009). The clustering coefficient of the network is 0.32, meaning that there is a 32% probability that adjacent nodes are connected. See Appendix A for a figure of the whole network and Appendix B for a figure of the network in which the gangs are the nodes.

Table 3: Network Statistics for Gang Network

Number of Nodes	2,908
Number of Edges (Ties)	17,139
Number of Isolates	336
Density	3.2×10^{-3}
Non-Isolate Density	4.1×10^{-3}
Transitivity	0.32
Mean Non-Zero Degree	11.8
Mean Edge Weight	2.02

The degree centrality of the gang members in the network, meaning the number of unique ties each individual has, ranges from 1 to 82, with a mean of 11.8 and a standard deviation of 11.1. The degree distribution is shown in Figure 2, displaying the right skew that is typical of distributions for co-offending networks, especially because so many gang members have only one unique tie in the network (Papachristos, 2006; Papachristos et al., 2013). Figure 2 shows that the degree distribution follows a power law, which suggests that the co-offending network is a scale-free network. This may indicate that the network was generated by preferential attachment, in which higher degree nodes were more likely to gain more ties.

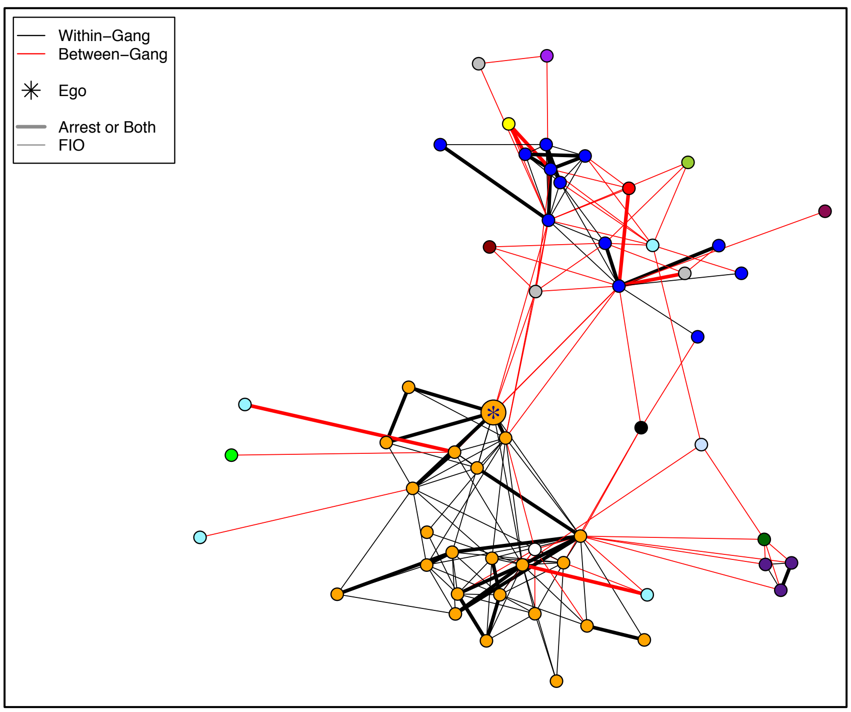
Figure 2: Degree Distribution in the Gang Member Network



Also consistent with past research on the social network of gangs (Papachristos et al., 2012), the largest component, or unique sub-network, consists of 2,848 individuals (98% of all individuals in the non-isolate network). There are 27 total components in the network and the range in size for the smaller components is from 2 to 9. It is clear that there is a great deal of connectedness throughout the whole network, since such a high proportion of gang members are in the largest component.

Results – Relationships between Gang Members

Figure 3: Second-Order Egocentric Network of a Node with a Degree Centrality of 12



Note: In the network, the ego is represented by the asterisk (*) near the center of the plot. Nodes are colored by gang membership and ties are colored by whether they are between-gang (red) or within-gang (black). The thicker edges indicate the tie is in the arrest data (and may recur in the FIO data), while thinner edges indicate ties present only in the FIO data.

Figure 3 is an example of the egocentric network of the node with degree 12, the network average. The network includes the second-order neighborhood of the ego because it contains the "friends" and "friends of friends" of the focal individual. For this study, these relationships are the most interesting because they indicate the closest co-offending relationships, especially given the tendency for closure in the overall network. This figure shows an example of how a member of one gang fits into a network of 16 gangs based on his second-order neighborhood alone. His degree centrality, 12, represents 9 ties within the gang (ties in black) and 3 with two other gangs (ties in red). In addition, the thickness of edges reflects the data source of the tie. Thicker edges show the tie is present in the arrest data, which may also recur in the FIO data, while thinner edges show the tie is present only in the FIO data.

As expected based on the nature of gangs and past research, within-gang ties are more common than between-gang ties. In addition, because past research focuses so much on defining alliances based on between-gang rivalries, Table 4 shows so much more about not only the quantity of between-gang ties, but also the quality. Specifically, 65 of the 170 ties in the sub-network are between-gang, over 38%. Furthermore, past research usually focuses on arrest data, and therefore misses the broader picture of the network as indicated by the thinner ties from the FIO. If one relied only on arrest data, 59 between-gang ties of the total 65 between-gang ties in the ego network would not be present.

Table 4: Number of Ties in the Ego-Network by Gang Membership and Data Source

<table>
<tr><th></th><th>Arrest Only</th><th>FIO Only</th><th>Both Arrest and FIO</th><th>Total by Type (% of Total)</th><th>Total</th></tr>
<tr><td>Between-Gang</td><td>2</td><td>59</td><td>4</td><td>65 (38%)</td><td rowspan="2">170 (100%)</td></tr>
<tr><td>Within-Gang</td><td>6</td><td>77</td><td>22</td><td>105 (62%)</td></tr>
</table>

The Nature of Between-Gang Ties in the Network

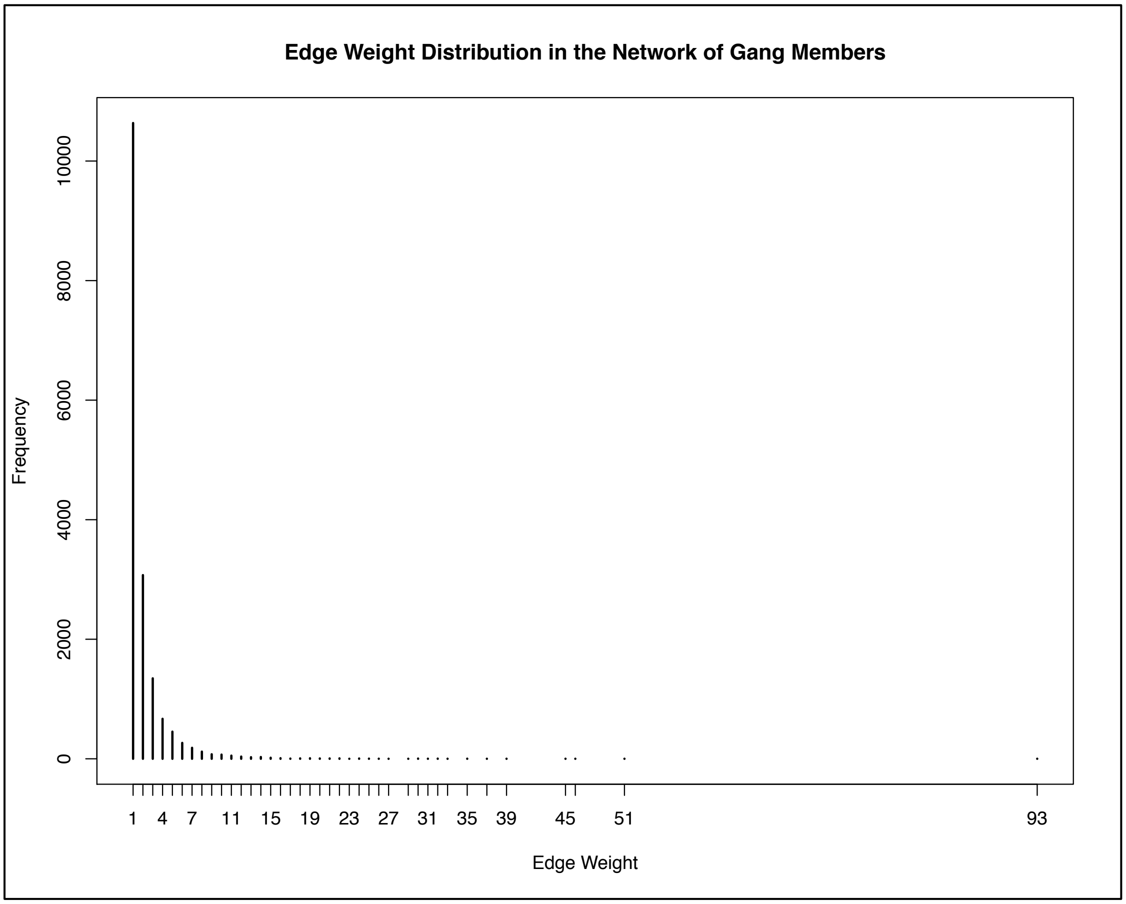
Table 5 shows the distribution of ties by gang relationship and data source. Of particular note is that 37% (6,358 of 17,139) of ties are between gangs. Thus, over one-third of the unique gang member relationships span across different gangs.

Table 5: Number of Ties by Gang Relationship and Data Source

	Between-Gang	Within-Gang			Between-Gang	Within-Gang	Total by Type
Arrest	297	482		**Arrest + Both**	494 (27%)	1315 (73%)	1809 (100%)
FIO	5864	9466		**FIO + Both**	6061 (37%)	10299 (63%)	16360 (100%)
Both	197	833					
Total by Type	6358 (37%)	10781 (63%)					
Total	17139 (100%)						

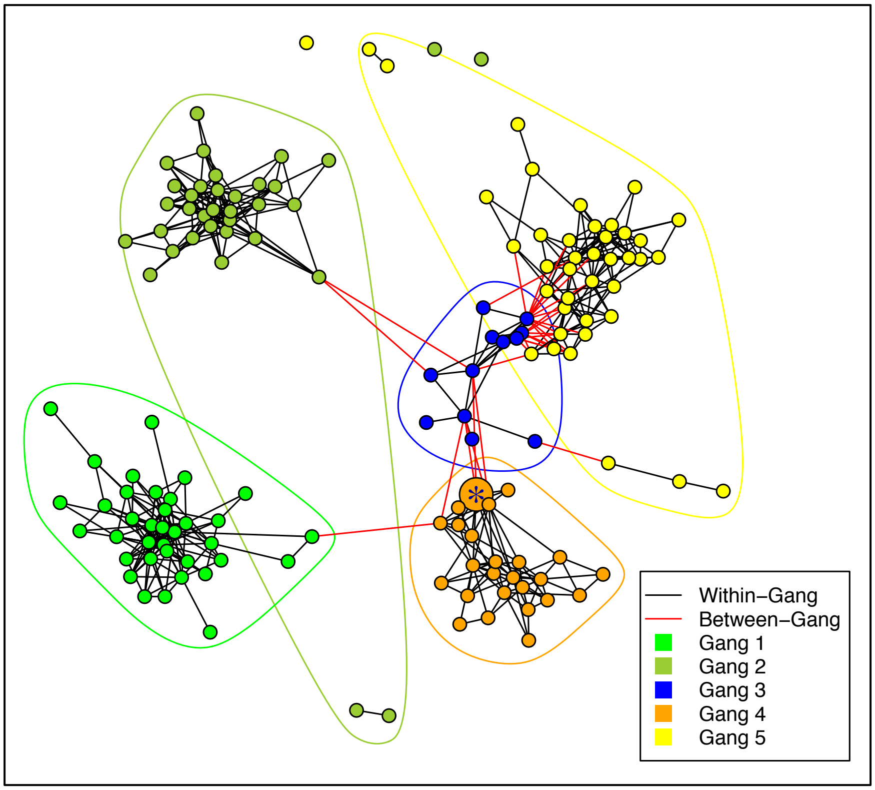
Accounting for the fact that some ties are represented both in the arrest and FIO data, Table 5 also shows that 27% of arrest ties are between two different gangs, while 37% of FIO ties are between-gang. These figures lend evidence for the first hypothesis; that is, that within-gang ties are more prevalent, though there is a sizable number of between-gang ties. Because FIOs are more common than arrests, it is difficult to directly compare the share of between-gang ties that can be attributed to arrests versus FIOs. However, as is evident from the over one-quarter to one-third share that between-gang ties have by the source of data, between-gang relationships at the individual level are neither all crime-related or all FIO-related. This means that relationships between members of different gangs do represent more than co-offending in the form of retaliatory violence, because two individuals from different gangs that are FIO-ed together merely appear to be hanging out. Thus, some between-gang contacts include physically being together for long enough to allow for police to observe or stop and question them together. The between-gang ties that were present in both the arrest and the FIO data also show that individual-level relations are mixed; they are not solely due to physical proximity and/or hanging out nor are they only due to committing crime together.

Figure 4: Distribution of Edge Weight for the Whole Gang Network



The distribution of tie strength is in Figure 4. As with the degree distribution, the distribution of edge weights (or tie strength) shows an expected right-skewed distribution, where most ties are not represented by more than one event (edge weight = 1) and few ties have an edge weight greater than 1, with a maximum of 93 and a mean of 2.

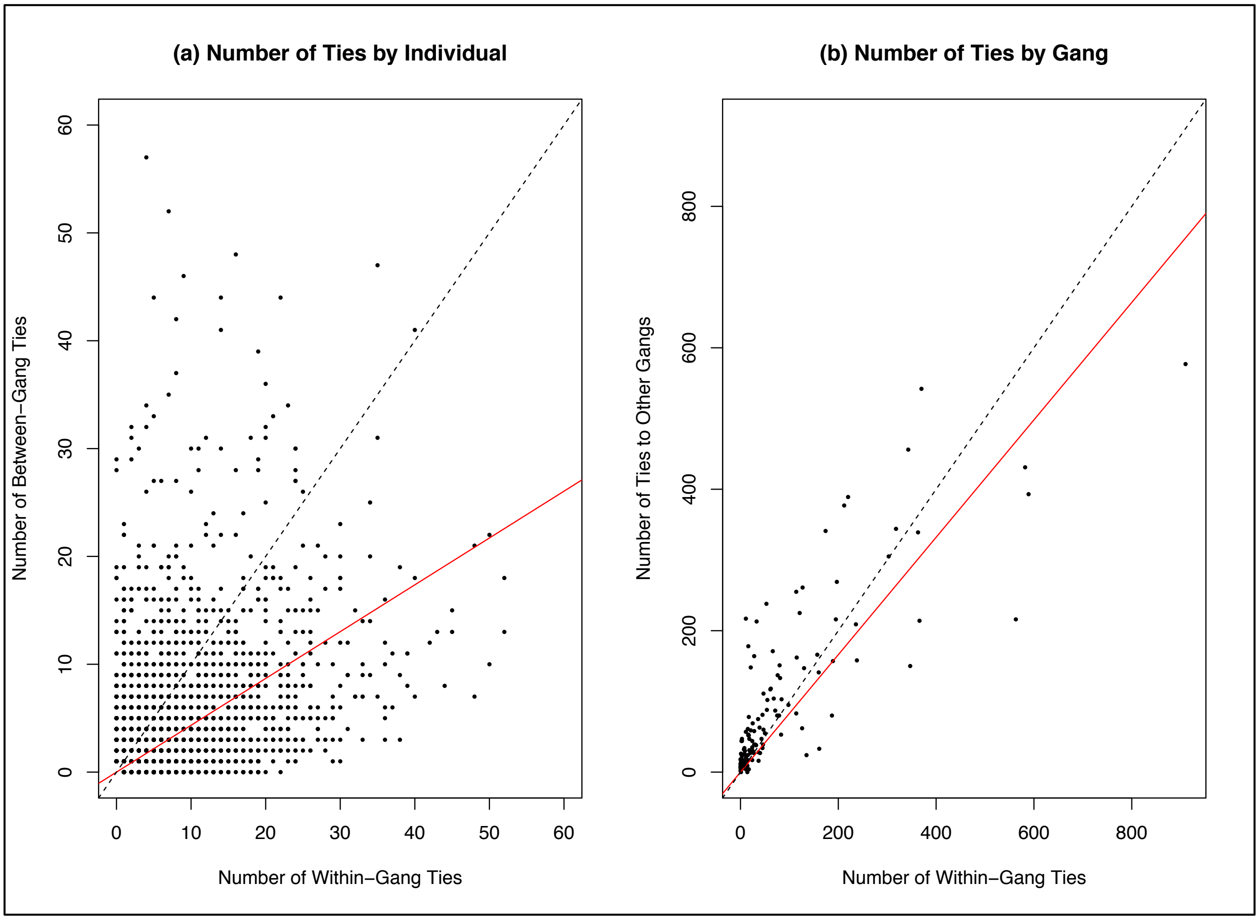
Figure 5: Sub-Network of Five Gangs from the Ego-Network (Figure 3) Grouped by Gang



Note: Nodes and group polygons are colored by gang membership. Ties are colored red if between gangs and black if within gang. The ego from Figure 3 is marked by the asterisk (*).

Figure 5 shows a sub-network of 5 gangs grouped by gang membership, with ties colored red if between-gang and black if not. These five gangs were sampled from the ego network in Figure 3, which means they show a greater number of between-gang ties than five random gangs because there is a greater chance that no rivalries are present (given that nodes in Figure 3 are connected to the ego either directly or through one intermediary). The figure gives a small glimpse at within-gang and between-gang ties. The sub-network shows the properties of the larger network in that ties within the gang are clearly more common than ties between gangs. However, it also shows the interconnectedness of gangs and its variation; multiple gangs have more than one gang with which they are tied, even across five gangs. Furthermore, some gangs are related through just one person (one node in the yellowgreen-colored gang is connected to multiple in the blue-colored gang), while other gangs are related through multiple individuals in both gangs (e.g., the blue and yellow gangs). In addition, the bright green gang is connected to only one of the other gangs and through just one individual. This glimpse at the network shows the variation in relationships between gangs, which can further be understood by studying the patterns of ties between and within gangs in the network.

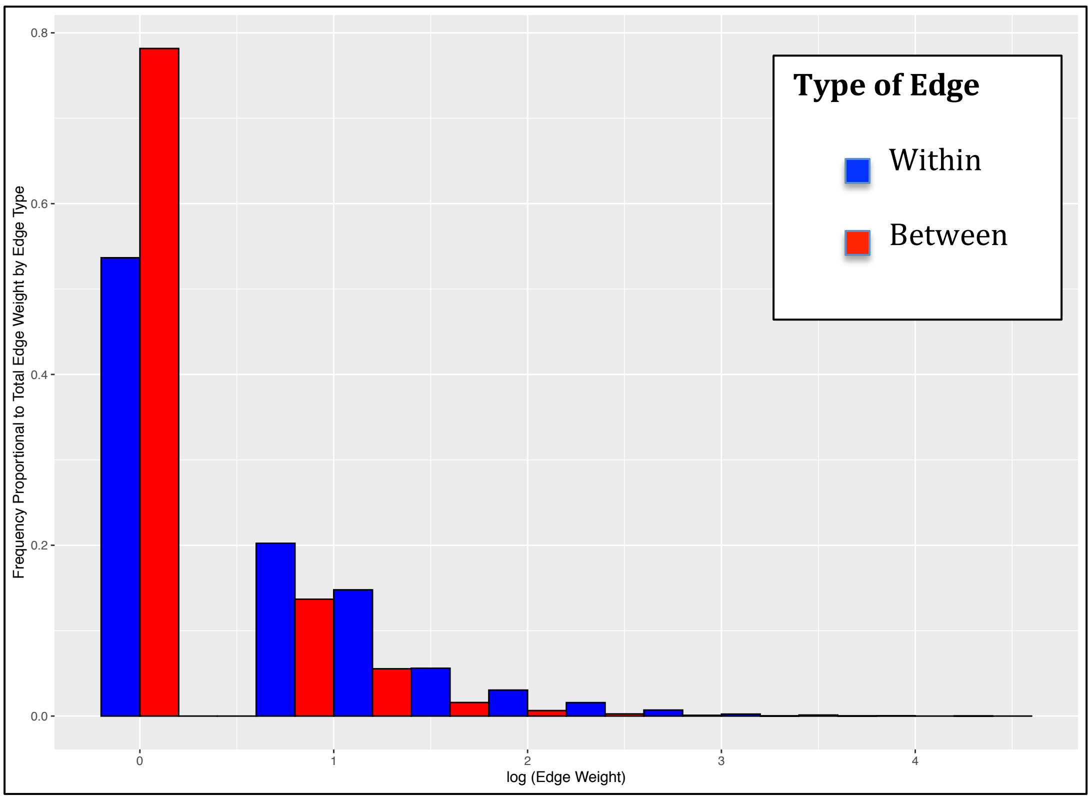
Figure 6: Number of Within-Gang vs. Between-Gang Ties by Individual and by Gang



Note: Scatterplot of degree by within-gang vs. between-gang. (6a) Points represent individuals and (6b) Points represent gangs. For both, the black dotted line plots x=y and the red line fits an OLS regression of y on x with the constant suppressed, where the coefficients are (a) 0.44 and (b) 0.83.

Figure 6 displays two scatterplots of the number of within gang ties (x-axis) versus the number of between gang ties (y-axis) for the gang members (Fig. 6a) and gangs (Fig. 6b) in the network. As seen by the red lines in both plots, linear relationships exist between the numbers of within gang and between gang ties for individuals (Pearson $R = 0.36$) and more strongly for gangs (Pearson $R = 0.82$). However, in both cases, the slopes of the linear regression lines are lower than if the number of within-gang ties and between-gang ties were equal. The discrepancy indicates that the number of within-gang ties tends to be greater than the number of between-gang ties, as would be expected, though the difference is smaller at the gang level than at the individual level.

Figure 7: Frequency of Edge Weights by Type of Edge



Note: Frequency proportional to total edge weight for between and within-gang ties (y –axis) for log-transformed edge weight (x –axis)

Figure 7 shows the proportion of total within-gang and between-gang ties, respectively, by log-transformed edge weights. The edge weights are log-transformed given their severe right skew. The figure shows that the majority of edge weights for between-gang ties are equal to 1 (i.e., log = 0). Overall, edge weights for between-gang relationships tend to be smaller than those for within-gang relationships. While 26% of within-gang ties have an edge weight above 2 (log = 0.69), only 8% of between-gang ties have such edge weights.

The gang network as a whole shows the importance of between-gang ties to the gang landscape. To further contextualize the ties, I examine the frequency of between-gang and within-gang ties by gang. In Table 6, I summarize the number of between-gang and within-gang ties that each gang has. In addition, I include a summary of the proportion of each gang's total ties that are within-gang versus between-gang.

Table 6: Summary Statistics for the Total Ties and Proportion of Ties that are Between and Within Gang at the Gang Level (*N* = 123)

	Total Between-Gang Ties	Total Within-Gang Ties	Proportion Between-Gang Ties	Proportion Within-Gang Ties
Minimum	0	0	0	0
Median	53	30	0.62	0.38
Mean	101.7	87.7	0.62	0.38
Maximum	577	910	1	1

Overall, 92 of the 119 (77%) gangs represented in the data have more between-gang ties than within-gang ties, while 4 additional gangs have the same number of between and within-gang ties. Given that the relationship between gang cohesion and survival is dependent on the size of the gang (Ouellet et al., 2019), it stands to reason that other gang characteristics may be related to the variation in gang cohesion. Table 5 showed that overall between-gang ties were less prevalent than between-gang ties. Interestingly, at the gang level, the mean number of between-gang ties is greater than that of within-gang ties, though this is not a significant difference (t = 0.944). These striking figures further highlight the importance of examining relationships between gang members in addition to understanding gangs as a whole.

The Relationship between Gang Ties and Crime Type

Beyond determining whether between-gang contacts are due to more than co-arrests, which is clearly the case based on the previous discussion, there is also the question of whether the arrest-based contacts are solely violence-based or whether other crimes are involved. Table 7 shows the breakdown of between-gang and within-gang ties by crime type. These ties are, of course, only those from the arrest data because an arrest requires probable cause of a crime, while an FIO merely requires reasonable suspicion, a much lower threshold.

Table 7: Arrest-Based Ties by Gang Relationship and Crime Type

	Violent	**Property**	**Drug**	**Other**	**Total Ties**
Between-Gang	165 (33%)	194 (39%)	85 (17%)	50 (10%)	494 (100%)
Within-Gang	533 (40%)	446 (33%)	147 (11%)	189 (14%)	1315 (100%)

Looking at the charges for the co-arrests, the most frequent types of crimes are violent, property, and drug crimes. Other crime categories include alcohol-related crime and vehicle-related crime, but they are not as common as these categories and are therefore not considered pertinent to this study. These categories were assigned by the author based on the description of the charge associated with an arrest incident. Ties with multiple charges attached were assigned the most serious charge, where violent was concerned the most serious of the three types, while drug was concerned the least. Some ties have missing data because the charge is "Other," which at the moment cannot be described in more detail. However, because of the severity and frequency of violent, property, and drug crimes, the missing data likely does not fall into the three categories, meaning they have little effect on the results.

Table 7 shows that between-gang ties are not solely a result of violent co-arrests. As hypothesized in H2, violence is the most frequent type of co-arrest charge for both types of contacts, representing 33% and 40% of between-gang and within-gang ties, respectively. However, property charges represent 39% and 33% of the same tie types. In addition, the ties attributed to drug charges are about 17% of between-gang ties and 11% of within-gang times. Therefore, a large proportion of between-gang ties is not related to violence and, instead, represents property and drug co-arrests. This elaborates upon the previous work on ties across gangs by offering more context. Moving beyond the focus on the violence associated with rivalries, co-offending and other between-gang relationships may be more than defending each other when challenged. They can represent joint business ventures, i.e. sharing drug markets, as well as other forms of activity, such as property crime. What is most interesting is that there is almost no difference in the proportion of between-gang and within-gang ties attributable to violence co-arrests. Therefore, between-gang relationships are not very different from within-gang relationships, indicating that boundaries between gangs are much more porous than previous work suggests.

Modeling the Probability of Forming a Between-Gang Tie

There are 12,357 unique co-arrest incidents from 2007 through 2014, of which 1,091 involve only gang members (rather than one gang member and a non-gang member). The discussion that follows focuses on these co-arrests over the eight-year span from 2007-2014, in order to account for the influence of arrest charge type on relationship. From 2007-2014, there were 1,091 gang co-arrest incidents involving 1,603 individuals. The incidents represent violent, property, drug, and other types of arrest charge. Table 8 shows the frequency of charges by the relationship of the co-arrestees. As reflected in the literature, violence is the most important co-offending charge type to gang relationships, representing just over 45% of both within-gang and between-gang incidents.

Table 8: Incidents by Gang Relationship and Arrest Charge Type

	Violent	Property	Drug	Other	Total
Within-Gang*	341 (46%)	240 (32%)	110 (15%)	56 (8%)	747 (100%)
Between-Gang	159 (48%)	111 (33%)	54 (16%)	20 (6%)	344 (100%)

*Within-Gang is defined as all co-arrestees are in the same gang. Between-Gang is defined as at least two co-arrestees are in different gangs.

Together, there are 2,527 person-incident records that capture the characteristics of co-arrests over eight years. There are 1,718 event-person records in which all co-arrestees are in the same gang, and 809 event-person records in which members of more than one gang are co-arrested. To illustrate the distribution of co-arrestees by incident, Table 9 shows the relationship between the maximum number of within-gang co-arrestees in an incident and the total number of co-arrestees. Incidents having two total co-arrestees account for 77% of incidents and most common of these incidents involved two co-arrestees from the same gang. In fact, over all incidents, it is most common for the maximal number of co-arrestees to be the total number of co-arrestees, meaning that all individuals involved are in the same gang. However, the variation in Table 9 provides clear evidence that there are many events in which not all co-arrestees share a gang affiliation.

Table 9: Summary of Arrests Incidents by Type and Total Co-Arrestees (*N* = 1,091)

Total Co-Arrestees	Between-Gang (Multiple Gangs)	Within-Gang (One Gang)	Total	
2	250	589	839	77%
3	74	109	183	17%
4	14	38	52	4.8%
5	5	7	12	1.1%
6	1	2	3	0.3%
7	0	2	2	0.2%
			1091	100%

Beyond understanding the distribution of ties within and between gangs, it is important to delve deeper into the factors that are related to the probability that an individual forms a between-gang tie. Therefore, I use logistic regression with gang fixed effects for the 118 gangs represented in the arrest data to determine how individual-level, incident-level, and gang-level factors impact the probability that a person is co-arrested with an individual in another gang.

Table 10: Description of Individual-Level Control Variables

Age Category	Frequency		Race	Frequency		Sex	Frequency
12-19	151		Black	1170		Female	8
20-24	737		Hispanic	398		Male	1596
25-29	546		Other*	36			
30-34	131						
35-39	32						
40-49	7		*Includes White and Asian				

The individual-level controls of interest are race and age at the end of the study period (December 31, 2014). Both were categorical variables, with the frequency of categories shown in Table 10. I treat age as a categorical variable because I expect the relationship between age and forming a between-gang tie is non-linear. Younger gang members are more likely to have the weakest attachment to their gang because of a shorter membership and they may have stronger attachments to other types of relationships, be it friendships or family. Therefore, the effect of increasing age on forming a between-gang tie varies across the distribution of age. Finally, because there are 8 females in the data, sex is not included as a control.

The incident-level controls of interest are charge categories and number of co-arrestees in the incident. The distribution of these variables is shown in Table 11. Charge categories are represented by a series of indicators for violent, property, drug, and other charge types, given that incidents often involve more than one type. There are 118 gangs represented in the co-arrest data, ranging from having 1 to 67 members, with a median of 23 and a mean of 24.2.

Table 11: Description of Incident-Level Control Variables

Charge Category	Frequency
Violent	512
Property	434
Drug	268
Other	286

	Number of Co-Arrestees
Minimum	2
Median	2
Mean	2.3
Maximum	7

Predicting Propensity to Form Between-Gang Ties

Based on previous literature, between-gang contact is most often portrayed as violent co-offending against a common rival. However, even the descriptive review of between-gang ties here shows that there is more to between-gang relationships than violence. What explains the propensity to form a between-gang tie? The dependent variable is, therefore, whether a person in an incident has any between-gang ties in that incident (*Between_Any*). Using a logistic regression model with gang fixed effects, I can determine how individual-level and incident-level characteristics influence the probability that a person will be co-arrested with a member of a different gang in a particular incident, here referred to as $\boldsymbol{p_{ijk}}$.

$$\mathbf{logit(p_{ijk}) = \alpha_j + \beta} x_{ijk} + \boldsymbol{\varepsilon_{ijk}}$$

Here, $\boldsymbol{\alpha_j}$ represents gang-level fixed effects, $\boldsymbol{\beta}$ represents the vector of coefficients for covariates (race, age, charge category, and number of co-arrestees involved), and $\boldsymbol{\varepsilon_{ijk}}$ represents the individual-incident error. More specifically, I will estimate the probability $\boldsymbol{p_{ijk}}$ using the dependent variable *Between_Any*. For individual *i* in gang *j* in event *k*, *Between_Any* is 1 if an individual (other than *i*) in event *k* is not in gang *j*, 0 otherwise. The model below includes all covariates, at both the individual level ($_i$) and incident level ($_k$).

$$\textbf{logit}(\textbf{\textit{Between\_Any}}_{ijk}) = \alpha_j + \beta_1\ \textbf{Hispanic}_i + \beta_2\ \textbf{Other Race}_i +$$

$$\beta_3\ \textbf{Age(13-19)}_i + \beta_4\ \textbf{Age(25-29)}_i + \beta_5\ \textbf{Age(30-34)}_i + \beta_6\ \textbf{Age(35-39)}_i + \beta_7\ \textbf{Age(40-49)}_i +$$

$$\beta_8\ \textbf{Violent Charge}_k + \beta_9\ \textbf{Property Charge}_k + \beta_{10}\ \textbf{Drug Charge}_k + \beta_{11}\ \textbf{Other Charge}_k +$$

$$\beta_{12}\ \textbf{Number of Co-Arrestees}_k + \varepsilon_{ijk}$$

Model 1 includes only gang fixed effects, suppressing the intercept so that all 118 gangs have an effect. Model 2 includes gang fixed effects and individual-level covariates (race and age). Model 3 includes gang fixed effects and incident-level covariates (charge category and number of co-arrestees). Finally, Model 4 is the full model with gang fixed effects and all individual and incident covariates. In all models, standard errors are clustered at the incident level, given that the value of the dependent variable is the same for each incident. See Table 12 for the results of each model.

Table 12: Logistic Regression on the Propensity of Forming a Between-Gang Tie

	Model 1 (Gang FE)	**Model 2 (Gang FE + Individual)**	**Model 3 (Gang FE + Incident)**	**Model 4 (Gang FE + All Covariates)**
Standard Deviation of Gang Fixed Effects [a]	0.929	0.932	0.931	0.935
Hispanic		-0.306 (0.181)		-0.304 (0.180)
Other		-0.332 (0.457)		-0.312 (0.456)
Age: 12-19		-0.218 (0.227)		-0.237 (0.227)
Age: 25-29		-0.046 (0.138)		-0.043 (0.139)
Age: 30-34		-0.404 (0.270)		-0.391 (0.269)
Age: 35-39		**-1.542*** (0.537)**		**-1.565*** (0.544)**
Age: 40-49		-1.016 (1.201)		-0.895 (1.225)
Number of Prior Arrests		0.033 (0.018)		0.033 (0.019)
Charge: Violent			0.053 (0.195)	0.037 (0.195)
Charge: Property			0.293 (0.203)	0.300 (0.203)
Charge: Drug			0.265 (0.206)	0.249 (0.208)
Charge: Other			-0.180 (0.187)	-0.178 (0.187)
Number of Total Co-Arrestees			0.170 (0.104)	0.169 (0.105)
Pseudo R^2	0.148	0.154	0.155	0.161
AIC	2934	2932	2922	2920
N	2,526	2,526	2,526	2,526

Note: FE: Random Effect; Total Number of Gangs= 118; significance levels: 0.001 (*), 0.01 (**), 0.05 (*). The reference category for race is Black and for age categories is 20-24.
[a] Excluding gangs with no between-gang or within-gang ties

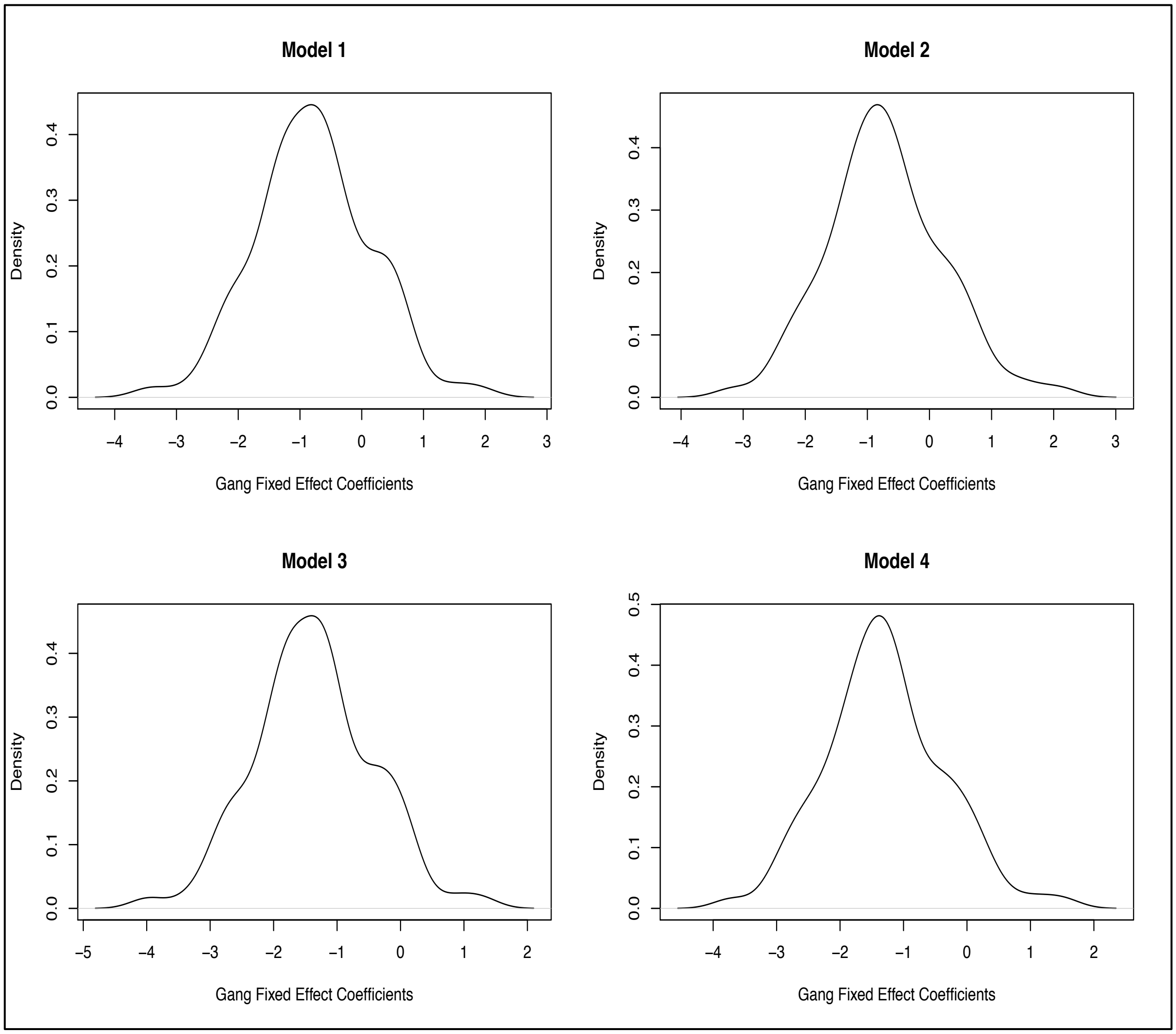
Across all models, the charges associated with the incident do not significantly predict the probability of being co-arrested with a member of another gang showing no evidence for the third hypothesis. These results further support that the type of arrest charge does not significantly differ between within-gang and between-gang ties. Specifically, the non-significant violence indicator does not explain between-gang activity. In addition, the race of the individual, using Black as the reference category, does not significantly influence the probability of forming a between-gang tie. However, in the individual-level and full models (Models 2 and 4), as compared to the reference category of 20-24 year-olds, being between the age of 35 and 39 reduces the probability by 79% (exp(-1.542) = 0.21), as indicated by the negative log-odds ratio associated with the age category. This may be because older gang members are less likely to form between-gang ties because of their longer history of allegiance to their gang or, as previous literature supports, less likely to engage in co-offending at all (van Mastrigt and Farrington, 2009).

Table 13: AIC Comparison between Models with and without Fixed Effects (FE)

	Model 2		**Model 3**		**Model 4**	
	No FE	With FE	No FE	With FE	No FE	With FE
AIC	3136	2932	3162	2922	3130	2920

Table 13 shows the comparison between Models 2-4 with and without fixed effects. Based on comparing the models by the Aikake Information Criterion (AIC), the gang-level fixed effects improve the fits of the models. There is evidence that there are gang-specific effects on the probability that an individual in a specific gang will be co-arrested with an individual in a different gang. The probability that an individual forms a between-gang tie thus depends on gang membership. Figure 8 shows the distribution of gang-level fixed effect coefficients, excluding gangs with no between-gang or within-gang ties. For gangs with no ties of either type, fixed effects ranged from 16.1 to 17.6 in both the positive and negative directions. For gangs with at least one type of both types, the magnitude for the fixed effects across all models ranges from -4.0 to 2.1, with a standard deviation of about 0.9. Future work can determine what gang-level characteristics help to explain individual-level propensities to form between-gang arrest ties.

Figure 8: Distribution of Gang Fixed Effect Coefficients by Model



Note: Gang fixed effects coefficients limited to gangs with more than one between-gang tie and within-gang tie.

Discussion

The analyses here shows that an important aspect of gang membership and expands on its interrelation with criminal social capital, in the form of social networks, and co-offending. Between-gang relationships consist of more than violent co-offending against a mutual rival and shared drug markets. As is clear from both the distribution of between-gang and within-gang ties by charge type and from the logistic regression models, there is no clear difference between the types of charges that constitute between-gang versus within-gang criminal activity. In addition, over a quarter of ties (27%) that indicate cooperative behavior unrelated to a suspected crime, i.e. from FIO data, are between individuals from different gangs. As with previous work on group survival, gang characteristics may explain the finding that the average number of between-gang ties is not significantly different from that of within-gang ties at the gang level. They similarly may improve the explanatory power of models predicting the propensity for gang members to form between-gang ties.

Of course, these data assume there is a social relationship between people arrested for the same crime as well as people who experience an FIO together. This assumption is not unreasonable, especially in the case of FIOs, because individuals must be in close physical proximity to one another in order to be recorded as associates. With arrests, it is possible that police arrest the wrong person as a co-offender in particular cases, especially if they confuse the victimized and acting groups and their members.

Another limitation of creating a co-offending network using arrests is that all cases in which someone was not detected are missing from the data set. If crimes involving more than one perpetrator are not detected or reported, then there is no way for the police to arrest the people involved. In addition, it is possible that there are more people involved in the crimes than are arrested for them, which can result in an underestimate of the number of nodes as well as ties in the social network. Using the FIO data in conjunction with the arrest data can help bolster the expanse of the co-offending network by including another type of tie between people- that of close physical proximity while engaging in suspicious behavior. With FIO data, it is less likely that those associated with an event are not actually socially related because they are in the same geographic space together. It is unlikely that rivals or people that do not know each other would "hang out" together in such a way and officers use their judgment in assessing whether a group of people they stop and question is actually related.

Finally, and most importantly, all the data are subject to the bias of police discretion. The presence as well as the strength of the ties between individuals in the network is based on how officers conduct their criminal investigations for arrests and how they observe and react to suspicious behavior in the case of FIOs. In addition, the gang database is maintained through observation and record tracking by officers and analysts and the label of "gang member" is wholly determined by their findings. It is important to keep in mind this bias as it may affect how conservative this network of co-offending is. Thus, the co-offending network at hand is a police-centric glimpse at the entire gang network of Boston.

The results presented here can help scholars and practitioners alike understand the nature of between-gang relationships. It is clear from the results that relationships between gangs are prevalent in Boston and that they take forms beyond violent, retaliatory co-offending (Kennedy et al., 1997; Papachristos, 2009; Papachristos et al., 2013). In fact, it also means more than just "hanging out" together on the street. Interactions between members of different gangs involve a mixture of relationships that include being in close physical proximity as well as violent, property, and drug co-arrests. In addition, this data suggest that relationships across gang boundaries are more than being "cool with" each other but not interacting. Instead, the relationships between members of different gangs are clearly recorded by official records.

Based on the gap in the literature concerning the relationship between criminal social capital, co-offending, and gangs, this study provides much-needed evidence concerning the prevalence of co-offending across gang boundaries and how the relationships are structured between gangs. I show that criminal social capital extends beyond gang boundaries, especially in the forms of behavior such as hanging out. While previous work provides evidence for the lack of cohesion within gangs (McGloin, 2005), it does little to explain the extent and characteristics of relationships across gang boundaries.

Gang members are embedded in a network of gang relationships, above and beyond the notion that between-gang relations are largely motivated by support against rivalries. In addition, examining the network in relation to charges involving co-arrestees further expands the knowledge of the behavior of urban gang members and their criminal social capital, especially as compared to the general behavior of those arrested.

The importance of understanding gang dynamics through relationships between gang members is both theoretical and practical. Theories of criminal social capital show that it can be important to the operation of gangs, with evidence of its benefits shown at the individual and gang level. However, evidence for its role in gang dynamics is lacking. This study provides support for the theory of criminal social capital and its important in social networks, particularly in the case of gangs. Furthermore, the nuances of criminal social capital as related to gang dynamics has implications for understanding crime patterns and thereby being in a more optimal position to address them.

Determining the nature of the relationship between gang membership and co-offending, especially through the lens of criminal social capital, shows that understanding between-gang relationships are important for not only law enforcement and crime prevention, but also for the social and economic outcomes of gang members. Given the prevalence of gang membership in inner-city, disadvantaged neighborhoods (Sampson and Wilson, 1995; Schaefer et al., 2013), understanding the exact involvement gang members have with one another helps to understand some of the pathways to involvement with the criminal justice system, by first getting arrested and then possibly convicted and incarcerated, which then has broader impacts for the life course of predominately young, male residents of disadvantaged neighborhoods. Research shows that involvement in the criminal justice system, especially incarceration, negatively affects individuals post-release with respect to employment, health, and social outcomes (Pager, 2003; Pettit and Western, 2004; Western, 2006). Knowing that gang members are not only intertwined within their own gang, but with others, allows for more potential to be in contact with the criminal justice system, which can lead to a greater probability of negative outcomes later in the life course, if incarceration is a result of between-gang associations.

In describing the behavioral nature of co-offending among gang members, the study has significant implications for the interventions best suited to addressing gang-related crime in Boston. Because of the frequency of between-gang ties both in arrest and FIO data, police can be sure that the gang violence problem in Boston cannot be addressed by solely focusing on one or two groups. Instead, the entire co-offending network of individuals and of gang relationships must be examined in order to reduce gang-related crime. In addition, even though arrests for violence are most common, property and drug arrests are also prevalent in between-gang interactions; this information can help the police formulate responses when certain types of crime issues become more common. Therefore, the study at hand has elucidated some of the overlooked aspects in the social network literature on gangs as well as some important implications for public safety, law enforcement, and the life course outcomes of gang members.

CHAPTER 2

There are approximately 2000 gang-related homicides every year nationally, about 13% of all homicides, though gang members make up only about one-fifth of 1 percent of the population (National Gang Center, 2012). Gangs account for a disproportionately large share of crime, especially violent crime (Pyrooz et al., 2016). Gangs, their structure, and their activities are thus an important facet of urban crime. Furthermore, gang membership is integral to the study of peer effects, delinquency, co-offending, and illicit networks, among many more aspects of criminology. Given gangs' involvement in crime, their members have a greater likelihood of contact with the criminal justice system. Though not all associations are causal, such contact is associated with negative outcomes, including incarceration and unemployment (Pager, 2003; Pettit and Western, 2004) In addition, the official label of gang membership from a law enforcement agency carries further consequences. Gang members are targets of increased surveillance as well as focused criminal justice policies (Gravel et al., 2013; Kennedy et al., 1997). The definition of gangs and their boundaries is critical because of the real consequences of gang affiliation.

Gangs are responsible for a high level of violence (Densley and Pyrooz, 2020; National Gang Center, 2012), while law enforcement direct strategies to address and reduce violence. Naturally, law enforcement target interventions on gangs in particular, requiring information on gangs and their members to do so. These gang classification data are integral to violence prevention, as identifying gang members enables better tracking of gang criminal activity and therefore better-designed responses. The data have additional effects on the consequences of criminal justice involvement given that legal interventions from gang injunctions and other policies can lead to increased sentences for gang members than those not involved in gangs (Gravel et al., 2013).

In this study, I analyze boundaries between gangs and how they inform our understanding of individual offending. This chapter answers the question: how do gangs, as defined by law enforcement, compare to other groups that commit crime together? As discussed in Chapter 1, Boston is an archetypical field site because the characteristics of its gangs are similar to typical gangs in the US in that they are generally less organized, geographically concentrated, and small in size (National Gang Intelligence Center, 2015). Boston law enforcement also includes a gang unit and maintains a gang member database, both of which are common in other cities. Over 54% of large cities with a gang problem have a gang unit (National Gang Center, 2012), nearly all of which (93%) maintain tracking systems of gang members according to survey data (Langton, 2010).

Given the reason gangs are classified into gang databases is their disproportionate involvement in crime, assessing said involvement as compared to other classifications of gangs has important theoretical and policy implications. I therefore utilize a variant of community detection, a social network analysis technique that aims to find clusters ("communities") of sub-networks within a given network (Missaoui and Sarr, 2014). Using the technique, I can determine criminal groups based on the network of individuals with recorded police contact during the study period. In this study, I first analyze administrative data on arrests and Field Interrogation and Observation reports (FIOs) to construct and describe the network of the individuals involved in them. Second, I find clusters in the network to obtain empirically-defined co-offending groups. My last analyses describe the differences between gangs and clusters with respect to involvement in arrests after the study period. The results of my analyses show that police-defined gangs and network-defined clusters are similar in characteristics, though clusters tend to be smaller. In addition, there are few significant differences between the proportions of gang members and cluster members involved in arrests in 2013-2014. Assessing whether police-defined groupings and the structure of co-offending help to explain the patterns of individual involvement in criminal activity, especially as compared to empirically defined groupings, is critical because of the consequences of gang membership and the similarity of between-gang and within-gang co-offending, as shown in Chapter 1. Given the impact of criminal justice system involvement on the life course, as well as the added interest from law enforcement that comes with being a gang member, we must understand how current practices capture the police-filtered view of offending. Furthermore, this analysis shows the improvements made to the study of gang-involved criminal activity when combining official data from law enforcement with social network analysis.

Gang Involvement in Crime

A fairly common definition for a street gang is “any durable, street-oriented youth group whose involvement in illegal activities is part of its group identity” (Klein and Maxson, 2006, p. 4). Therefore, it is unsurprising that gangs are responsible for a disproportionately large share of violence and crime (Pyrooz et al., 2016). In Boston from 2007-2014, identified gang members made up 4.5% of arrestees, though they accounted for 26% of arrests for homicide and 10% of arrests for violent offenses. At the individual level, it is clear from previous literature that peers affect an individual’s offending (see Warr, 1993 for a review). However, gang membership influences delinquency beyond the effects of associating with delinquent peers (Battin et al., 1998). Therefore, the gang has a particular impact on individual criminal activity that is not simply due to having more peers involved in crime. Though individual and macrosociological factors may explain this gang-related crime and violence (Decker, 2007; Papachristos, 2009), policing strategies are nonetheless motivated to focus on gang activity in order to address violence and increase public safety.

Criminal Social Capital in Gangs

As discussed in Chapter 1, criminal networks, related criminal social capital, and co-offending are key factors associated with involvement in criminal activity and gang membership. An individual's criminal social capital potential increases with more contacts and weak ties with individuals involved in crime (for a review, Nguyen, 2020). Criminal social capital is therefore inherent to a network, where each individual is surrounded by potential sources of resources.

Co-offending is a form of leveraging one's criminal social capital, while gang membership increases one's criminal social capital, given its amelioration of a member's criminal network. In particular, gang membership imparts criminal social capital benefits for gang member, ranging from greater potential for alliances at the gang level to a larger network of potential co-offenders at the individual level. Both co-offending and gang membership are positively related to the benefits of criminal social capital (illegal earnings) (Augustyn et al., 2019; Rowan et al., 2018). Therefore, the positive relationships between criminal social capital, gang membership, co-offending highlight the interconnection between criminal networks, gang membership, and crime.

Their relationship bolsters the importance of understanding the gang boundaries within an urban area because the criminal social capital benefits of gang membership often translate into more involvement in criminal networks and criminal activity. As shown in Chapter 1, gang relationships often cross gang boundaries, enabling diffusion of criminal capital resources within and between gangs. Greater involvement in crime for individuals has long term consequences for individuals, including increased contact with the criminal justice system and its potential negative effects (Pager, 2003; Pettit and Western, 2004), as well as for society in general, as risk of victimization increases with more crime in an area.

Furthermore, brokerage across structural holes also provides social capital in networks (Burt, 2004). Between groups with no overlap are structural holes that would provide a social bridge across the groups if people were positioned near them. The individuals who are able to broker across groups have more social capital as they have access to the resources, including ideas and information, of both groups, which are more likely to differ between groups than within groups. Therefore, the broker is exposed to more heterogeneity in thinking and behaving, allowing for greater options for ideas and actions from which to learn and select. Synthesizing across structural holes also enables new ideas to form, some of which enable the broker to have greater benefits in their chosen field.

Applied to the field of criminology, McGloin (2005) uses the term cut-points for such individuals, following Wasserman and Faust (1994). I keep with the social capital literature and use the term “brokers” to describe individuals that are the sole conduit between gangs, as they are not important for their potential to only “cut” the network. They are important to the structure and actions of a criminal network as they have a great deal of criminal social capital and are, according to the theory of structural holes, the most likely to be prolific in their involvement in crime. Therefore, the most methodical choice for intervention strategies are brokers because using them to spread information reaches the most amount of individuals in the network quickly. In addition, removing them can potentially reduce crime as well as sever the ties and therefore the operations within a disjointed gang or between two gangs in the network (Papachristos, 2006). Classification methods for groups involved in crime therefore have greater policy implications when they can identify brokers, in addition to their implications for improving understanding of criminal group structure, behavior, and processes.

Law Enforcement Responses to Gang Activity

To design policies and strategies aimed at reducing violence perpetrated by gangs, law enforcement require information on gangs and their members. Agencies need this data to determine and assess the landscape of gangs in urban areas. The landscape further enables them to create gang units aimed at tracking and reducing gang activity (Braga, 2015; Decker, 2007), focus deterrence tactics on groups and individuals (Braga et al., 2013; Deuchar, 2013; Kennedy et al., 1997), and identify members who may be helped with social services or persuaded to leave the gang (Roman et al., 2017), among other strategies. Gang classification is therefore paramount to the operation of law enforcement, especially in large cities (Langton, 2010).

According to the National Gang Center, law enforcement agencies rank committing crimes together as the most important definitional characteristic of a gang, 15% above having a name, the second characteristic in importance (2012). In addition, the majority of law enforcement agencies use arrests with known gang members very often to designate gang membership, with displaying gang symbols and self-nomination being the other major criteria. Individuals identified by police databases as gang members have high agreement with individuals that self-report gang membership, though it's not 1:1 correspondence (Curry, 2000). Additionally, law enforcement likely do not capture the extent of the full gang network, with the National Youth Gang data showing that police may underestimate juvenile gang membership by 70% (Densley and Pyrooz, 2020; Pyrooz and Sweeten, 2015). Correctly identifying gang members still does not account for how law enforcement assigns individuals to particular gangs. Therefore, it is important to assess the gang database and how it performs compared to classification based on behavior and interactions, as well as understand how behavior relates to the designation of gang boundaries.

Gang boundaries are important for identifying strategic points of intervention, especially brokers between gangs and potential alliances. In addition, gang classification is partially, but not systematically, based on activities with previously classified gang members, though survey analysis shows that wearing gang paraphilia or colors is the tactic most used very often to identify gang members (National Gang Center, 2012). A more systematic approach taking into account both co-arrests and suspicious behavior can better capture not only the nature of the gangs, but also the brokers that are connectors between gangs and can be the key to law enforcement strategies to reduce violence and other crime.

In addition, current policing practices can be based on more subjective measures such as wearing gang colors (National Gang Center, 2012); in contrast, a systematic approach based on activity may have less unintended and intended detrimental effects, though it is still police-filtered due to the official data. There are collateral consequences for individuals identified in gang databases, which have been the source of many critiques from Amnesty International (2018). Consequences include greater chances of criminal convictions as well as legal sentencing enhancements in 34 states (Kennedy, 2009). Furthermore, designation as a gang member affects pretrial and prosecutorial outcomes, such as dismissal, informal supervision before adjudication, or deferred prosecution (Caudill et al., 2017; Howell, 2011). Any and all of these criminal justice system consequences of gang member designation affect the life course of the individuals, making more systematic and "correct" delineations of gang affiliation paramount to the operations of law enforcement. In this study, findings regarding the similarities and differences in arrest frequency and characteristics between police-defined and network-defined gangs will further highlight the potential consequences of designation as gang members. Arrests have real consequences for the individuals involved including risk of false conviction as well as implications for the broader society, as incorrect arrests may lead to more crime by actual perpetrators. Any contact with the criminal justice system creates the possibility for future contact, as stops increase chance of future surveillance, surveillance increases chance of arrest, arrest increases chance of conviction, and so on up the chain of the criminal justice system.

Empirical Approaches to Gang Boundaries and Classification

Network approaches to sociological studies have interlaced theoretical and methodological advantages. They can inform both the theory of the boundary specification of gangs and how to study it. They allow scholars to focus on the nature of the group, its relationships, and interactions between actors, rather than choosing between focusing on the actor or on the group as more traditional methods do. Specifying the boundary of a group, that is, defining its membership - who is in it and outside of it - is inherent to the study of social networks.

In their seminal work, Laumann, Marsden, and Prensky (1983) outlined two types of approaches to boundary specification; that is, defining the social border between who is inside and outside of a group. First, in the realist view, group boundaries are defined by taking the perspective of the actors in the network. Second, in the nominalist view, boundaries are defined according to the analyst's conceptual framework. The realist view assumes that individuals within the boundary understand where the boundary is, implicitly assuming there is a natural boundary or boundary definition (i.e. student of High School X). For gangs, though they may understand the extent of their geographical area, it is unlikely that all individuals within every group understand the extent of group membership or operations of the gang (Bouchard, 2020). Therefore, the nominalist view is best suited to the question of defining gang boundaries. In particular, community detection is the technique that addresses the boundary specification problem in social network analysis with various methods to arrive at a set of groups ("communities") within a network.

There are few studies that utilize community detection to define the boundaries of crime-related groups using various types of data. Community detection is a technique that identifies community structure;[2] that is, it divides a network into groups (Newman and Girvan, 2004). Kreager and colleagues identified delinquent friendship groups using friendship nominations from a survey of two grades in 27 schools (2011). Similarly, Schaefer and colleagues defined subgroups of prison inmates using "get along with" nominations, finding that the network structure resembled adolescent subgroups in schools (2017).

In addition, studies have used community detection algorithms to identify deviant subgroups within a criminal network, using official law enforcement data to deduce links between individuals (Calderoni et al., 2017; Lantz and Hutchison, 2015; Ouellet et al., 2019). Lantz and Hutchinson (2015) use data on co-convictions and suspected co-offenses to examine subgroups within a burglary network. Expanding beyond one type of crime, Ouellet and colleagues (2019) study group boundaries in criminal networks in Montreal, Canada using police records on gang members and associated individuals. They use co-arrestees, co-suspects, co-victims, and co-participants in police stops to define individuals linked to the sample of 261 gang

[2] Community structure is sometimes called clustering, but this can refer to a different property in social networks. I use the term community structure to avoid confusion, following Girvan and Newman (2002).

members. In the organized crime context, Calderoni and colleagues (2017) use police records on joint mafia meeting attendance to examine subgroups (approximating mafia families) within a mafia organization network in Calabria, Italy. Given that previous work often utilizes official data to arrive at subgroups within criminal networks, I also utilize law enforcement data in this study.

Data

The data for this research comes from three sources provided by the BPD for the January 1, 2007 to December 31, 2014 study period: (1) arrest records, (2) Field Interrogation and Observation (FIO) reports, and (3) the gang membership database.

Network Data

As will be discussed below, BPD arrest data were used to link individuals who were co-arrestees in specific crimes during the study period and to create individual prior arrest histories dating back through 1984. Arrest records included individual names, dates of birth, demographic information, arrest charges, arrest dates, and other information. Although police decision-making practices introduce bias to arrest data as a measure of potential offending activity (Black, 1970), social scientists commonly use arrest data as a proxy for offending. The demographic characteristics of offenders are usually unknown whereas the demographic characteristics of arrestees are easier to establish (Blumstein, 1995). Studies that have compared victim reports of the demographics of offenders with those of arrestees find the two tend to be closely related (Hindelang, 1978).

The use of co-arrest records as a proxy for co-offending more broadly carries some important caveats. First, arrest data captures only a small portion of the crime and victimization relative to self-reported measures, since only some crime and victimization is reported to the police and less still results in an arrest. Second, arrest records are generated by police and likely carry with them other biases generally associated with criminal justice system behavior (see Klinger, 1997). Furthermore, using network data in studies of crime has its challenges, such as data being limited to the subset of the network that has been officially recorded (for a review, Bright et al., 2021).

FIOs are records of non-criminal police encounters or observations made by the police; these reports include information such as: reason for the encounter, location, demographic information on FIO report subjects, and the names and dates of birth of all subjects. If an encounter initiated as an FIO leads to an arrest, no FIO will be recorded. While FIO reports are also subject to police decision-making bias, these data capture a broader range of social connections among individuals who are not arrested for the commission of a crime.

Throughout this study, I use the naming convention of "co-offending network" from network studies of police data to refer to the network of joint police contacts (co-arrests and co-FIOs). Regardless of culpability, the arrest and FIO data provide official records of relationships between individuals in the data. To be clear, this issue of culpability extends to all of the analyses—I make no judgments as to anyone's involvement in a crime. Rather, because my analysis is focused on the outcomes of different classifications of groups, I use both arrest and FIO data to determine empirically defined groups of individuals and their risk of later arrest. While arrests are not equivalent to involvement in crime, they are nonetheless substantial in their consequences both in the criminal justice system and beyond it. Therefore, arrests as an outcome measure invoke the important policy and theoretical implications that accompany contact with the criminal justice system.

Gang Membership

Gang membership was determined by matching the names and dates of birth of arrested individuals and FIO subjects to individuals in the gang member database. To be classified as a gang member, the BPD requires that a person accumulate a certain number of points based on a fixed set of criteria that includes self-admitted gang membership, gang memorabilia, participation in gang-related crimes, and other factors. Prior studies have found that police-reported data on gang activity and violence have consistent internal reliability, strong construct validity, and robust external validity (Decker and Pyrooz, 2010). Relative to police departments without gang units, police departments with gang units, such as the BPD, have been noted to generate more reliable and valid indicators of gang activity and violence (Katz, Webb, and Schaefer 2000).

Methods

Co-Offending Network

As describe in Chapter 1, BPD arrests (*N*= 121,047) and FIO reports from 2007 through 2014 (*N*= 346,767) were used to construct the co-offending network using methodologies developed in other similar studies (e.g., Papachristos et al., 2012). I projected the two-mode network of events and individuals into a one-mode network connected individuals directly. Therefore, given an arrest for the same crime, we assume that two people involved in the same incident had a co-offending relationship in the sense that they engaged in risky behavior together, and thus, there was a tie between them.

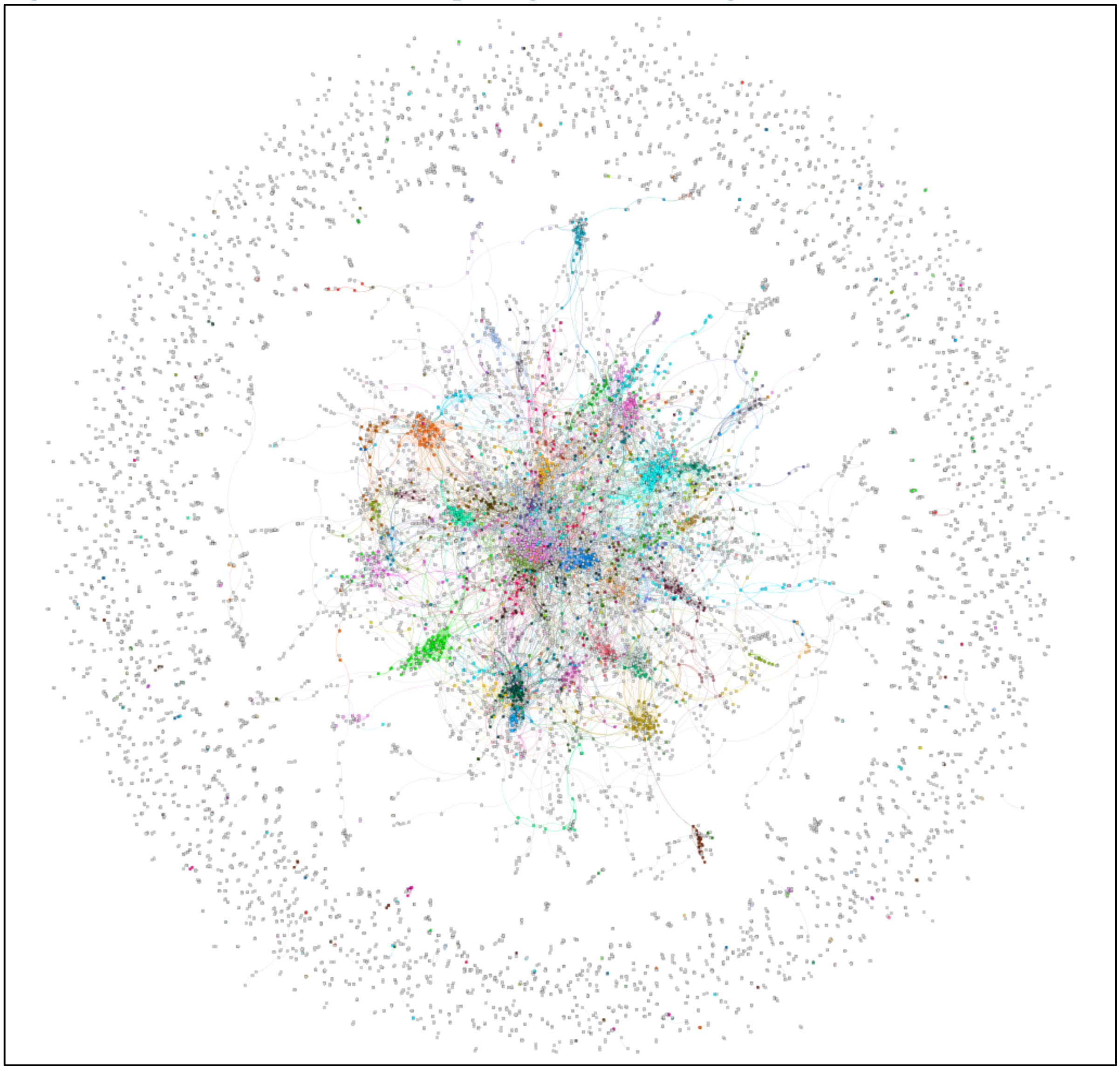
It is important to note here that we excluded ties, and corresponding individuals, that that fit three criteria: (1) from co-arrests for a mutually antagonistic crime (e.g. a bar fight where the arrested individuals were combatants); conservatively, we excluded arrests with a charge for affray, simple assault, or assault and battery; (2) from co-arrests and co-FIOs that involved more than 10 people, since I assume that there is a social relationship between all individuals involved in an event (Schaefer, 2012); (3) from co-arrests from 2013 and 2014, so that these can be subsequent measures of criminality. These exclusions resulted in a reduction in the network by 4.1 % (*N*= 6,253) individuals and 7.2 % (*N*= 11,560) ties. Ties between individuals were derived for all situations in which two or more individuals were observed or officially contacted in each other's presence by the police and recorded in FIO data—those two people observed by the police in the same time and place are taken to be "associates." We analyze the weighted network, meaning that we take into account whether two individuals are connected to one another through multiple events.

The group nature of delinquency and crime is a well-established pattern in criminology (Warr, 2002) and decades of qualitative research studies suggest that "hanging out"—standing on street corners while associating with one's friends—is an important social behavior among young urban males as well as a key mechanism driving street-level violence (Anderson, 1999; Warr, 2002). Since these data include only arrests, official contacts, and observations by the police, the data provide a conservative measure of one's social networks as individuals have more friends and associates than those with whom the police report contact.

In total, 141,078 unique individuals were involved in arrests from 2007-2014 and FIOs from 2007-2012, 50.7% of which were involved in arrest and FIO incidents with at least one other person. Of the 147,342 ties in the network, 9.6% (*N*= 14,180) were connections from arrests alone, 88.0% (*N*= 129,628) were connections from FIOs alone, and 2.4% (*N*= 3,534) were connections from both. These individuals comprised the 74,767 non-isolates in the whole network: i.e., individuals with at least 1 co-offending tie to another person. The non-isolate network comprised 11,231 components (subgraphs) ranging in size 2 (dyads) to 46,314 (the largest connected component), where individuals in the components are not connected to anyone outside of them.

My analysis was limited to the sub-network in which ties (edges) with weight greater than 1. Edge weight is a measure of the number of unique incidents in which two individuals co-participated. Therefore, a weight greater than 1 indicates that individuals participated in more than one event together. I limit the study to this sub-network as I assume that gangs are defined by multiple interactions over the study period, as would be expected for members of the same gang based on prior research (Charette and Papachristos, 2017). The sub-network contains 15.8% (*N* = 11,820) of all individuals in the non-isolate network. The sub-network is depicted in Figure 9, in which nodes are colored by gang, with gray indicated a non-gang member. In the figure, it is clear from the multiple clusters of nodes of various colors that gangs are concentrated in the most central part of the network, though still present throughout the periphery.

Figure 9: Network Visualization Depicting Ties with Weight > 1



Note: Node colors denote gang membership by gang, gray nodes denote no gang membership.

Network-Defined Criminal Groups

Most studies of subgroups within co-offending networks use subsets of law enforcement data to deduce the sample of individuals and their connections (Calderoni et al., 2017; Lantz and Hutchison, 2015). In their study of the relationships between cohesion and group survival, Ouellet and colleagues (2019) expand on this method slightly using a network version of snowball sampling to collect their data. Their sample used 261 police-identified Haitian gang members (“seeds”), identifying their contacts using police records on arrests, suspects, victims, and police stops. The second stage repeated the procedure to obtain the contacts of those contacts, resulting in a network version of snowball sampling. They thus unified the egocentric networks of the sample gang members, including associates and associates-of-associates. The community detection and subsequent analysis were conducted on the unique individuals who had at least one recorded affiliation to another individual. Though the design is effective for a subset of co-offending groups, it is not optimal for the purpose of finding all co-offending groups or gangs in an urban area as it limits the study to one part of the network. The design enables omitting any group and associated individuals that do not have a direct tie to this part of the network. Using police data on the whole network can give information about the groups throughout the jurisdiction, rather than one part of the gang network.

Furthermore, the methods in all of these studies utilize community detection algorithms that aim to find the optimal community structure. Using various algorithms such as Louvain (Blondel et al., 2008) and Girvan-Newman (Girvan and Newman, 2002), the studies classify nodes into groups with the goal of maximizing modularity, which measures the relative density of edges inside communities with respect to edges outside communities (Newman, 2006). In particular, the Louvain algorithm, which is used in three previous studies on groups (Calderoni et al., 2017; Ouellet et al., 2019; Schaefer et al., 2017), has a major advantage in its ability to scale well to larger networks. The algorithm is designed to divide the network fully into communities, rather than excluding non-isolated nodes that are not connected enough to any group. Small communities are found first by optimizing modularity for all nodes locally. Then, each small community is treated as a node and the first step is repeated until modularity is optimized

(Blondel et al., 2008). Therefore, some individuals who are on the periphery of one group, but do not have links to others, will be forced into the group though they may not be members.

In the Montreal study (Ouellet et al., 2019), it is possible that an associate-of-an-associated of a gang member is not associated with the gang. They may have had police contact (a stop) only once because of a family connection or unlucky timing, rather than a stronger link to the group. Therefore, these techniques do not aid in distinguishing gang members from non-gang members. They additionally force brokers to be in only one group, making their identification more difficult without network techniques. Based on Chapter 1 and previous research, it is clear that gangs may not be as cohesive as we think, with many ties between gangs being quite common. Therefore, a methodology that does not classify all nodes into groups, allows for better identification of brokers, and allows for relatively more ties between communities would be more appropriate.

The method used in this study is called link analysis, in which links between nodes are classified into groups rather than just the nodes themselves (Ahn et al., 2010). Identifying link communities using ties allows for the communities to overlap. Because of this, nodes can be classified in multiple, overlapping clusters, allowing for identification of brokers, unique individuals with membership in multiple clusters. In addition, the overlap is in line with the findings of Chapter 1, which shows that ties between gangs in Boston were half as likely as ties within gangs. On the other hand, the police-defined gang database does not allow for such identification of brokers using overlapping memberships.

In addition, the link analysis method does not require that all individuals be grouped into clusters, only those involved in the most similar links. The communities are also hierarchical, revealing subgroups and their larger group, which can reveal subgroups within gangs as well as alliances between gangs. Because using networks to define groups is driven by the behavior and interactions between the nodes and networks also allow for more porous boundaries, using link communities is a natural innovation to the study of groups in co-offending networks.

Link communities are clusters defined by organizing links (ties) into groups. In the link community procedure (Ahn et al., 2010), the similarity between links, e_{ik} and e_{jk}, that share a node, k, is calculated using the Jaccard coefficient:

$$S(e_{ik},e_{jk}) = |\mathrm{intersect}(n_{+}(i), n_{+}(j))|/\mathrm{union}(|n_{+}(i), n_{+}(j))|$$

where $n_{+}(i)$ refers to the first-order node neighborhood of node i, which includes node i itself (inclusive neighbor set). Once similarities are assigned to the links, they are hierarchically clustered using single-linkage clustering. The resulting dendrogram shows links occupying unique positions, while nodes may occupy multiple positions. It is cut at the partition density, a point that maximizes the density of links within the clusters normalizing against the minimum and maximum numbers of links possible in each cluster (Kalinka and Tomancak, 2011). I use R (version 4.0.3) with the packages *linkcomm* (Kalinka and Tomancak, 2011) and *igraph* (Csardi and Nepusz, 2006) to build the network and get the link communities.

Results

Link Communities

The network of analysis consists of 11,820 nodes, with 16,937 ties between them. The result of the link community analysis classified 4,916 of these nodes into 1,243 clusters.[3] Of these, 844 nodes (17%) were in more than one cluster, with nodes in up to 12 clusters. Clusters ranged from 3 to 48 members, with a mean of 5.2. The summary statistics describing the clusters and their makeup in terms of gang members and their gangs are shown in Table 14. The number of gang members per cluster ranges from 0 to 42, with a mean of 2.3 gang members. These gang members represent from 0 to 4 gangs per cluster (mean = 0.7). In terms of the percent of cluster members that are also gang members, the mean and median are 35.7% and 25.0%, respectively, with a range from 0% (no gang members) to 100% (all gang members).

Table 14: Summary Statistics for Clusters

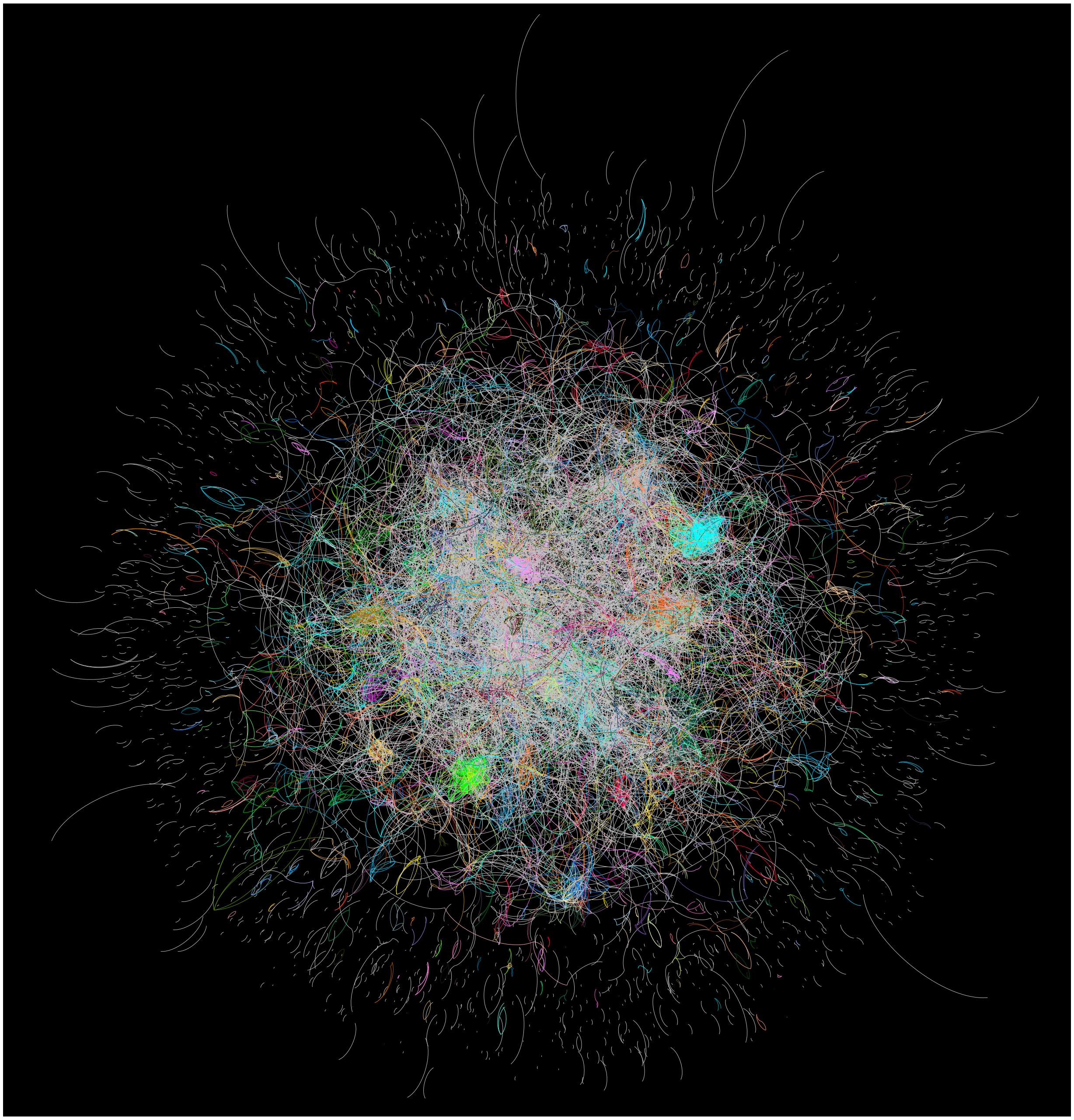
	Min	Median	Mean	Max
Cluster Size	3	4	5.2	48
Number of Gang Members	0	1	2.3	42
Percent of Cluster in a Gang	0%	25.0%	35.7%	100%
Number of Gangs Represented in Cluster	0	1	0.7	4

Figure 10 shows the same network as in Figure 9, though its ties are now colored by cluster, with light gray ties signifying links not attributed to any cluster. Concentrations of ties of the same color show the clusters and their relationships. As can be seen from the "hairball" figure, there are a great deal of ties even in the central, most connected part of the graph that are not in communities. In addition, the various clusters are connected throughout the network, not

[3] Link community analysis yielded 1,310 clusters, though 67 of these were nested in another community. These 67 sub-clusters had a maximum of 10 people, with the mean being 3.7; 84% had 4 or fewer members. Because of their tendency to be trivially small, they were subsumed into the cluster they were nested in, leaving 1,243 clusters.

just in its most connected parts. Though clusters are concentrated in the most connected part of the network, they are still present throughout its periphery. This structure mirrors the structure of gangs seen in the previous figure.

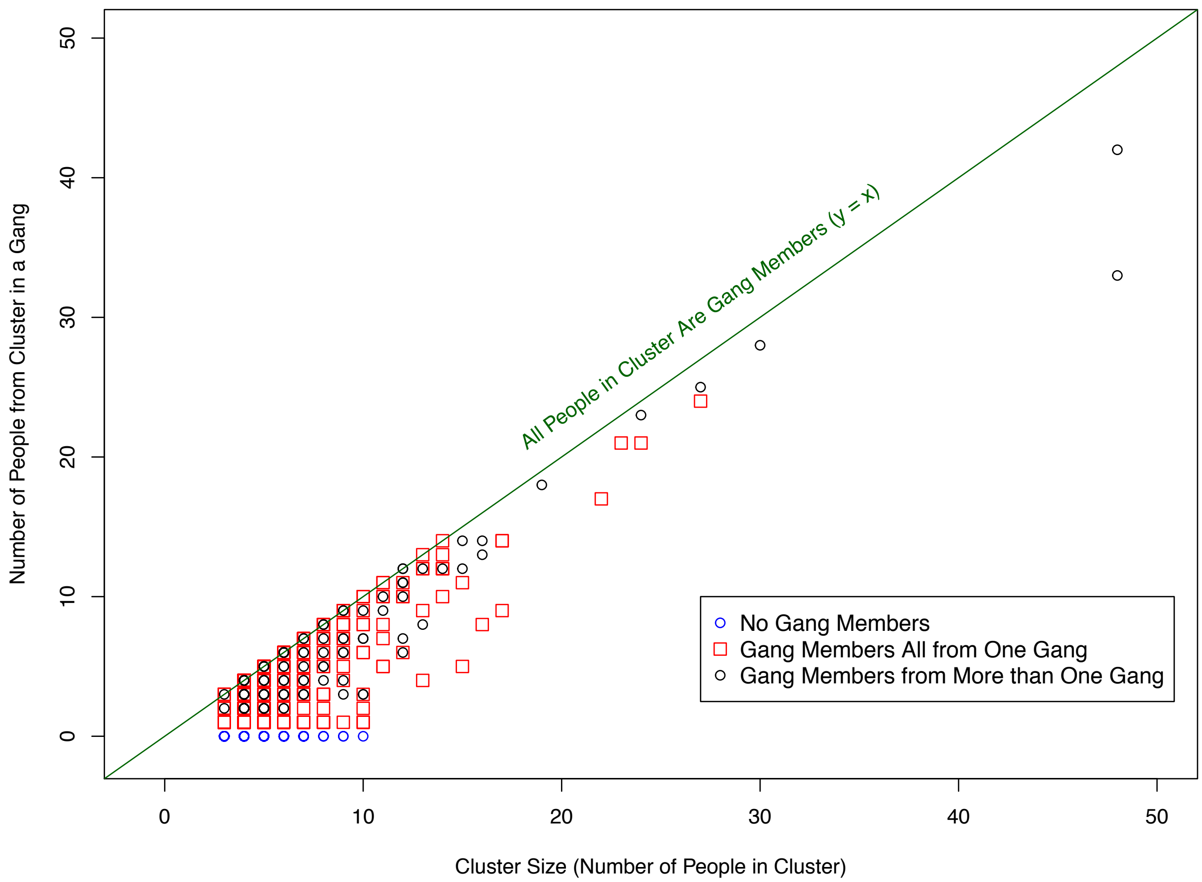
Figure 10: Link Communities within the Sub-Network



Note: Ties (links between nodes) are colored by cluster, with light gray ties signifying that a link is not attributed to any cluster. Concentrations of ties of the same color are the clusters from the link community analysis and their relations.

While it is visually clear that both cluster members and gang members are well embedded in the network, comparing the groups shows more nuance to the difference between empirically defined and police-defined criminal group classifications. First, I show how gang members situate in the clusters found using link community analysis. Figure 11 depicts the number of people in a cluster that are in a gang, by the cluster's size, with point shapes and colors indicating how many gangs are represented in each cluster.

Figure 11: Number of People from Cluster that Are in a Gang, by Cluster Size



Note: Blue circles indicate a cluster with no gang members. Black circles indicate a cluster with more than one gang represented by its members. Red squares indicate a cluster in which gang members are all from one gang. The green line shows cases in which all of the people in the cluster are gang members.

In the figure, the dark green line shows cases in which all of the people in the cluster are gang members ($y = x$). The clusters of sizes 3 through 10 have almost every value of gang members possible for each cluster size, shown by the almost complete triangle formed by the points in this range. Of the 9 largest clusters, the minimum percentage of members that are in a gang is 69%. While the smallest clusters (less than 10 members) run almost the full range of no gang members to all gang members, 33 of the 56 clusters with more than 10 people represent just one gang, as indicated by red squares, with their percentage gang members averaging 77.1%. As expected, as shown by the black circular points, the largest three clusters represent more than one gang, though clusters representing one gang and more than one gang are present throughout the rest of the range of cluster sizes.

Limiting to clusters that contain gang members from just one gang (though not necessarily made up of only gang members), I examine the number of clusters into which a gang is "split." That is, for each gang, how many clusters contain only members from that gang. This tells us more about how often clusters represent subgroups of a police-defined gang, without members of other gangs, and how many clusters comprise such gangs.

Table 15 shows the summary statistics for the number of clusters that contain members of one gang, limiting the sample to clusters whose gang members are all affiliated with the same gang. The mean number of clusters with gang members of a single gang is 5 clusters, meaning that the average gang is at least split into 5 subgroups, though it could also include individuals that are not in any gang. The maximum number of clusters is 35, which represent one of the largest gangs, with a total of 132 members in the gang database maintained by law enforcement.

Table 15: Summary Statistics for the Number of Clusters Representing One Gang

Minimum	Median	Mean	Maximum
1	3	5	35

In comparing gangs and clusters, it is important to understand their makeup. Therefore, for each gang and each cluster, I calculated group size as the number of members and average age as the average age of the members as of 2009, the midpoint of the network data period (2007-2012). I also report percent male and the number of arrests before 2007 (prior arrests) per member. In addition, I calculated a measure for diversity developed by Stanley Lieberson (1969) to surmise ethnic heterogeneity. The classifications for race were Black, Hispanic, White, and Other races. The index varies from 0 in cases where individuals are all of one race to 0.75 in cases where individuals are distributed across races evenly. Therefore, figures nearer 0.75 indicate greater diversity. The summary for these measures is in Table 16.

Overall, gangs from the gang database are much larger than clusters, with a range of 1 to 123 members and a mean of 24.84 members, compared to a range of 3 to 38 members and a mean of 5.17 members for clusters. Mean ages and ethnic diversity were much similar, with the means for gangs being 26 years old and 0.25 for ethnic diversity, and 28 years old and 0.21 for clusters. Both gangs and clusters average over 90% male, with gangs having 3.58 prior arrests per member and clusters have 2.56 prior arrests per member.

Table 16: Summary Statistics for Gang and Cluster Members (Mean, Median [Min, Max])

	Clusters	**Gangs**
Group Size	5.17, 4 [3, 38]	24.84, 18 [1, 123]
Mean Age (as of 2009)	23.27, 21 [11.25, 57]	19.35, 20.75 [13.47, 36]
Ethnic Heterogeneity	0.21, 0.18 [0, 0.67]	0.23, 0.20 [0, 0.67]
Percent Male	91.46%, 100% [0%, 100%]	98.43%, 100% [66.67%, 100%]
Number of Collective Prior Arrests per Member (Arrests before 2007)	2.56, 1.75 [0, 16.25]	3.58, 3.23 [0, 10.67]

Note: Cell values are as follows: Mean, Median [Minimum, Maximum]

Comparing Cluster and Gang Involvement in Arrests and Specialization

Given part of a gang's definition is its involvement in crime, it is important to assess how the two types of gang classifications compare in terms of arrest involvement. While arrests are not equivalent to involvement in crime, they do carry substantial consequences both in the criminal justice system and beyond it. Here, we measure individuals, incidents, and total arrests based on arrests records for 2013 and 2014, which were not used to make the network. We must compare these to individuals in the network (rather than individuals arrested in 2013-14) because the basis of gang databases is for better understanding of their activities and prediction of who will later be involved in an arrest. Individuals arrested in 2013-14 would have never been in the network and thus are not an appropriate comparison to the police-defined gangs and the network-defined clusters. Gang members were also limited to only those in the complete network (including isolates) to be conservative. In addition, I summarized members, incidents, and arrests. Because of co-offending, examining unique incidents does not account for the full scope of individuals and incidents involved. The total number of arrests better approximates a group's involvement in the criminal justice system.

In Table 17, the summary of arrest involvement is shown for gangs, cluster, and individuals in the full network. Because cluster members made up 13.8% of individuals arrests, while gang members made up 10.7%, to directly compare the percentages across groupings, the percentages related to gang arrests must be scaled. Therefore, "Gang (Percent in FN)" are multiplied by the ratio of percent members arrested in clusters to percent members arrested in gangs, that is 13.8%/10.7% = 1.29. For violent incidents, 17.1% is attributable to clusters, while 18.8% is attributable to gangs. Otherwise, gangs and clusters have great similarity with respect to proportions of incidents, total arrests, solo arrests, and co-arrests, though in all cases, the proportion is higher for clusters. Table 17 highlights that, though their composition may differ in terms of size, the involvement in arrests by group is similar enough to bring into question the utility of the police focus on gangs rather than on empirically defined groups.

Table 17: Summary of Arrest Involvement for Gangs, Clusters, and Full Network

	Clusters		Gangs		Full Network (FN)	
	N	Percent in FN	*N* (Percent in FN)	Adjusted to Cluster Percentage^	*N*	Percent in FN
Members Arrested	1,817	13.8%	1,449 (10.7%)	13.8%	13,572	100%
Incidents	3,205	16.7%	2,402 (12.6%)	16.2%	19,135	100%
Violent Incidents	1,090	17.1%	927 (14.6%)	18.8%	6360	100%
Total Arrests	3,435	16.0%	2,622 (12.2%)	15.8%	21,470	100%
Solo Arrests	2,533	15.1%	1,962 (11.7%)	15.1%	16,767	100%
Co-Arrests	902	19.2%	660 (14.0%)	18.1%	4,703	100%
Total Members	4,916	--	3,534	--	141,078	--

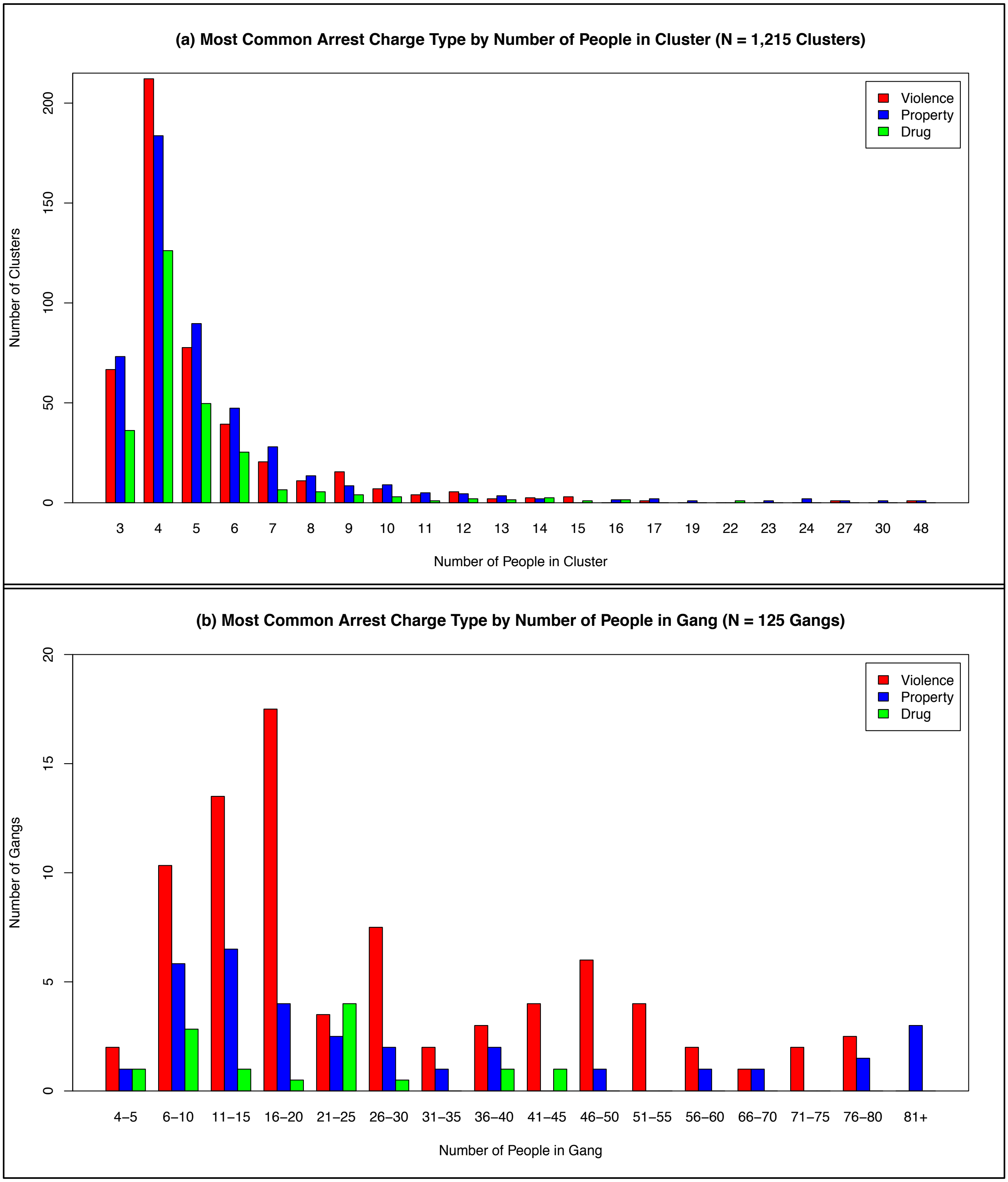
^To compare the percentages across groupings, the percentages related to gang arrests must be scaled. Therefore, "Gang (Percent in FN)" are multiplied by the ratio of percent members arrested in clusters to percent members arrested in gangs, that is 13.8%/10.7% = 1.29. Therefore, the columns in red are directly comparable.

The similarity may be due to behavior predicting later behavior. Because arrest and FIOs are used to construct the network, individuals are grouped together based on shared past behaviors, as recorded by law enforcement. Research has shown that continuing a co-offending relationship is most common for gang members (Charette and Papachristos, 2017), providing evidence for the co-arrest finding and a potential explanation for the rest of similarities. In addition, it is possible that past involvement in contacts with the criminal justice system increases police surveillance of particular individuals. These individuals would therefore be more likely to be arrested or otherwise recorded by law enforcement. This type of increased surveillance, however, also applies to gang members. Therefore, these results show important evidence that network-defined gangs do not significantly differ from police-defined gangs in terms of later arrest, save for violent incidents.

I also used data spanning the study period, 2007-2014, to better understand differences in specialization between clusters and gangs. The underlying data are the same for a sizable portion of both populations, given that 57% of individuals in clusters are also in gangs and 80% of gang members are in a cluster. However, individuals are distributed across gangs and clusters differently. Aggregating at the group level, I examined the most common arrest charge type committed both individually and together by each group (clusters and gangs). The three types of focus are non-robbery violence, robbery and property crime, and drug crime. I adjusted typical categorization of crime types, specifically excluding robbery from violence and adding it in with property crime, because non-robbery violence is the typical focus of studies of gangs, especially murder and other violent retaliation cycles between gangs that typically do not comprise of robbery (Kennedy et al., 1997; Papachristos, 2009).

Figure 12 shows the distribution of the most common arrest charge by group size for each (a) cluster and (b) gang, proportionally weighting any ties in the most common type so that each group contributes a total of one unit to the figure. That is, if a group were equally involved in non-robbery violence and property crime, they would contribute 0.5 units to each type. Figure 12a shows the most common crime type for clusters based on their size, showing that for all group sizes under 14, except for 4 and 9, property crime (including robbery) is the most common type of arrest charge, though violence is close behind. Drug crime is the least common at almost all cluster sizes.

Figure 12: Most Common Arrest Charge Type by Cluster and Gang

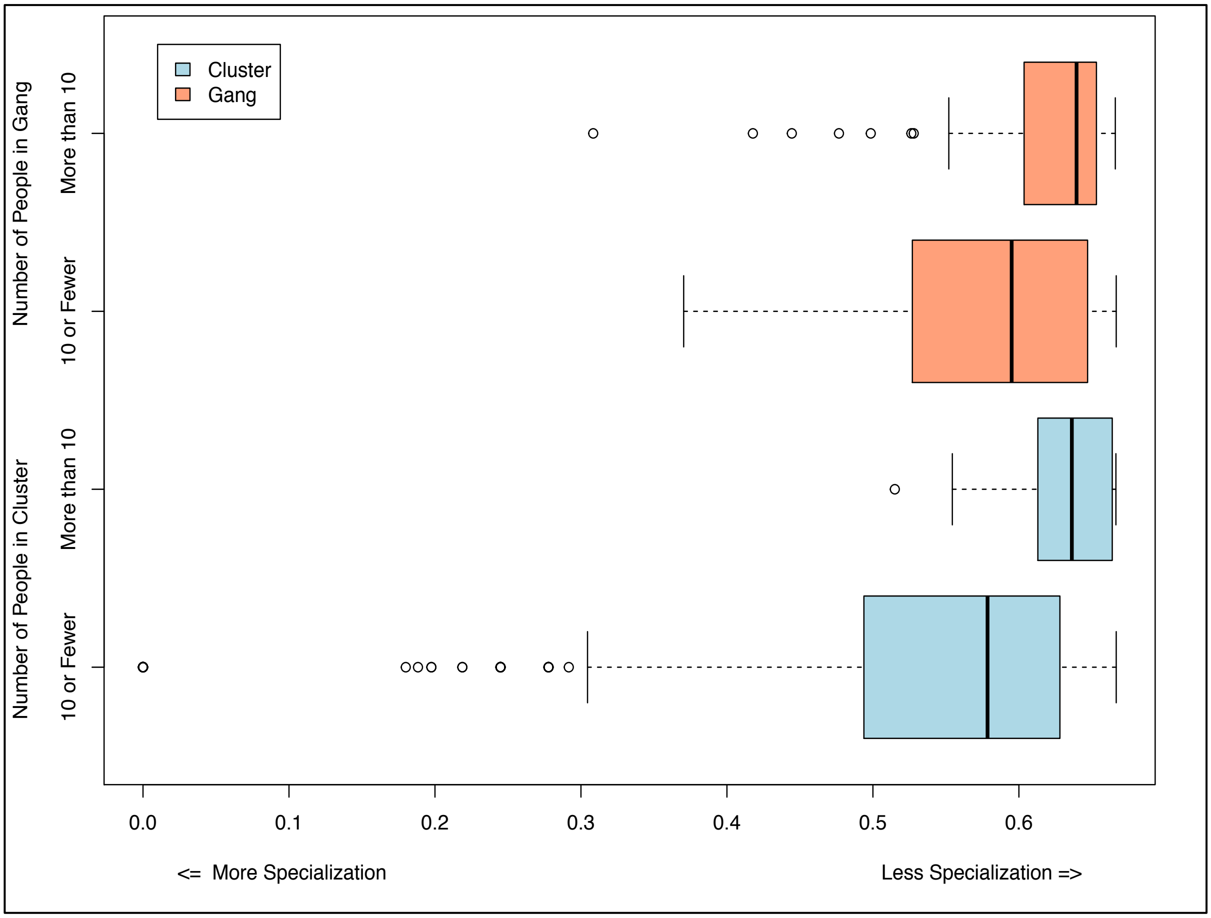


Note: The figure shows the distribution of the most common arrest charge by group size for each (a) cluster and (b) gang, proportionally weighting any ties in the most common type so that each group contributes a total of one unit to the figure.

For gangs, Figure 12b aggregates gang sizes in bins of 5, which shows that across all categories of gang size, except for gangs with 81 or more people, violence is the most common arrest charge type. These findings show that, while individuals in both clusters and gangs overlap, their configurations tend toward property crime and robbery for clusters, especially small ones, and toward violence for gangs, showing a key difference between clusters and gangs. Though they are similar involved in arrests, the groups are much different in size distribution, which is likely related to the differences in the types of charges by group.

Following previous research on specialized offending and co-offending, I calculated an index similar to that for ethnic heterogeneity to investigate specialization by group size, using the same three charge types for groups (Agresti and Agresti, 1978; McGloin and Piquero, 2010). Given that there are three groups of charge types, the maximum value is 0.67, which indicates minimum specialization and equal distribution of charges across categories ($1-(0.33^2 + 0.33^2 + 0.33^2) = 0.67$). More specialization is indicated by lower values of the index, with 0 indicating that a group has just one type of arrest charge. Figure 13 illustrates a boxplot of specialization by considering all arrest charges for individuals in each cluster, split into two groups by whether the number of people in the cluster is 10 or fewer. Given that clusters tend to be smaller in size than gangs, examining specialization by the cluster size may give better insight into the workings of smaller clusters. As shown in the figure, clusters with more than 10 people are much less likely to specialize, with a minimum of 0.52, a median of 0.64, and a maximum of 0.67. On the other hand, clusters with 10 or fewer people represent all levels of specialization, with a minimum value of 0, a median of 0.57 and a maximum of 0.67. Over 85% of these clusters have an index less than the minimum for larger clusters, indicating they are more likely to specialize.

Figure 13: Specialization by Group Type (Cluster or Gang)



Note: Clusters that were involved in 3 or less arrests are excluded, given that they do have the opportunity to be involved in at least one arrest type of each category and thus it cannot be determined whether they specialize.

On the other hand, Figure 13 shows that the minimum and maximum specialization value for gangs ranges from 0.31 to 0.67 across both group sizes, showing a tendency towards less specialization. The tendency for less specialization is more concentrated for larger gangs. The median for gangs with more than 10 members is 0.64 and for 10 or fewer members is 0.60. As compared to clusters of size 10 or less, clusters larger than 10 and both size categories of gangs are much less likely to specialize. Taking the most common arrest charges and specialization together, it is likely that the smallest clusters specialize in robbery and property crime, potentially representing robbery crews rather than gangs, though still involved in a similar amount of crime. On the other hand, both larger clusters and all gangs are less likely to specialize, though gangs are more involved in violence overall according to their arrest patterns.

Using link community analysis, which allows for communities to overlap, I can identify individuals that bridge clusters. Nodes in more than one cluster that are the only link between groups represent brokers in the network. In a typical social network, brokers are bridging ties between segments of the network, allowing for the flow of resources, be it information or other benefits (Burt, 2004). In a co-offending network, brokers similarly allow for information and other resources to flow through different parts of the network, though typically of the types that enables crime in some way (Descormiers and Morselli, 2011; Papachristos, 2006). To illustrate the importance of brokers to the network, I identify 142 brokers based on their unique position as the sole member connecting two clusters.

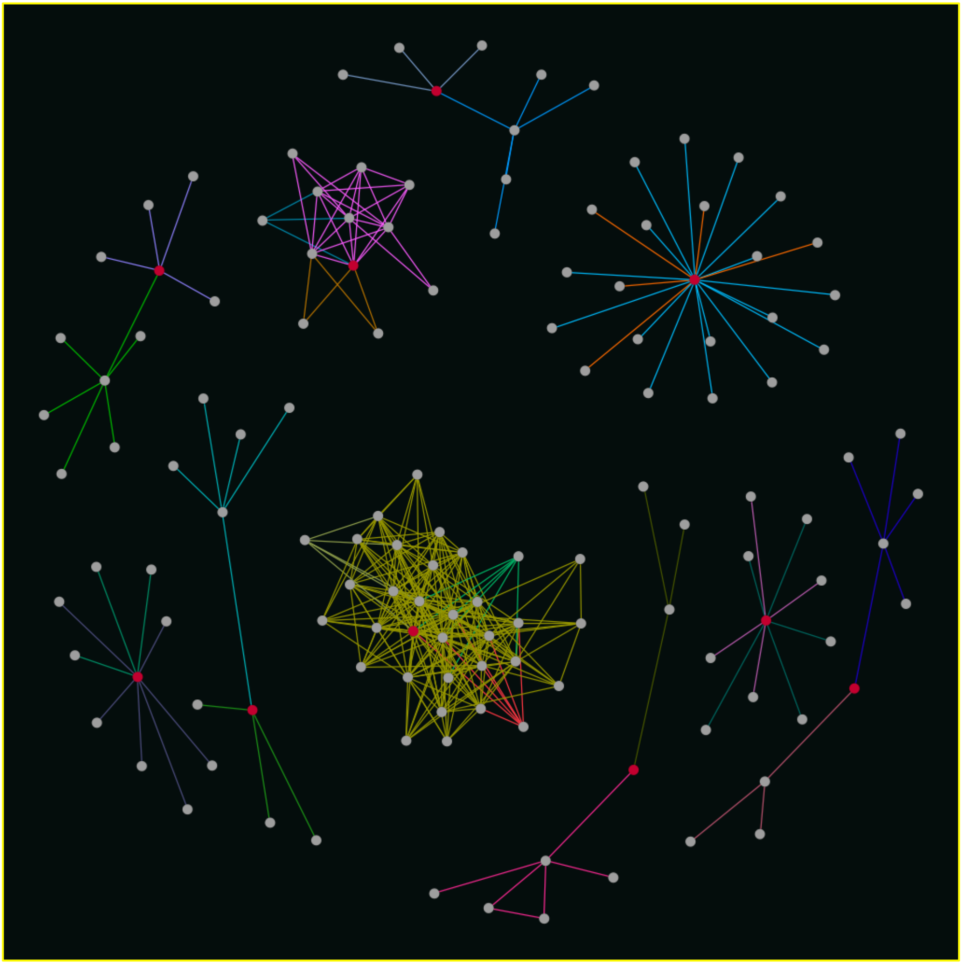
Table 18: Comparison between Brokers and Gang Members

	Brokers	**Gang Members**
Percent Arrested 2013-2014	58.5%**	44.4%
Mean Total Arrests	2.12*	1.81
Mean Solo Arrests	1.72*	1.35
Mean Co-Arrests	0.40	0.46
N	142	3,534

Note: Results of Two-Proportions Z-Test for the first row and t-tests for the remaining rows indicated by asterisks: Significance levels: *p<0.05, **p<0.01, ***p<0.001

Of the 142 brokers, 120 (84%) are gang members in 37 gangs. In Table 18, I compare brokers to gang members with regards to their involvement in arrests. While 44.4% of gang members were arrested in 2013-2014, over 58% of brokers were arrested in this time. There is a significant difference in the mean number of total arrests and solo arrests between brokers and gang members, with brokers' a greater mean for each types. There is no significant difference in the mean number of co-arrests.

Figure 14: Sub-Network of Clusters and Their Relationships



Note: The sub-network of a sample of 10 brokers (in red) and the clusters they belong to, including all ties between everyone in the clusters. Ties are colored by cluster, while all nodes that are not brokers are in gray.

Figure 14 shows the sub-network of a random sample of 10 brokers (in red) and the 23 clusters they belong to, including all ties between everyone in the clusters. Ties are colored by cluster, while all nodes that are not brokers are in gray. The figure highlights that brokers are the only connection that many clusters have to one another. Were they to be removed, most of the clusters in the figure would be cut off from another. Brokers are instrumental in being able to provide information quickly across groups, as well as in their involvement in crime. As connectors between groups, they are ideal targets of interventions from which to gather intelligence and otherwise reduce their potential impact on the network.

Discussion

This study uses a novel technique to the study of co-offending networks to define criminal groups empirically. Analyzing link communities rather than traditional community detection techniques allowed for the network to define the group boundaries, rather than official sources. Furthermore, link communities allowed for the identification of brokers, who are potential key points of contact for criminal justice intervention, including crime prevention strategies and intelligence gathering.

The results of the link community analysis yielded 4,916 nodes, while the gangs in the full network, including isolates, included 3,534 members. Given that previous research suggests that gang databases underestimate the true number of gang members (Pyrooz and Sweeten, 2015), these results are in line with the potential for a greater number of individuals to be classified as gang members. Furthermore, given the prevalence of between-gang ties in police-defined gangs as shown in Chapter 1, the range of cluster sizes from 3 to 48 members may be more appropriate for the true nature of gang-related activity in Boston.

Gangs and clusters as groups were quite similar with respect to their composition, including average age, sex composition, ethnic diversity, and arrest history, with their main difference being size. The benefit of using networks to define co-offending groups is that it focuses on behavior and is less likely to allow for discrimination based on demographics or other factors. Using networks to define gangs or gang-like groups is a more systematic approach that can better capture the nature of the gangs, given its basis in recorded behaviors. Current policing practices can be based on more subjective measures such as assessing whether individuals are wearing gang colors. A systematic approach based on activity may have less unintended and intended detrimental effects, though it is still police-filtered due to the official data. There are significant collateral consequences for individuals identified in gang databases, including criminal convictions, sentencing enhancements, and lower chances of favorable prosecutorial outcomes.

Furthermore, the utility of the results of the new technique is shown in how its clusters compared to police-defined gangs with respect to involvement in crime, measured by arrests. When comparing percentages of incidents and arrests for which cluster members and gang members were responsible, the only large difference lay in violent incidents. While violent incidents, calculated as the number of unique incidents involving a charge of violence, are perhaps the most likely measure to be impacted by gang activity, all other measures were similar between the two groups. In fact, perhaps the most important measure was total arrests. Because incidents often involve more than person, accounting for more of the total person-incidents (i.e., arrests), account for more of the crimes overall. If two people commit a crime together, it is really two crimes, one by each person. Each person has their own role in the incident and neither can be reduced to one role because it is possible that the crime would not have occurred if just one individual were involved. Therefore, on the most appropriate measures of arrests, the shares for which clusters and gangs were responsible were not significantly different.

A particular advantage to using network defined gang classification over law enforcement defined classification is the identification of brokers. As stated earlier, due to the capacity for overlapping clusters, link community analysis allows for identification of brokers as individuals with unique membership in multiple clusters; that is, brokers are the only cluster members that connect two clusters. Brokers are important both to the studies of sociology and criminology and to the practice of law enforcement. As seen in the illustrated sub-network in Figure 14, brokers are important bridges, through which resources, especially those that may enable future crimes, may flow throughout a criminal network. They connect not only groups of individuals involved in crime, but also enable connections between individuals within those groups. For these reasons, they are also potential people that can help to dismantle areas of criminal networks, cutting different segments off from one another, thereby reducing the pool of potential co-offenders.

Because contact with the criminal justice system is detrimental to both offenders and victims alike, classification of high-risk individuals is paramount, which is the goal of gang databases. Getting a better understanding of the shares of arrests attributable to individuals in criminal groups, network-defined and police-defined, allows us to evaluate the practice of classifying gang members, its methods, and its utility. In practice, results from this analysis will help law enforcement and academics better understand how both gang membership and the structure of co-offending affect individual behavior. Furthermore, this analysis shows the improvements made to the study of gang-involved crimes when combining official data from law enforcement with social network analysis.

Future research can compare the predictive power of clusters and gangs with respect to future involvement in crime and other measures of contact with the criminal justice system. Given the disadvantages of using police data to study gangs, ethnographic and other qualitative work on gang classification may give further support to using network-defined gangs that may improve the understanding of the gang landscape and network as well as aid in the identification of important cut points that provide opportunities for reducing crime and individuals' contact with the criminal justice system more generally. In addition, evaluations of interventions aimed at brokers in a network may provide additional evidence for the utility and importance of networks and their properties to the understanding of urban crime patterns.

CHAPTER 3[4]

The U.S. experiences more gun homicides than any other developed nation and was one of six countries that accounted for more than half of gun deaths worldwide between 1990 and 2016 (GBD 2016 Disease and Injury Incidence and Prevalence Collaborators, 2017). In 2017, there were nearly 11,000 gun homicide victims (Federal Bureau of Investigation, 2017) and some 456,700 victims of nonfatal firearm crime in the U.S. (Morgan and Truman, 2018). The consequences and risks of gun violence are not evenly distributed, however. Fatal and non-fatal shootings are highly concentrated in specific population groups and in particular places. At the population level, Black males between the ages of 18 and 24 are over 50 times more likely to be the victims of gun homicide relative to their white counterparts (Institute of Medicine and National Research Council, 2013), with one recent study suggesting that assaultive gun violence reduces the life expectancy of Black Americans by more than four years (Kalesan et al., 2019). Furthermore, gun homicides concentrate in disadvantaged minority neighborhoods (Peterson and Krivo, 2010), often clustering at specific street blocks characterized by housing projects, gang turf, drug markets, and other high-risk spatial contexts (Braga et al., 2010). Exposure to gun homicides in disadvantaged communities—even secondary exposure—further contributes to a host of other negative social and health outcomes, including increased levels of trauma (Buka et al., 2001), reduced cognitive and verbal ability among children (Kling et al., 2007; Sampson et

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[4] This article has been previously published. See end of footnote, as well as Bibliography, for citation. The major change to the published version of the article for this dissertation is the discussion of criminal social capital (throughout, especially in **Background** section).

Ciomek, A.M., Braga, A.A., Papachristos, A.V., 2020. The influence of firearms trafficking on gunshot injuries in a co-offending network. Social Science & Medicine 113114. https://doi.org/10.1016/j.socscimed.2020.113114 al., 2008), elevated stress (Miller et al., 2018) and impaired self-regulatory behavior among children (Sharkey et al., 2012).

Recent research has further shown that the greatest concentration of gun homicide and nonfatal shooting occurs within small networks of individuals who are usually well known to the criminal justice system (Cook et al., 2005; McGonigal et al., 1993) and often involved in gangs and other high-risk co-offending networks (Papachristos et al., 2012, 2015b). The rates of non-fatal and fatal shootings *within* such co-offending networks are considerably higher than city-level rates. In Chicago, for example, one study found that 70% of all gunshot injuries occurred in identifiable networks of individuals arrested in previous years. These networks comprised less than 6% of the city's total population, while the rate of gun homicide in the network was over nine-times higher than the city as a whole (Papachristos et al., 2015b).

Individuals with prior contact with the criminal justice system are by far the most likely to commit and be victims of gun involved violence (Braga, 2004). They represent one of few categories of U.S. citizen prohibited from owning firearms legally, due to exclusions such as felony convictions and juvenile status (Braga and Cook, 2016). These "prohibited persons" often rely on others – such as friends, family members, fellow gang members, drug dealers, and gun brokers – in their immediate social networks to acquire firearms (Cook et al., 2015; Hureau and Braga, 2018). In this way, individuals can employ their criminal social capital to gain access to an important resource, guns. These guns can be obtained through theft and a variety of illicit diversions from legal firearms commerce (Braga et al., 2002). Research on the workings of illegal gun markets suggest that many crime guns are acquired through off-the-books transactions in unregulated secondary markets (Cook et al., 1995; Hureau and Braga, 2018) and tend to migrate from states with lax gun controls to cities located in states with strong gun controls (Braga et al., 2012).

This study considers whether the sources of guns recovered from high-risk individuals differ relative to the sources of guns recovered more generally in a large U.S. city and how the availability of guns in co-offending networks increases individual risk of being shot. It builds on prior work on criminal social capital by expanding the understanding of resources beyond skills for the purpose of committing crime into a resource that can serve the purpose of both offending and protecting an individual from victimization. Following previous research in other cities, we begin by recreating the co-offending networks of all individuals in the City of Boston who were arrested or subjected to official police contact with at least one other individual between 2007 and 2014. We then identify individuals in the network who possessed a firearm that was recovered by the police and/or had prior involvement in a gun-involved crime. Our analysis first considers whether the kinds and sources of guns associated with the highest risk sector of the Boston network are different from other recovered guns. We next analyze whether an individual's risk of shooting victimization increases relative to their network proximity to a gun—especially, guns with indicators of illegal trafficking– net of individual and gang characteristics. Understanding the contours of such risky social networks and the availability of illegally trafficked firearms within them might help reduce fatal and non-fatal gun injuries by limiting access to high-risk individuals.

Background

A small set of individuals in the US is prohibited from owning firearms, including juveniles, individuals with documented mental health illnesses, and individuals with certain prior felony convictions. Many of these prohibited persons are actually at some of the highest levels of risk of gun violence victimization, especially individuals with certain types of previous criminal justice system contact (McGonigal et al., 1993, Cook et al., 2005). The risk of violent gunshot injury is much greater for individuals in co-offending networks. For example, individuals who were arrested with at least one other person (co-arrest) were over nine-times more likely to be a gunshot victim in Chicago (Papachristos et al., 2015b) and five-times more likely in Boston (Papachristos et al., 2012).

Individuals at extreme risk of fatal and non-fatal gunshot injury, and yet prohibited to legally purchase a firearm, tend to rely on underground gun markets (Cook et al., 2007). Two recent surveys of state and federal prison inmates show that the majority of respondents who possessed a gun – roughly 68% and 54%, respectively – acquired their guns through informal transactions, including social connections (friends and family) or through "street" sources (fences, drug dealers, illicit gun brokers, and gangs), who may also have direct or indirect connections to the respondent[5] (Cook et al., 2015). The individuals involved in informal transactions can be thought of as comprising the criminal social capital that prohibited individuals utilize in order to gain an important resource for both protection and offending, guns.

From Bourdieu to Coleman to Granovetter, social capital has developed as a concept with multiple definitions aimed at describing the advantage gained from social relations, either as an individual or as a group or community (Bourdieu, 1985; Coleman, 1988; Granovetter, 1973; Putnam, 2000). In particular, Granovetter emphasizes the importance of social networks, particularly weak ties, as an effective form of social capital in job searches and other contexts

[5] The study notes that the questionnaire does not include an item to determine whether "street" sources are strangers or not, allowing for the likely possibility that the "street" sources are in some way connected to the respondent.

(1973). Moving from the legal economy to the illegal economy, McCarthy and Hagan applied the construct to the criminal setting, introducing the term “criminal capital,” (1995) and later implying the need to delineate “the social and human dimensions of the [an individual’s] criminal capital” (2001, p. 1043). Further conceptualization has emphasized the multidimensionality of criminal capital and differentiated criminal social capital from criminal human capital, where more contacts and weak ties with individuals involved in crime increase potential criminal social capital and criminal knowledge, information, and skills increase criminal human capital (for a review, see Nguyen, 2020). Throughout prior work, criminal social capital has been operationalized in multiple ways, with a measure of the number of deviant alters, nodes directly tied to an individual, or the proportion of alters that are deviant being the most common (Loughran et al., 2013; McCarthy and Hagan, 2001; Morselli and Tremblay, 2004).

Applying the idea of criminal social capital to the study of gun access allows for a better understanding of the importance of an individual’s network to their outcomes. While typical studies of social capital examine outcomes ranging from the labor market to migration (Boxman et al., 1991; Garip, 2008; Granovetter, 1973), a more immediate need in the most vulnerable, high-risk networks is protection from victimization. Therefore, as prohibited persons find themselves unable to secure firearms legally for protection, they can activate their social capital to access firearms, utilizing both direct and indirect ties. Though the bulk of research on both social capital and criminal social capital focuses on economic outcomes, such as legal and illegal earnings, emphasizing the potential for protection from victimization through access to otherwise prohibited resources, like guns, expands on how social capital differs in the criminal context. Furthermore, understanding the unique characteristics of illegal firearms, an important resource that can be accessed through activating criminal social capital, can provide more insight into criminal networks, their perceived benefits, and potential areas of policy intervention.

Analyses of Bureau of Firearms, Alcohol, Tobacco, and Explosives (ATF) firearm trace data and firearms trafficking investigations provide the bulk of evidence on the illegal supply of firearms, and show that a meaningful share of recovered crime guns were recently diverted from the legal market (ATF, 2002; Braga et al., 2012). Recovered crime guns seem to move rapidly into the hands of criminal possessors through illegal diversions of new guns from retail outlets (Cook and Braga, 2001) and illegal diversions of older guns from retail outlets and private transfers in secondary firearms markets (Braga and Hureau, 2015). On average, about one third of crime guns used in a community are acquired in that same community, another third are obtained from elsewhere in the same state, and the last third are brought into that community from other states (ATF, 2002; Cook and Braga, 2001).

Taken together, the concentration of risk within small social networks of individuals and the prohibition of legally acquiring firearms generates a concentration of demand for firearms from illegal sources, which can be accessed through individuals' social capital resources. While there is prima facie evidence that firearms traffickers provide supply lines of illegal guns to high-risk offenders who, in turn, use these guns in violence (ATF, 2000; Hureau and Braga, 2018), these studies do not establish a direct link between gun trafficking and risk of violent gun injury. From a public health perspective, it is crucial to understand the population level risk factors of those most likely to be involved in violence, the contours of the networks through which risk might flow, and the point sources of risk within such networks and populations—in this case, illegally trafficked firearms. Furthermore, as studies have already shown the economic outcomes related to criminal social capital, it is perhaps even more important to understand the public health and social impacts of criminal social capital, especially when the advantage it affords is illegal firearm access.

The limitations of data on firearms have severely hindered the ability to analyze the citywide or even network-wide impact of illegally trafficked firearms on victimization. One of the few studies to do so found that gang membership increased access to illegal firearms within networks and also increased risk of gunshot victimization (Roberto et al., 2018). The present study extends this line of research by, first, expanding the analyses to cover a broader set of network connections and, second, by more finely analyzing the types of guns within networks and their possible disparate impact on victimization. The present study also advances our understanding of the potential role gun trafficking plays in driving urban violence by considering how the presence of firearms with indicators of illegal diversion in high-risk networks not only increases individual risk of violent gunshot injury for the possessor but also increases the risk of violent gunshot injury of associated individuals in the network through exposure.

Research Setting: Guns and Serious Gun Violence in Boston

Consistent with research on the social concentration of gun violence, gun violence in Boston is highly concentrated among a small number of high-risk people involved in gang or group conflicts (Braga et al., 2008). In a recent study of one disadvantaged Boston community, roughly 85 percent of all gunshot victims were in the community's co-offending network, which represented less than 5 percent of its population (Papachristos et al., 2012). In 2014, eighty percent of adult gun offenders arrested by the Boston Police Department (BPD) had prior criminal records, and, based on their criminal history data, illegal gun possessors were as involved in crime as those who were arrested for gun violence – murder, robbery, and assault (Braga and Cook, 2016).

Massachusetts has some of the strongest gun laws in the United States. In 2018, the Giffords Law Center to Prevent Gun Violence ranked Massachusetts gun laws as the fifth strongest among those in the 50 states. Given how difficult it is to purchase guns in Massachusetts, prohibited persons need to develop alternative pathways to acquire guns. A longitudinal study analyzing Boston firearm recoveries noted that the percentage of high-capacity semiautomatic pistols among recovered handguns increased dramatically between the 1980s and 1990s (Braga, 2017). Furthermore, a persistent share of traced handguns was imported from licensed dealers in I-95 southern states and an increasing share of traced handguns was purchased at licensed dealers in nearby New Hampshire and Maine (Braga, 2017). A recent study of gun acquisition by Boston gang members suggests that they acquire older handguns diverted by illicit gun runners who exploit unregulated secondary market transactions in states with weak gun controls (Hureau and Braga, 2018).

Data

The data for this research comes from five sources provided by the BPD for the January 1, 2007 to December 31, 2014 study period: (1) arrest records, (2) Field Interrogation and Observation (FIO) reports, (3) fatal and non-fatal shooting incidents, (4) the gang membership database, and (5) ATF firearms trace data.

Network and Control Data

As will be discussed below, BPD arrest data were used to link individuals who were co-offenders in specific crimes during the study period and to create individual prior arrest histories dating back through 1984. Arrest records included individual names, dates of birth, demographic information, arrest charges, arrest dates, and other information. Although police decision-making practices introduce bias to arrest data as a measure of offending activity (Black, 1970), social scientists commonly use arrest data as a proxy for offending. The demographic characteristics of offenders are usually unknown whereas the demographic characteristics of arrestees are easy to establish (Blumstein, 1995). Studies that have compared victim reports of the demographics of offenders with those of arrestees find the two tend to be closely related (Hindelang, 1978). The use of co-arrest records as a proxy for co-offending more broadly carries some important caveats. First, arrest data captures only a small portion of the crime and victimization relative to self-reported measures, since only some crime and victimization is reported to the police and less still results in an arrest. Second, arrest records are generated by police and likely carry with them other biases generally associated with criminal justice system behavior (see Klinger, 1997).

FIOs are records of non-criminal police encounters or observations made by the police; these reports include information such as: reason for the encounter, location, demographic information on FIO report subjects, and the names and dates of birth of all subjects. If an encounter initiated as an FIO leads to an arrest, no FIO will be recorded. Throughout this study, we use the naming convention of "co-offending network" from network studies of police data to refer to the network of joint police contacts (co-arrests and co-FIOs), even though FIOs and arrests are not equivalent to offenses. While FIO reports are also subject to police decision-making bias, these data capture a broader range of social connections among individuals who are not arrested for the commission of a crime. Regardless of culpability, those individuals in the FIO data might be at risk because of exposure to the risky behaviors that are proximate to gun use. To be clear, this issue of culpability extends to our entire analyses—we make no judgments as to anyone's involvement in an arrest, crime, or act of violence. Rather, because our analysis is focused on victimization, we use both sets of data simply to determine exposure to possible risky behaviors and gunshot victims.

Dependent and Independent Variable Data

Gunshot victimization was measured by linking individual identifiers to computerized records of BPD official reports of Homicide by Firearm and Assault and Battery by Means of a Deadly Weapon—Firearm (ABDW—Firearm) incidents during the 2007-2014 study period. In the Commonwealth of Massachusetts, ABDW—Firearm incidents represent shooting events in which guns were fired and victims were physically wounded by the fired bullets. Studies of wounds inflicted in gun assaults demonstrate considerable overlap between fatal and non-fatal attacks and suggest that the difference between life and death is just a matter of chance (e.g., Braga and Cook, 2018). Crime incident data suffer from the absence of crimes not reported by citizens to the police and by police decisions not to record all crimes reported by citizens (see Black, 1970). However, fatal and non-fatal shootings generally do not suffer from these biases due to the presence of the physical bodies in the case of fatalities and the required medical attention for assault survivors with gunshot wounds.

Gang membership was determined by matching the names and dates of birth of arrested individuals and FIO subjects to individuals in the gang member database. To be classified as a gang member, the BPD requires that a person accumulate a certain number of points based on a fixed set of criteria that includes self-admitted gang membership, gang memorabilia, participation in gang-related crimes, and other factors. Prior studies have found that police-reported data on gang activity and violence have consistent internal reliability, strong construct validity, and robust external validity (Decker and Pyrooz, 2010). Relative to police departments without gang units, police departments with gang units, such as the BPD, have been noted to generate more reliable and valid indicators of gang activity and violence (Katz et al., 2000).

Since 1991, the BPD has submitted all recovered firearms to ATF for tracing (Kennedy et al., 1996). This BPD firearm recovery data has information on the type, caliber / gauge, manufacturer, model, recovery circumstances, and possessor information for each firearm recovered. Firearms were considered low quality if their manufacturers were generally recognized as manufacturers of cheap firearms (see Braga and Hureau, 2015). We use the data on firearms recovered in 2007-2014, which also allow us to identify individuals associated with a recovered gun during the study period. Subsequent ATF firearm tracing determines the chain of commerce for a recovered gun from the point of import or manufacture to its first retail sale. Unfortunately, not all guns are able to be traced for various reasons, including that they were manufactured before the passage of the Gun Control Act of 1968, the trace request form was completed incorrectly, the serial number was obliterated, or the gun was reported stolen. Trace data also suffer from some well-known limitations (Cook and Braga, 2001). For instance, illegal gun trafficking cannot be confirmed through analysis of these data; rather illegal diversions from firearms commerce are inferred from indicators of suspicious sales and purchase patterns. Nevertheless, the National Academies' Committee to Improve Research Information and Data on Firearms (2005) found that the validity of conclusions drawn from firearm trace data research depends on the care taken in the application and analyses of these data.

Methods

Co-Offending Network

BPD arrests (*N*= 121,047) and FIO reports from 2007 through 2014 (*N*= 346,767) were used to construct the co-offending network using methodologies developed in other similar studies (e.g., Papachristos et al., 2012). We assumed, given an arrest for the same crime, that two people involved in the same incident had a co-offending relationship in the sense that they engaged in risky behavior together, and thus, there was a tie between them. It is important to note here that we excluded ties, and corresponding individuals, that resulted from co-arrests for a mutually antagonistic crime (e.g. a bar fight where the arrested individuals were combatants). Conservatively, we excluded arrests with a charge for affray, simple assault, or assault and battery. This resulted in a reduction in the network by 3.1% (*N*= 4,767) individuals and 0.8% (*N*= 1,310) ties. For the largest connected component, the reduction was by 1.0% (*N*= 499) individuals and 0.8% (*N*= 1,118) ties. Further, ties between individuals were derived for all situations in which two or more individuals were observed or officially contacted in each other's presence by the police and recorded in FIO data—those two people observed by the police in the same time and place are taken to be "associates." We analyze the weighted network, meaning that we take into account whether two individuals are connected to one another through multiple events.

The group nature of delinquency and crime is a well-established pattern in criminology (Cloward and Ohlin, 1960) and decades of qualitative research studies suggest that "hanging out"—standing on street corners while associating with one's friends—is an important social behavior among young urban males as well as a key mechanism driving street-level violence (Anderson, 1999; Warr, 2002). Since these data include only arrests, official contacts, and observations by the police, our data provide a conservative measure of one's social networks as individuals have more friends and associates than those with whom the police report contact.

In total, 146,800 unique individuals were involved in arrests and FIOs from 2007-2014, 52.6% of which were involved in arrest and FIO incidents with at least one other person. Of the 158,678 ties in the complete network, 12.2% (*N*= 19,354) were connections from arrests alone, 85.1% (*N*= 135,009) were connections from FIOs alone, and 2.7% (*N*= 4,315) were connections from both. These individuals comprised the 77,186 non-isolates in the whole network: i.e., individuals with at least 1 co-offending tie to another person. The non-isolate network comprised 11,231 components (subgraphs) ranging in size 2 (dyads) to 48,218 (the largest connected component). Our analysis was limited to the largest connected component (LCC), which contains 62.5% of all individuals in the network (see Appendix C). Following base network research, we limit our analysis to the LCC for three reasons: (1) because both victimization and guns are highly concentrated in the LCC, it is the highest-risk sector of the network: of the 1,332 shooting victims in the non-isolate network, 95.6% (*N*= 1,274) are located in the LCC, while 4.4% (*N*= 58) are located in all of the other components combined (in particular, victims are in components of only sizes 2 to 10) and, of the 2,018 guns in the non-isolate network, 92.6% are located in the LCC (*N*= 1,868); (2) network size plays a key role in the determination of network metrics, including the ones of theoretical relevance here, such as distance; and (3) because there is an undefined distance between network components, cross network metrics have distances of infinity or -infinity making analyses incomprehensible across networks.

The 48,218 unique individuals in the LCC accounted for only 7.3% of Boston's 661,103 residents in 2014 (U.S. Census Bureau, 2018). In total, 4,613 individuals in the network – 9.1% of the total LCC (*N*= 4,371) – were identified as members of a street gang. These gang-involved individuals belonged to 149 distinct street gangs. During the study period, Boston experienced 2,154 fatal and non-fatal gunshot injury victimizations, 61.8% (*N*= 1,332) of which were in the total network and 59.1% (*N*= 1,274) of which were in the LCC.

Measuring Firearm Access in the Co-Offending Network

Between 2007 and 2014, the BPD recovered 4,194 total firearms. We associated 2,412 (57.5%) of these recovered guns with specific individuals in the complete co-offending network. 44.5% of all recovered firearms (*N*= 1,868) and 80.9% of all individuals (*N*= 2,035) linked to a recovered gun were found in the LCC. Given that recovered guns do not represent the entire population of guns available to offenders in Boston, determining whether an individual was directly linked to a recovered gun is a conservative measure of firearm access in the co-offending network. Therefore, we also included a less conservative measure of firearm access based on an individual's prior gun arrest history. This measure assumes that an individual in the network at some point in his/her criminal career had access to a firearm to commit a crime and the source of this firearm could be exploited again if the individual or one of their associates needed access to a firearm. In our analyses, we used binary indicators to represent whether an individual had been arrested for a gun-related crime in the study period, and whether or not each individual in the network at any time possessed a crime gun.

Following previous work (Roberto et al., 2018), we used a network metric to measure firearm access for all individuals in the LCC. This metric summarizes an individual's potential for criminal social capital towards the goal of acquiring an important resource, a firearm. After assigning a binary indicator of firearm access to each individual in the LCC, we measured the distance between each individual and the nearest individual with firearm access. This distance was measured as the smallest number of ties between the individuals, also called the minimum geodesic distance. The shorter this distance, the closer an individual was to a gun. For example, a distance of three means that an individual was three co-offending ties away from the nearest gun. We use five measures of firearm access: the conservative distance to an individual who was associated with a gun recovered by the BPD, the inclusive distance to an individual who committed a gun crime in the past, the combined measure for distance to closest individual who either committed a past gun crime or was associated with a gun recovery, the distance to an individual associated with a gun recovery that has characteristics suggestive of illegal gun running (described further below), and the distance to an individual associated with a gun recovery that does not have such features. We measured an individual's distance to a gang member in the same manner.

Multivariate Logistic Regression Models

We used multivariate logistic regression models on the gun-level recovery data to test our hypotheses that guns recovered from individuals in the LCC have different characteristics than guns recovered from individuals not in the network. We also tested whether individuals in the LCC who are closer to guns are more likely to be shot than those who are further away from guns and whether individuals in the LCC who are closer to guns with indicators of illegal trafficking face an even greater risk of being shot relative to those who are not close to trafficked guns. In Models 1-3, we used the shortest distance to an individual linked to a recovered gun, an individual involved in a past gun crime, or either measure of gun presence in the network combined, respectively. In Models 4-5, we tested whether the shortest distance to a potentially *trafficked* handgun was related to the risk of gunshot victimization, controlling for shortest distance to a recovered gun and shortest distance to a non-trafficked traced gun, respectively.

Although transaction information in ATF data cannot definitively identify trafficked guns, we use three indicators that suggest suspicious sales and purchase patterns: out-of-state origins, the purchaser and possessor at the time of recovery were different people, and time-to-crime (a measure of the time between the first retail purchase of a firearm and its ultimate recovery by a law enforcement agency; ATF, 2002). We therefore defined a "trafficked" handgun as recovered with obliterated serial numbers (Kennedy et al., 1996) or having out-of-state origins, suspicious time-to-crime suggesting an unregulated transfer, and a possessor who was not the original retail purchaser. We focus on handguns as they are much more prevalent in the LCC and, relative to long guns, their concealability makes them much more likely to be carried by gun offenders on Boston streets. These "trafficked handguns" accounted for 58.5% (594 of 1,015) of the recovered traced handguns associated with LCC individuals.

Results

Network Summary Statistics

Table 19 provides summary statistics on the LCC and the total non-isolate network. In the LCC, the average number of ties per person (i.e. average degree) was 5.5, while the median was 3. The right-skewed degree distribution shows that most people have a small number of ties and few people have many ties, as is consistent with previous work on co-offending networks and social networks more generally (see, Appendix D). The average number of ties per person in the network was 4.1, with a median of 2.

Table 19: Summary Statistics of the LCC and Full Co-Offending Network

Characteristic	Largest Connected Component (LCC)	Full Co-Offending Network
Number of Individuals (Nodes / *N*)	48,218	77,186
Number of Ties	133,833	158,678
Degree (N of unique ties per node in network) Mean, Median [Min, Max]	5.5, 3 [1, 149]	4.1, 2 [1, 149]
Geodesic distance to nearest recovered gun Mean, Median [Min, Max]	2.4, 2 [0, 14]	---[a]
Geodesic distance to nearest past crime gun Mean, Median [Min, Max]	1.6, 1 [0, 10]	---[a]
Geodesic distance to nearest gun Mean, Median [Min, Max]	1.6, 1 [0, 10]	---[a]
Gunshot Victim	2.6%	1.7%
Connected to a Recovered Firearm	4.2%	2.9%
Arrested for a Past Gun Crime	13.3%	9.5%
Connected to Recovered or Past Crime Gun	13.8%	9.9%
Sex (Male)	76.1%	75.3%
Average Age (in years)	32.0 (SD=11.9)	32.3 (SD=12.0)
Race/ethnicity		
Black non-Hispanic	48.9%	41.8%
White non-Hispanic	22.5%	29.9%
Hispanic	19.2%	18.8%
Asian	1.0%	1.8%
Gang Member	9.1%	6.0%
Average Number of Prior Arrests	1.6 (SD=3.3)	1.2 (SD=2.9)

[a] Geodesic distances are not defined for the non-isolate network because there are individuals who have an infinite distance to a gun, since there is no possible path to a gun possessor. In the LCC, all individuals are connected so there is always a non-infinite path to an individual with a gun.

Recovered Firearm Summary Statistics

Table 20: Summary Statistics of Recovered Firearms, In and Not In Network

	Firearms in Complete Network (%), *N*= 2412	Firearms Not in Network (%), *N*= 1782
Firearm Type		
Pistol	62.3	48.6***
Revolver	28.3	25.3*
Rifle	3.9	12.5***
Shotgun	3.7	11.7***
Derringer	1.5	1.0
Other/Unknown	0.2	0.8**
Handgun Caliber Size (% of handguns)		
Small Caliber	28.7	24.0***
Medium Caliber	46.1	48.3
Large Caliber	24.5	26.7
Manufacturer Quality		
Low Quality ("Junk") Manufacturer	28.9	20.8***
Reputable Manufacturer	71.1	79.2***
Recovery Circumstance		
Illegal gun possession	69.8	53.4***
Found in public place	22.0	42.5***
Violent Crime	6.1	3.7***
Drug Offense/Other	2.2	0.4***
Trace Results		
Traced	58.7	53.8**
Not traced – Obliterated serial number	11.4	8.5**
Not traced - Pre-1968 manufacture	7.5	9.4*
Not traced – Issues with trace form	21.5	27.6***
Stolen	1.0	0.7*

Note: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$; Significance levels are based on a chi-squared test of the significance of the difference in group proportions.

Of the 4,194 firearms BPD recovered during the study period, roughly 57% (*N*= 2,412) could be associated with individuals in the network. The most common firearm types in and outside the complete network were pistols and revolvers (Table 20). Handguns were more common in the network while long guns were more common outside of the network. The calibers of network and non-network handguns were similarly split across categories, with about 26% being small (.22, .25, .32 caliber), 47% medium (.38, .380, 9mm), and 25% large (.357 magnum, .40, .44 magnum, .45). In both groups, over 70% of recovered guns were from reputable manufacturers rather than low quality manufacturers. The most common recovery circumstances involved illegal gun possession crimes and guns "found" in public places. In addition, over 53% of network and non-network guns were traced to a first retail purchaser. Some 2,373 guns overall were traced to a first retail purchase and 1,073 of these traced guns could be located to individuals in the LCC (45.2%).

Table 21: Summary Statistics of Traced Firearms, In and Not In LCC

	Firearms In LCC Traced (%), *N*= 1073	**Firearms Not in LCC Traced (%), *N*= 1300**
Source State		
Massachusetts	21.2	50.5***
New Hampshire or Maine	23.3	13.2***
I-95 Southern States	29.5	15.9***
Other States	25.9	20.3**
Purchaser and Possessor Identification		
Purchaser and Possessor are Different People	85.4	25.5***
Purchaser and Possessor is the Same Person	0.6	13.5***
Purchaser Identified, No Possessor	13.8	60.8***
Fast Time-to-crime (recovered within 3 years of first retail sale)	16.4	25.7***
Mean Time-to-crime (minimum, maximum)	13.9 years (3 days, 47.3 years)	13.5 years (3 days, 51.0 years)

Note: ***p < 0.001, **p < 0.01, *p <0.05; Significance levels are based on a chi-squared test of the significance of the difference in group proportions, except for mean time-to-crime, which is based on a t-test of the significance of the difference in group means

Moving on to *traced* guns in the network, Table 3 separates guns by whether they are in the highest-risk sector (LCC). As shown in Table 21, traced guns in the LCC were more likely to be imported from New Hampshire or Maine, I-95 Southern states, and other states relative to non-LCC traced guns. The vast majority of LCC guns had a different purchaser and possessor and tended to be older guns recovered more than three years after its original purchase.

Predicting Firearms Associated with Individuals in the LCC

The results in Table 22 show the probability that a recovered firearm is associated with an individual in the LCC based on its trace characteristics. LCC firearms were 2.3 times more likely to be handguns, relative to firearms not recovered in the LCC. In addition, recovered guns involving illegal possession circumstances have 60% higher odds of being in the LCC. The LCC and non-LCC traced firearms did not significantly differ in terms of time-to-crime.

LCC guns, however, were more likely to have changed ownership at least once before being recovered by the BPD. The odds of being recovered in the LCC were 51.9 times greater for guns with a different purchaser and possessor compared to other guns. The odds of a gun being in the LCC were also half as great for in-state guns.

Table 22: Multivariate Logistic Regression Comparing Traced Boston Firearms Recovered from LCC vs. Non-LCC Individuals

Predictor	Odds Ratio	Coefficient	SE
Handgun	2.336**	0.848	0.268
Illegal Gun Possession Recovery	1.598**	0.468	0.146
Violent Crime Recovery	1.481	0.392	0.361
Low quality Manufacturer	0.984	-0.016	0.155
Medium Caliber	0.943	-0.059	0.181
Large Caliber	0.889	-0.118	0.206
Fast Time-to-Crime (<3 years)	0.947	0.055	0.174
Purchaser and Possessor are Different People	51.883***	3.949	0.431
Massachusetts FFL	0.504***	-0.685	0.150
Constant	0.023	-3.788	0.500
Pseudo R^2	0.560		
Log-Likelihood	-719.498		
N	1,426		

Note: ***p < 0.001, **p < 0.01, *p <0.05; Individuals that did not have an identified purchaser and possessor are excluded from this analysis.

Predicting Gunshot Victimization

Using individual level data for persons in the LCC, we regressed the probability of gunshot victimization on the shortest distance to a firearm, using five different measures of distance as independent variables. Table 23 shows that, for an increase of one tie (or "handshake") in the distance between an individual and a recovered gun (Model 1), there was a 38% decrease in their odds of being a shooting victim net of other factors. When measuring the distance to a past crime or using both measures of gun presence in the LCC (Models 2 and 3, respectively), a one-unit increase in an individual's distance to a gun was associated with a 47% decrease in their odds of gunshot victimization, controlling for the other covariates. The presence of trafficked handguns was associated with an increased risk of gunshot injury for individuals in the LCC, controlling for individual characteristics and varying measures of distances to other kinds of guns. Model 4 shows that, controlling for the shortest distance to any recovered gun, an increase in the distance to a trafficked handgun by one additional tie is associated with about a 16% decrease in the odds of being a shooting victim. Based on Model 5, for an increase in the distance to a trafficked handgun by one tie, we expect to see about a 27% decrease in the odds of being a shooting victim, controlling for the distance to a non-trafficked gun. For a one-tie increase in the distance to a non-trafficked gun, we expect to see about a 21% decrease in the odds of victimization, considering the other covariates.

Table 23: Multivariate Logistic Regression Models Predicting Gunshot Victimization Using Geodesic Distance to Nearest Firearms [Odds Ratio; Coefficient, Standard Error]

	Dependent variable: Probability of Being a Gunshot Victim				
	Model 1	Model 2	Model 3	Model 4	Model 5
Geodesic distance to nearest recovered gun	0.625***			0.716***	
	-0.470, 0.040			-0.334, 0.058	
Geodesic distance to nearest past crime gun		0.532***			
		-0.632, 0.050			
Geodesic distance to nearest gun (recovered or crime)			0.526***		
			-0.642, 0.051		
Geodesic distance to nearest trafficked [a] handgun				0.838***	0.727***
				-0.177, 0.053	-0.319, 0.041
Geodesic distance to nearest other firearm (non-trafficked handgun)					0.790***
					-0.236, 0.040
Geodesic distance to nearest gang member	0.441***	0.449***	0.450***	0.452***	0.465***
	-0.819, 0.047	-0.802, 0.045	-0.799, 0.045	-0.794, 0.048	-0.766, 0.050
Black	3.471***	3.818***	3.792***	3.423***	3.448***
	1.244, 0.200	1.340, 0.200	1.333, 0.200	1.231, 0.200	1.238, 0.200
Hispanic	3.018***	3.234***	3.213***	2.996***	3.022***
	1.105, 0.206	1.174, 0.206	1.167, 0.206	1.097, 0.206	1.106, 0.206
Other race/ethnicity	1.610	1.610	1.595	1.640	1.687
	0.476, 0.546	0.476, 0.546	0.467, 0.546	0.495, 0.546	0.523, 0.546
Male	3.777***	3.664***	3.656***	3.771***	3.823***
	1.329, 0.168	1.299, 0.168	1.296, 0.168	1.327, 0.168	1.341, 0.168
Age [b]	0.968***	0.962***	0.963***	0.969***	0.969***
	-0.033, 0.005	-0.038, 0.005	-0.038, 0.005	-0.032, 0.005	-0.032, 0.005
Number of prior arrests	1.073***	1.056***	1.056***	1.074***	1.076***
	0.071, 0.007	0.055, 0.008	0.055, 0.008	0.072, 0.007	0.074, 0.007
Constant	0.014***	0.011***	0.011***	0.015***	0.018***
	-4.294, 0.266	-4.491, 0.263	-4.490, 0.263	-4.188, 0.268	-4.001, 0.272

Table 23 (Continued)

Pseudo R^2	0.238	0.240	0.240	0.239	0.240
Log Likelihood	-4,484.470	-4,473.917	-4,473.618	-4,478.582	-4,476.357
N	42,592	42,592	42,592	42,592	42,592

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$. Values are: Odds ratio; Coefficient, Standard Error.
[a] Trafficked handguns include obliterated handguns and handguns that have a different purchaser and possessor, an out-of-state FFL, and a slow time to crime (more than 3 years from purchase to recovery).
[b] Age is mean-centered across all models.

As a robustness check for our results, we accounted for dependence within the network using multiple membership (MM) models (Tranmer et al., 2014), defining clusters based on each individual's ego network (See Appendix E for full results). The MM models show that there is a significant negative relationship between social distance to a gun, regardless of gun type, and risk of gunshot victimization, controlling for distance to a gang member, demographics, and criminal history. The parameter estimates for the key independent variables and covariates in all five models are very similar to our findings in Table 23. Other limitations notwithstanding, the analysis incorporating network dependence aligns with our core results.

Discussion

Consistent with prior research, our findings suggest that gunshot risk varies with demographic factors and criminal history. Gunshot victimization was more likely when an individual is Black non-Hispanic or Hispanic, male, younger, and had a greater number of prior arrests. Some earlier work on network exposure focused on racially and ethnically homogenous samples because of their concentration of homicide risk factors, including poverty (Papachristos et al., 2012). Our study, like other more recent work, broadens the study to all individuals in the network because they shared key commonalities: they have previous contact with the criminal justice system and are highly connected to others like them and such network connections might be important for understanding risk and exposure. In addition, broadening the study to all individuals in the network gives a better understanding of the extent of criminal social capital and its relationship to victimization within the network.

The findings of Models 1-3 suggest that the closer individuals were to guns in their network, the more likely they were to suffer a fatal or non-fatal gunshot injury. For instance, the predicted probability of a 32-year-old Black male gang member with the average number of previous arrests (1.6) was 16.7% if he was linked to a recovered gun, 11.1% if he was one handshake away from (associate with) someone linked to a recovered gun, and 7.3% if he was two handshakes away from (associate-of-an-associate) someone linked to a recovered gun. Therefore, going from being an associate-of-an-associate to directly linked to a recovered gun more than doubled this individual's predicted probability of gunshot victimization.

In all of the models, gunshot victimization was more likely when the distance to the closest gang member was shorter—a finding consistent with previous research in Chicago (Papachristos et al., 2015b). Our models combine these findings to show that individuals close to both gang members *and* guns have increased risk of gunshot victimization. Prior research has found that increased embeddedness in gang networks decreases individuals' desistance from crime (Pyrooz et al., 2013) and increases their individual risk of gunshot injury even if they are not a gang member or directly connected to a gang member (Papachristos et al., 2015a). Our findings suggest increased embeddedness in co-offending networks populated by gang members and characterized by multiple gun recoveries increases individual risk of gunshot injury even if you are not a gang member or possess a gun. Thus, though individuals may benefit from greater potential for criminal social capital based on their embeddedness in the network by being closer to individuals with gun access, the increased criminal social capital is also the factor that increases their risk of victimization.

Our findings also suggest that closeness to guns that originate from illegal diversions from firearms commerce increases the risk of violent gun victimization in co-offending networks. Model 4 highlights the heightened risk of gunshot injury associated with the presence of trafficked handguns in a co-offending network. For a 32-year-old Black male gang member with the average number of previous arrests (1.59), assuming a trafficked gun is the closest gun in general, the predicted probability of gunshot victimization is 18.0% if he is linked to a trafficked handgun, 11.6% if he is one handshake away from (associate with) someone linked to a trafficked handgun, and 7.3% if he is two handshakes away from (associate-of-an-associate) someone linked to a trafficked handgun. Therefore, going from being an associate-of-an-associate to someone with a trafficked handgun to directly having a trafficked handgun more than doubled the predicted probability of gunshot victimization.

Limitations

Using police data to study firearm access and victimization has its limitations. Our data are subject to potential biases in the police reporting of crime. The literature has long recognized the potential for police data to reflect their own activity rather than true criminal activity (Black, 1970). In a sensitivity analysis in a study of co-offending networks in Chicago, Papachristos and Bastomski (2018) analyzed and compared co-offending data (such as those used here) against complaints filed against police on "false arrest" reports; the results suggested no consistent relationship between violence crime, co-arrests, and police bias at the neighborhood level. While this prior study was not directly related to individual risk of victimization within co-offending networks, it provides some evidence that police biases do not directly impact the core structure of the observed networks.

As discussed above, police data likely underestimate both the number of individuals in a network as well as the number of ties. While this is undoubtedly true, some evidence suggests this limitation does not undermine our core results. A recent study utilizing DNA to include "unknown offenders" in a network found that combining DNA and police data creates a larger network with a different structure, but that known offenders in the police data are just as central in both networks (De Moor et al., 2019). This work underscores the importance of relying on the LCC—which may not capture all, but likely captures more of the known universe of offenders—when studying co-offending. With the addition of the FIO data to arrest data in this study, we also have more information available concerning connections between individuals. Future work can utilize self-report and qualitative data on offending and co-offending to compare how well police data capture the true nature of co-offending networks. Given the potential of police bias to underreport some crime, and therefore exclude ties, our results are a conservative measure of the effect of network exposure to firearms.

We also do not have the complete criminal history data with prior convictions for the individuals who were associated with recovered crime guns. As such, we are not able to definitely establish that these individuals were indeed prohibited from possessing a firearm. As our data suggests (Table 21), 99.4% of the guns associated with individuals in the LCC were not the legal first purchasers of that firearm. Further, 59.6% (*N*= 28,717) were previously arrested by the BPD and 9.3% (*N*= 4,468) were prohibited from legally carrying a firearm on Boston streets because they were under 21 (the minimum age in Massachusetts to be issued a license to carry firearms). As described above, some 80% of Boston gun arrestees were prohibited from possessing guns (Braga and Cook, 2016). The same study reported that only 1% of Boston residents had licenses to carry handguns in public spaces and less than 4% of Boston households had handguns. As such, it seems very likely that a majority of the individuals in the LCC were likely to be prohibited from acquiring and/or carrying firearms.

In addition, because our results rely on police data on nonfatal and fatal gunshot injuries, it is possible that we are underestimating nonfatal injuries that went unreported, either because they do not always require medical attention or because medical facilities do not adequately report them to law enforcement; once again, our results are likely biased toward a conservative measure of the extent to which gunshot victimization is associated with firearm access.

Finally, our study is based on one city, Boston, which means it may not generalize to other cities. However, work on Chicago shows similar patterns of co-offending and firearm access (Roberto et al., 2018), which can bolster our confidence in potential generalizability because Boston and Chicago are quite different from one another, from their population size and land area to crime rates and nature of gangs. Future research should not only focus on other cities and types of areas, but also consider the causal processes that impact firearm access and its relationship to gunshot victimization. In addition, given the lack of data, our research utilizes only recovered guns, rather than all guns. Therefore, our results likely underestimate both the extent and the associational effect of firearm access on gunshot victimization. Future directions can include more qualitative studies on the illegal trafficking of guns, their relationship to high-risk networks, and their direct effects on the individuals in those networks.

Conclusion

Our results suggest that gun violence is indeed highly concentrated in cities, especially within networks of individuals with prior contact with the criminal justice system. Within this network—especially, the largest connected sub-network—gang members and younger minority males with prior criminal records were much more likely to be victims of gunshot injuries relative to individuals who were older, white, female, or without a prior criminal history. Our analyses suggest that the presence of any firearm in the LCC is associated with increased individual risk of gunshot victimization, but that illegally trafficked firearms presented an even greater risk. Individuals caught up in these high-risk networks, whether gang-involved or not, continue to acquire and possess guns. Boston is not a gun-rich environment and, as such, it is not easy for local prohibited persons to acquire firearms. Recent qualitative research suggests that gang members and drug dealers report paying inflated prices for handguns diverted by gun traffickers exploiting unregulated secondary market transactions, and that they pay significant price premiums for high-caliber semiautomatic pistols (Hureau and Braga, 2018).

Our research suggests that interventions aimed at curtailing illegal transfers of firearms could be used to reduce gun availability to criminals and decrease gun violence victimization. In turn, fewer guns on the street could *increase* the life expectancy of young Black men who are most likely to suffer serious injury and death from victimization by those who criminally misuse guns. Victimization is a key outcome that should continue to be considered in studies of criminal networks and social capital, adding an important health aspect to the typically economic study of the correlates and effects of criminal social capital. Reducing firearms trafficking could also reduce the trauma experienced by these individuals and other residents of disadvantaged neighborhoods that are particularly vulnerable to persistent gun violence problems.

The case for *a supply-side approach* to gun violence as suggested above is well supported by the empirical evidence on illegal gun market dynamics (Braga et al., 2012, 2002). Indeed, some research suggesting that specific supply lines of illegal guns can be shut down in Boston

(Braga and Pierce, 2005) and elsewhere (Webster et al., 2006). To date, however, little empirical evidence indicates such a supply-side approach reduces rates of gun violence. We believe that it is time to develop experimental evidence on whether interventions designed to limit illegal transfers of firearms can reduce gun violence. If properly focused on disrupting the pipelines of guns to the riskiest people in a particular jurisdiction, an effective supply-side intervention could possibly have a large impact on urban gun violence.

CONCLUSION

My dissertation provides evidence for the role of criminal social capital in gang dynamics and associated implications for gang boundaries, gun access, and the probability of victimization for and beyond gangs. Understanding Boston gang dynamics elucidates mechanisms involved in both violence reduction strategies and criminal group processes. The interconnectedness of gang members not only has clear consequences, such as increased risk of gunshot victimization, but also general impacts on involvement in crime.

Criminal social capital operates within, between, and beyond gangs, providing access to benefits at the individual level and group level, often through co-offending. In particular, gang membership imparts criminal social capital benefits for gang members, ranging from greater potential for alliances at the gang level to a larger network of potential co-offenders at the individual level. Both co-offending and gang membership are positively related to the benefits of criminal social capital (illegal earnings) (Augustyn et al., 2019; Rowan et al., 2018). Therefore, the positive relationships between criminal social capital, gang membership, co-offending highlight the interconnection between networks, gang membership, and crime.

Furthermore, research shows that gangs are not always as cohesive as expected and their activities affect more than just their own members. In fact, connections between gangs – in other words, gang networks – predict the social contagion of violence across a city. In Chapter 1, I find that, though fewer in number than the within-gang ties, there is great similarity in the proportion of ties by arrest charge type between and within gangs, suggesting that gang co-offending is similar in form within and between gangs. This finding, among others in previous work, begs further examination of gang boundaries.

Along with risk of contact with the criminal justice system, there are significant collateral consequences for individuals identified in gang databases, including criminal convictions, sentencing enhancements, and lower chances of favorable prosecutorial outcomes. For this reason, in Chapter 2, I use social network analysis to classify arrestees into criminal groups and compare them to official classifications of gangs to determine the utility of gang databases in identifying those most involved in crime. Given that cohesion is an assumed key characteristic of gangs and their groupness, I examine the implications of another form of criminal groups, those that are empirically identified, based on their involvement in arrests. I find that individuals in gangs and empirically defined clusters differ only in their involvement in violent arrests, not in total, solo, or co-arrests. This finding calls into question whether the negative effects associated with gang databases are worth the identification and tracking of "gang members." A systematic approach based on activity may have less unintended as well as intended detrimental effects.

As both Chapters 1 and 2 show, gang boundaries can be porous and individuals involved in crime are not limited to gang members. Prolific connections within, between, and beyond gangs allow for efficient and far-reaching information and resources, the most deadly of which is firearm access. Therefore, in Chapter 3, we examine the entire co-offending network of individuals with contact with the criminal justice system in Boston. Previous work on firearm access in a network was focused on only gang members, so this study further shows the strength of the relationship for all individuals in the co-offending network and is the first to look at markers of gun trafficking. Results suggest guns with markers of illegal diversion are more likely to be recovered in the highest risk sector of the network and that the probability of gunshot victimization increases with decreased distance to an individual linked to firearms with markers of illegal trafficking.

Policy Implications

Given these findings, this dissertation informs public policy on public safety and social welfare. Understanding gang member relationships and classifications of criminal groups has implications for crime prevention and the life course outcomes of members, including employment opportunities and mortality, because of the negative effects of contact with the criminal justice system. Furthermore, the analyses in this work show the improvements made to understanding gang and group-involved crimes when combining official data from law enforcement with social network analysis.

The first chapter elucidates the structure and characteristics of criminal social capital between and within gangs. The lessons from the chapter can impact how law enforcement and policymakers formulate strategies aimed at reducing crime, encouraging gang desistance, and improving social, health, and employment outcomes of those with contact or close to those with contact with the criminal justice system. They show that focusing on the social network, rather than particular gangs or sets of gangs, is important to understanding the structure, character, and frequencies of connections between and within gangs.

The second chapter gives evidence for the efficacy of empirical definitions of co-offending groups, which are similarly involved in arrests as compared to gangs, but do not have the same negative impact as gang databases and the gang member label. The benefit of using networks to define co-offending groups is that it focuses on behavior and is less likely to allow for discrimination based on demographics or other factors. Using networks to define gangs or gang-like groups is a more systematic approach that can better capture the nature of different patterns of offending and those involved in them, be there gang members or not. It provides an option to optimize the data the law enforcement have in order to focus on the most involved individuals, rather than just labeled gang members.

The third chapter not only highlights the importance of focusing on co-offending networks, rather than just gang members, but also gives evidence for the importance of examining and addressing markers of illegal firearm trafficking. While trafficking itself is a crime, the risk of gunshot victimization related to access to illegal firearms, especially those with markers of trafficking, makes gun control policies even more prudent. If properly focused on disrupting the pipelines of guns to the riskiest people in a particular jurisdiction, an effective supply-side intervention could possibly have a large impact on urban gun violence.

Limitations and Future Work

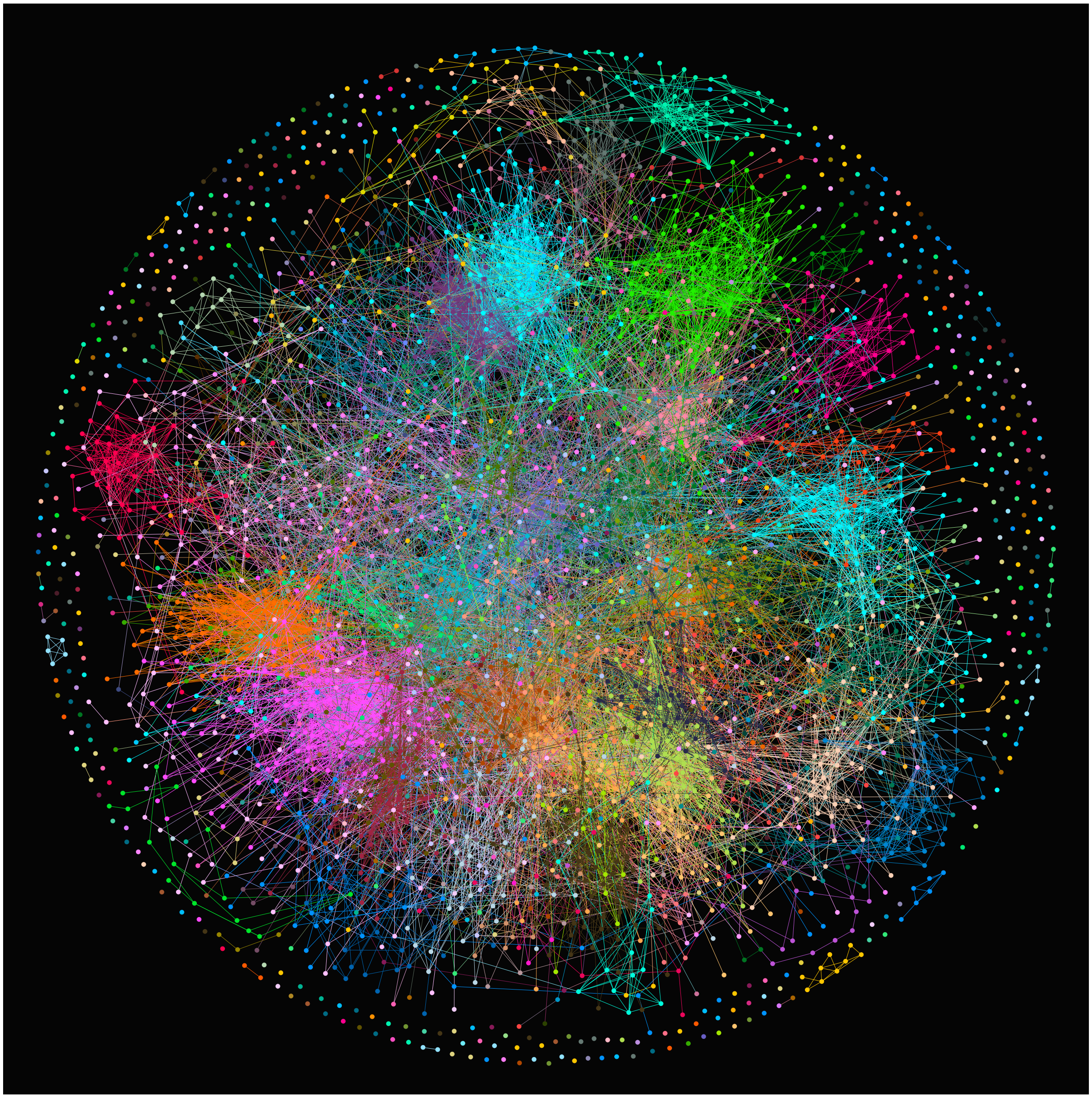
Throughout this study, I use administrative data, especially on arrests and FIOs. These data are limited to those events that are captured and recorded by law enforcement and are also subject to the bias of police discretion. In addition, throughout the dissertation, I assume a social relationship between the individuals involved in events together. This assumption may be reasonable given the burden of proof associated with arrests and that FIOs record instances in which individuals are physically proximate to one another, though it is worth further examination. A benefit of the data is that they provide information on as much of Boston's network as visible to law enforcement without requiring survey or qualitative methods, which can be difficult given the population. Regardless of culpability, the arrest and FIO data provide official records of relationships between individuals in the data.

Using the gang database to identify gang members also has its limits, in that biases are introduced from officer discretion to record an individual and throughout the criminal justice system. Previous research suggests that gang databases underestimate the true number of gang members (Pyrooz and Sweeten, 2015), which may be a result of a focus on those already identified. In addition, using network data in studies of crime has its challenges, such as data being limited to the subset of the network that has been officially recorded (for a review, Bright et al., 2021).

Future work can expand on this dissertation in a few ways. First, it is important to examine the gang-level factors that promote between-gang co-offending ties as potential explanatory variables for the findings in Chapter 1. Second, for all of the chapters in this dissertation, there is a potential issue of generalizability, even though Boston is typical of many cities in the U.S. Investigations of the social networks of individuals with contact with the criminal justice systems of other cities and rural areas will confirm and expand upon my findings on the relationships between gang members, definitions of criminal group boundaries, and consequences of increased criminal social capital, such as greater access to firearms, legal and illegal, and higher risk of gunshot victimization. Future research should not only focus on other cities and types of areas, but also consider the causal processes that impact firearm access and its relationship to gunshot victimization. Furthermore, work on the differences between official and empirical identification of criminal groups and their members can move forward by investigating different classification methods and using them to predict individual offending, providing supplementary understanding of gang classification and its meaning. The academic and practical contributions of this dissertation range from informing the study of group processes to providing support for the importance of preventing illegal gun trafficking, all of which add important knowledge and evidence to the study of gangs and criminal groups and its policy implications.

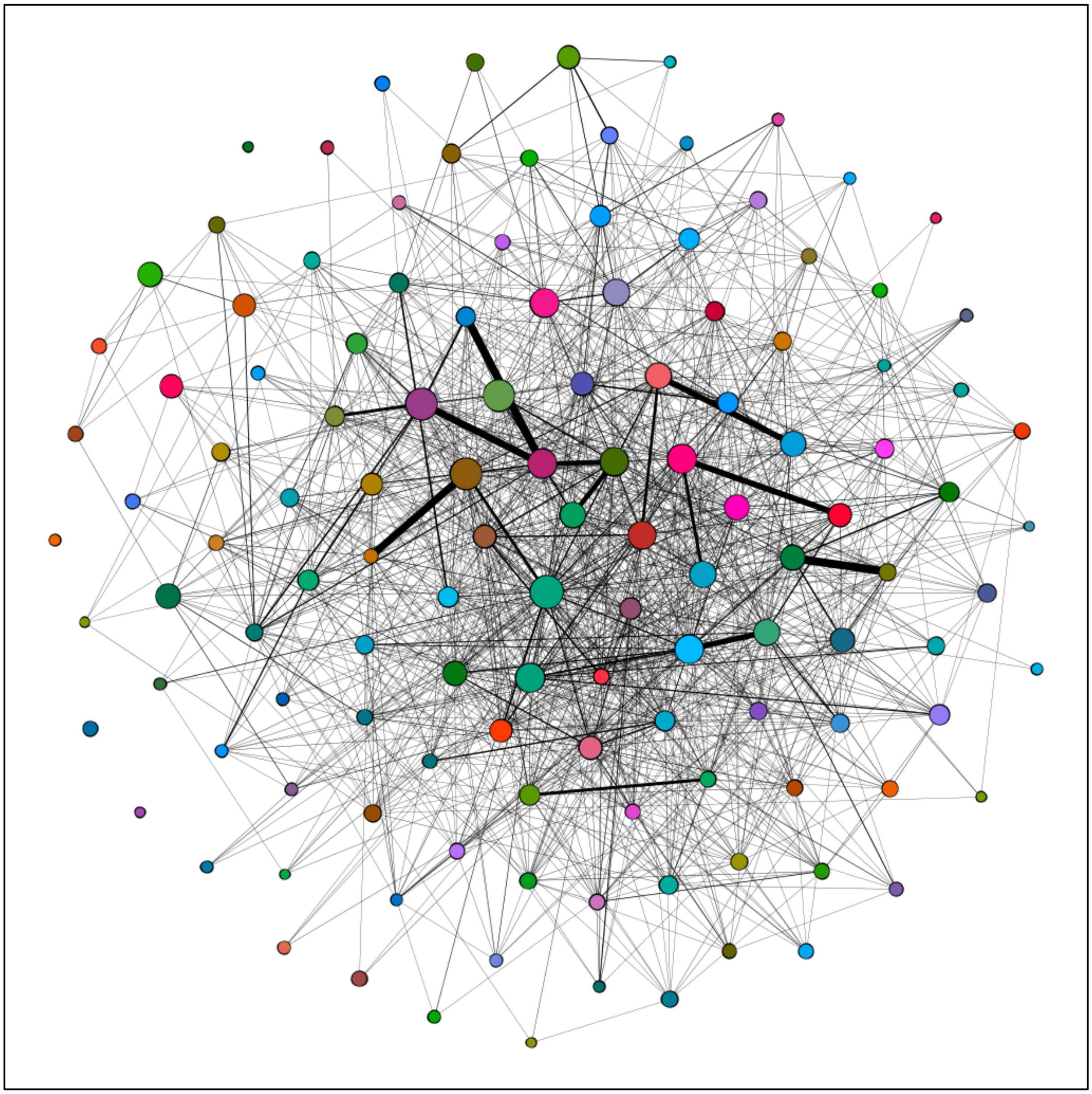
APPENDICES

Appendix A: Visualization of the Gang Network (Colors indicate gang membership)



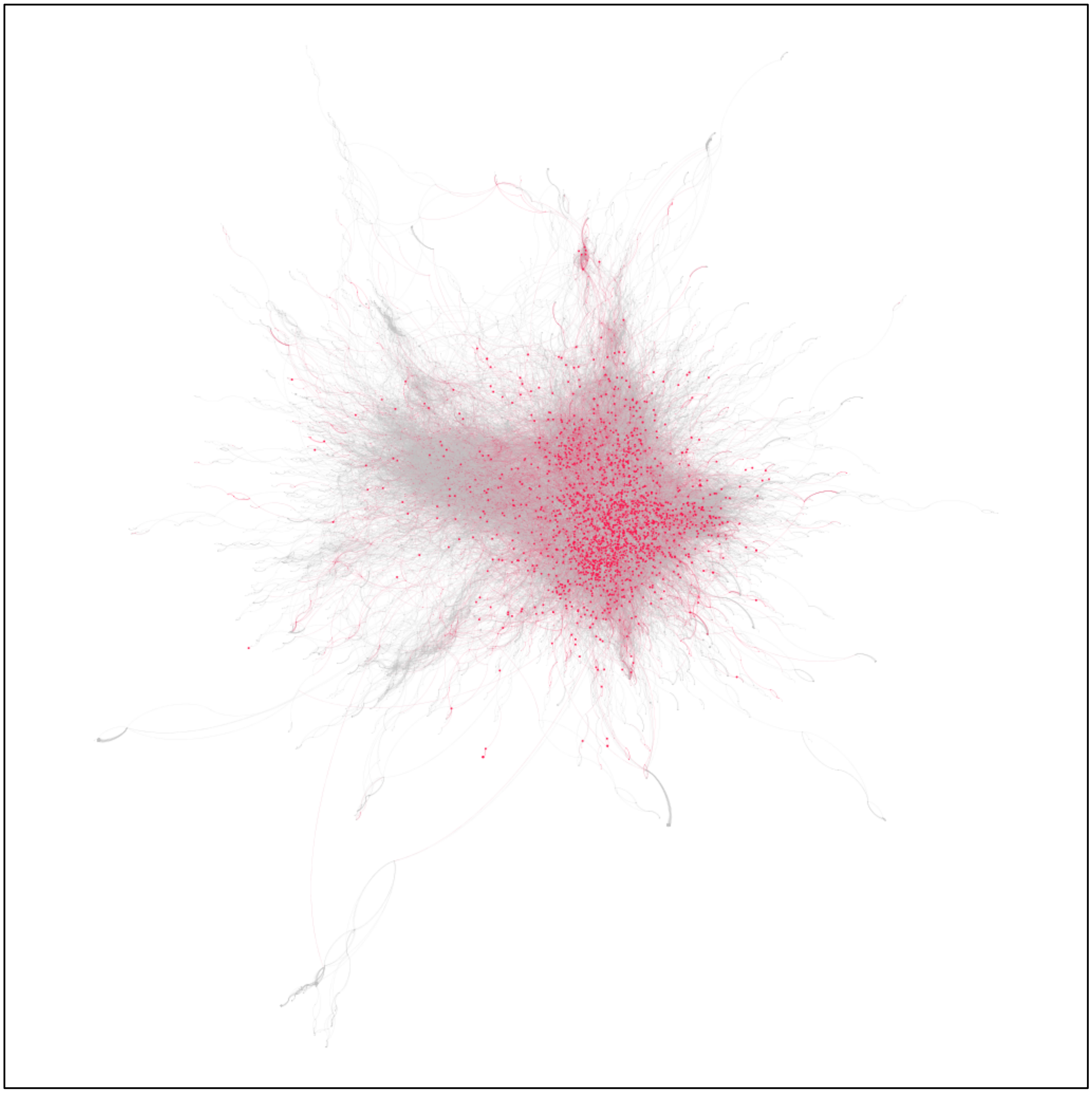
Note: Nodes are colored by gang.

Appendix B: Network Represented at the Gang Level with Nodes showing Gangs

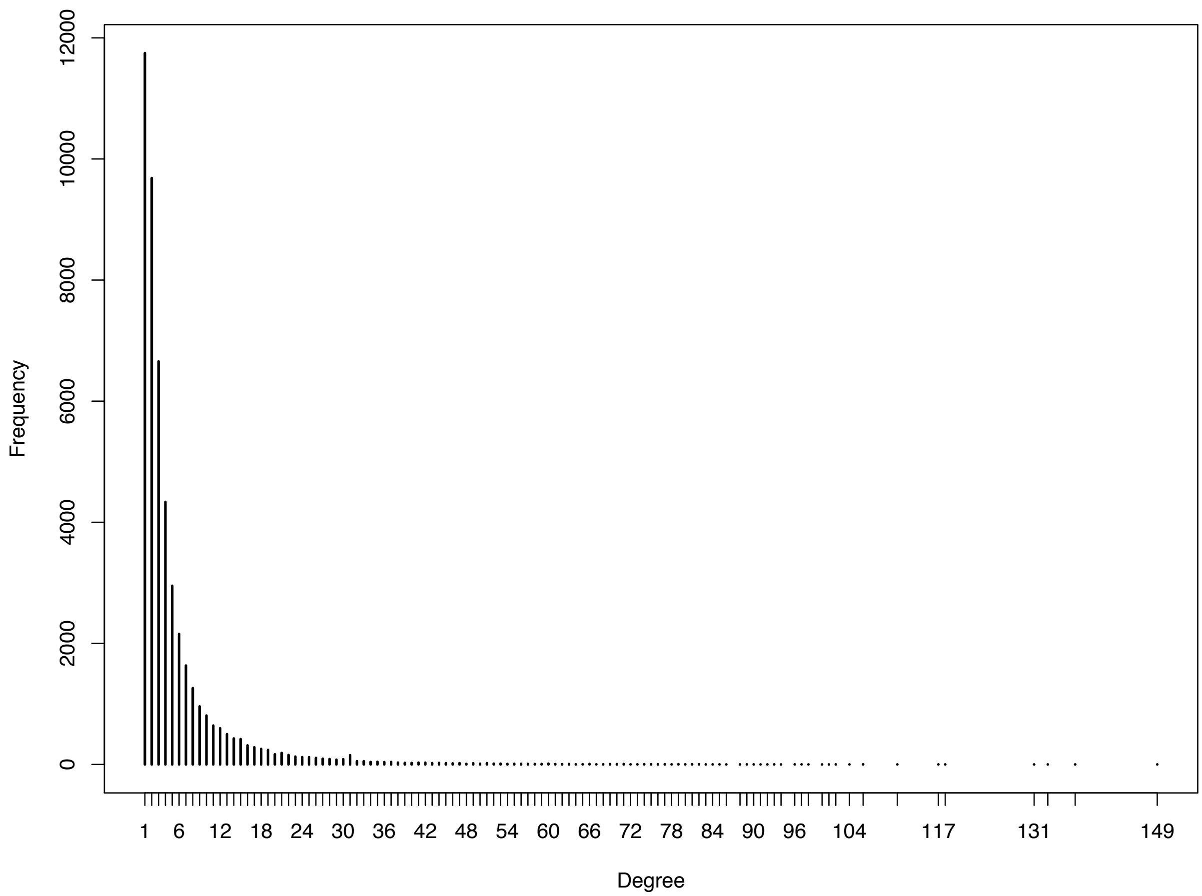


Note: Nodes are colored differently for each gang. Tie thickness is based on the number of between-gang ties each gang has with the gang to which it is connected. Node size is scaled by the number of within-gang ties the gang has.

Appendix C: LCC visualization, with individuals linked to guns in red (N = 48,218)



Appendix D: Degree Distribution within the LCC.



Appendix E: Multivariate Logistic Regression Models Predicting Gunshot Victimization Using Geodesic Distance to Nearest Firearms [Odds Ratio; Estimate, Standard Error]

	Dependent variable: Probability of Being a Gunshot Victim				
	Model 1	Model 2	Model 3	Model 4	Model 5
Geodesic distance to nearest recovered gun	0.624*			0.716*	
	-0.472, 0.040			-0.334, 0.058	
Geodesic distance to nearest past crime gun		0.530*			
		-0.634, 0.050			
Geodesic distance to nearest gun (recovered or crime)			0.525*		
			-0.644, 0.051		
Geodesic distance to nearest trafficked [a] handgun				0.836*	0.726*
				-0.179, 0.053	-0.320, 0.042
Geodesic distance to nearest other firearm (non-trafficked handgun)					0.789*
					-0.237, 0.040
Geodesic distance to nearest gang member	0.440*	0.448*	0.449*	0.451*	0.464*
	-0.820, 0.048	-0.803, 0.045	-0.800, 0.046	-0.795, 0.048	-0.768, 0.050
Black	3.514*	3.862*	3.844*	3.481*	3.497*
	1.257, 0.202	1.351, 0.200	1.346, 0.200	1.247, 0.202	1.252, 0.202
Hispanic	3.054*	3.269*	3.257*	3.044*	3.061*
	1.116, 0.208	1.185, 0.207	1.181, 0.207	1.113, 0.209	1.119, 0.209
Other race/ethnicity	1.433	1.426	1.426	1.479	1.515
	0.360, 0.575	0.355, 0.588	0.355, 0.576	0.391, 0.572	0.415, 0.572
Male	3.825*	3.704*	3.701*	3.821*	3.877*
	1.342, 0.170	1.309, 0.167	1.309, 0.168	1.341, 0.168	1.355, 0.168
Age [b]	0.968*	0.962*	0.962*	0.968*	0.969*
	-0.033, 0.005	-0.038, 0.005	-0.038, 0.005	-0.032, 0.005	-0.032, 0.005
Number of prior arrests	1.073*	1.056*	1.056*	1.074*	1.076*
	0.071, 0.007	0.055, 0.008	0.055, 0.008	0.072, 0.007	0.074, 0.007
Constant	0.013*	0.011*	0.011*	0.015*	0.018*
	-4.321, 0.268	-4.516, 0.262	-4.519, 0.265	-4.220, 0.269	-4.030, 0.270

Appendix E (Continued)

Bayesian R^2	0.084	0.084	0.084	0.085	0.085
WAIC	8988.4	8967.3	8966.6	8978.6	8974.2
N	42,592	42,592	42,592	42,592	42,592

Note: *The 95% confidence interval for the parameter estimates does not include 0. Values are: Odds ratio; Parameter Estimate, Standard Error.
[a] Trafficked handguns include obliterated handguns and handguns that have a different purchaser and possessor, an out-of-state FFL, and a slow time to crime (more than 3 years from purchase to recovery).
[b] Age is mean-centered across all models.

As seen in Appendix E, to account for network dependencies, five logistic multiple membership (MM) models were fitted (Tranmer et al., 2014), with the probability of shooting victimization as the dependent variable. We defined network clusters using each individual's ego network, which is the set of individuals (or "alters") that are directly connected to a particular individual ("ego"). The egos defined the clusters and their alters were the members of that cluster, allowing individuals to be members of multiple clusters if they were directly connected to multiple individuals (Tranmer and Lazega 2016). Therefore, because there are 42,592 individuals in our sample, there were 42,592 clusters with varying numbers of members. We weighted each member of a cluster proportional to the total number of members. All MM models presented in the table were estimated via a Markov chain Monte Carlo algorithm by using priors defined by *auto_prior* from the sjstats package (Lüdecke 2020) and a chain of 20,000 samples implemented using the brms package in R, accounting for multiple membership and accompanying weights (Bürkner 2017). The results of the models accounting for network dependence are substantively the same as those in Table 5.

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