ABSTRACT

Purpose – Criminal groups have long been central to explanations of crime and deviance. Yet, challenges in measuring their dynamic and transient nature meant that group-level explanations were often displaced in favor of individual-level ones. This chapter outlines how network methods provide a powerful tool for modeling the dynamic nature of criminal groups.

Approach – The chapter starts by providing a brief introduction to social network analysis, including key concepts and terminology. The chapter then focuses on the types of relational data available to study criminal groups, and how network methods can be used to delineate group boundaries. The chapter concludes by presenting a framework for understanding group dynamics from a network perspective, describing the contributions of network analysis to theories of group processes.

Findings – Network methods have provided meaningful advances to the study of group dynamics, leading scholars to revisit assumptions about the impact of group’ structure on delinquent behavior. Network studies of group dynamics have primarily focused on the cohesion–delinquency link (within-group structure) and the social contagion of conflict (between-group structure), highlighting important opportunities for the intersection of these two inquiries.

Value – Network methods provide a means to revisit and extend theories of crime and delinquency with a focus on social structure. The unique affinity between group dynamics and network methods highlights immense opportunities for expanding the knowledge of collective trajectories.
Keywords: Network methods; group dynamics; relational data; group boundaries; delinquency peer influence

INTRODUCTION

The wide array of criminal groups has been well documented by decades of research (e.g., Klein, 1971; Miller, 2001; Thrasher, 1927). There are groups that seize to exist beyond a single crime incident, and others that survive for decades. There are groups that maintain stable membership, and those that undergo high turnover. There are groups that engage in episodic delinquent activity, and those for which delinquency is a staple of their existence.

These variations create difficulties for defining, delimiting, and measuring criminal groups. Earlier explanations of criminal group processes often relied on extensive field research, spanning years of observations of group members and their interactions. This research has yielded important insights about group processes and delinquency, including the role of a group’s structural features in shaping group processes. Indeed, this was the basic premise of Short and Strodtbeck’s (1965) seminal piece on Chicago gangs. They observed that delinquent behavior was directly related to social processes that emerged in the day-to-day of gang members lives, including their interactions with one another and with other groups. Similarly, Block’s (1979) work on organized crime in mid-century New York City showed that criminal syndicates operated in “alliance networks” that structured around the groups ability to maximize profits and evade sanctions. Yet, despite many decades of research, group-level studies have been primarily descriptive in nature, creating important gaps in explanatory accounts of group dynamics.

The gaps in our knowledge are, in part, due to a lack of group-level data. Although group dynamics were once central to explanations of crime, advances in survey research during the 1970s shifted individual-based research to the forefront of criminology (e.g., Bursik, 1998; Kreager, Rulison, & Moody, 2011). The shift allowed for important methodological and theoretical developments, including the ability to generate representative samples, a major critique of early field research on criminal groups. However, it virtually displaced group-level explanations of crime – a phenomenon that was observed across the study of gangs (Pyrooz & Mitchell, 2015), criminal enterprises (Paoli, 2002), delinquent peer groups (Kreager et al., 2011), and terrorist organizations (Miller, 2012).

This chapter aims to outline how a network framework can be leveraged to address these gaps and foster explanatory research. Network methods are uniquely suited to measure the dynamic and transient nature of groups, mapping out social relations, delineating group structure, and allowing for cross-comparisons across groups. Network methods have led to meaningful advances in the structure of criminal operations; however, a large proportion of these studies have conventionally focused on the role that networks play in shaping individual
behavior (Carrington, 2011). This chapter aims to foster group-level research, by demonstrating how network methods can be used to move up the analytical ladder to examine variation in collective trajectories.

In this chapter, we start by providing a brief introduction to a network perspective, including key terminology and concepts. We then outline the various relational data sources that scholars have relied on to study group dynamics, and how network methods provide a set of methodological techniques for delineating group boundaries. Next, we present a framework for examining group dynamics, distinguishing between studies that focus on within-group and between-group social structures. We conclude by highlighting how these two areas intersect, and opportunities for moving the field forward.

A NETWORK PERSPECTIVE OF DELINQUENT GROUPS

Networks refer to the mathematical representations of the relationships that link different units within a system. These units – referred to as vertices – may represent entities across different levels of analysis, including individuals (e.g., gang members and youth), groups (e.g., gangs and peer groups), or larger collectives (e.g., gang task forces). The links – referred to as edges – represent relationships between the vertices. Edges may be operationalized as binary links – the presence or absence of a relationship (however defined) or can be built up to further characterize the relationship. For instance, edges may be directed, representing the flow of information or resources (e.g., A phones B, but B never phones A); valued, indicating the intensity or frequency of interaction (e.g., the number of times A phones B), and/or multiplex, representing the presence of multiple relationship types (e.g., A and B are both part of the same gang and siblings). Network methods provide a set of tools to identify and describe the structural properties of these networks, as well as a set of models and techniques to examine the sources and patterns of interactions in social relationships (Carrington, Scott, & Wasserman, 2005).

To start, the application of network methods to the study of delinquent groups requires distinguishing between complete-network data and ego-network data. Studies of criminal groups require complete-network data when the unit of analysis are individuals (e.g., gang members), providing a complete representation of all the actors and their links within the social system. Network analysis can then be used to assess the structural properties of a group, including the degree to which it is structured as a cohesive entity or centralized around a subset of highly connected members. In contrast, when the unit of analysis is groups (e.g., gangs), studies of criminal groups may rely on either complete-network data, the full set of relationships between all groups, or ego-network data, capturing the “local” connections around any one group. These relationships can be used to examine larger network structure, including the degree to which a group is embedded in a network of alliances and/or rivalries, and how interdependence between these groups influences social processes.
STUDIES rely on network methods to examine criminal group dynamics have acquired network data from various sources, including: (1) field observations, (2) police records, (3) archived materials, (4) self-reports, and (5) online data. Ideally, network data should reflect the full population of interest; however, who to include or exclude is often restricted by practical constraints – “who is in the data” rather than theoretical questions “who should be considered part of the network.” While some data sources may be more reliable, they may be less relevant, and conversely, while some data sources are relevant, they may be less reliable.

Some of the earliest applications of network analysis to criminal groups drew from field observations of gang members. For instance, the Boston Special Youth Project a study of juvenile delinquency founded in the 1950s by Water J. Miller, relied heavily on detached workers and their interactions with gangs and gang members to obtain relational data. Specifically, contact cards maintained by the workers detailing the nature of their interactions with gang members (e.g., name, date, location, and group), the author’s interactions with outreach workers, as well as the author’s personal interactions with gang members, and group meetings were used to address gang delinquency and restructure the activities of adolescence street gangs (see Miller, 1957, 1958, 1962). More recently, scholars have revisited the detailed field notes of early gang scholars to reconstruct the social structure of gangs and their members (See Papachristos, 2009). Relational data collected from field observations provide a valuable source of network data, affording in-depth coverage of the set and types of relationships between actors. However, data collection is labor-intensive and often restricted to a subset of groups, that are more readily accessible, creating concerns about the representativity of results.

More recent research has relied on relational data present in police records, including arrest and field incident reports. Arrest records afford information on two types of ties: (1) Offender-offender relationships, cases where more than one individual has been arrested for the same criminal incident and (2) offender–victim relationships, cases where the crime incident records both an alleged perpetrator(s), and the alleged victim(s). In contrast, field incident records provide information on non-criminal ties, cases where officers document the individuals they encounter in their daily routines (e.g., Hashimi & Bouchard, 2017). These non-criminal ties may overlap with criminal-ties found in arrest records, or present distinct relationships not previously recorded. Police records thus provide a two-mode data structure (ties to incidents), where individuals are linked based on their joint involvement in the same incident or behavior. Researchers can then rely on a one-mode projection (ties between individuals) of these incidents, connecting individuals through their co-involvement in the same event. Police records have been increasingly used to understand group dynamics to delineate the scope of organized crime groups (e.g., Hashimi, Bouchard, Morselli, & Ouellet, 2017), examine trends in group crime (e.g., Carrington, 2002; Lantz & Hutchison, 2015; Sarnecki, 2001), and conflict between groups (e.g., Papachristos, 2009; Hashimi & Bouchard, 2017).
Police records are impressive in their scope, creating networks of co-offenders, co-arrestees, and co-associates, on a scale that may not otherwise be available. But the breadth of the data comes at a cost to its depth and representativity. Official records are limited to the individuals for which there was available evidence, were present at the crime incident, and who were detected by police, thus imposing boundaries on groups that may be much more fluid and dynamic than they seem. Discrepancies in how agencies record and define crime incidents, departmental mandates, and variation in resources mean that some individuals (and their interactions) are more likely to be detected than others. Further, police records only tell us about behavioral ties, instances where individuals were observed (or alleged) to be engaging in the same type of behavior together. These networks only provide a subset of an individual’s larger network, and limits our considerations of individuals beyond those involved in the behavior and the larger group from which the behavior emerged.

Archived records, including court files, meeting minutes, and public inquiries, have also formed the foundation of many network studies. The sources of archived records are extensive. For instance, Crossley, Edwards, Harries, & Stevenson (2012) relied on the UK Home Office files, which detailed all individuals who were in court for suffragette-related incidents from 1906 to 1914. This allowed them to extract “co-offending” links between suffragettes who appeared in court together for the same incident. Others have relied on archived electronic surveillance records of illicit organizations, such as wiretaps, to map out the networks of their operations (e.g., Campana, 2011; Malm, Bichler, & Nash, 2011; Morselli, 2009). Electronic wiretaps provide valuable information on both the network of phone calls, but also the content of these calls, which allows researchers to understand the context of the relationships between callers (Campana, 2015; Campana & Varese, 2012; Baker and Faulkner, 1993). Similar to police sources, archived records provide valuable information, but are restricted to the individuals and interactions detected and then recorded into files.

Self-report data collected from surveys and interviews provide a valuable resource for researchers wanting to surmount limitations in official and archived sources. Surveys and interviews may be marshaled to collect network data by asking respondents to nominate or select their peers according to a pre-defined criterion. As part of the National Longitudinal Study of Adolescent to Adult Health (Add Health) in-school questionnaire, students were asked to nominate up to five male and five female friends from all students enrolled in the respondent’s school or their sister school (Harris et al., 2009). Importantly in 16 of the 145 schools (i.e., the “saturation” sample), all students were solicited to participate in the network component of the survey. From this sub-sample, the complete network of friendships within a high school may be analyzed through student nominations (see Gallupe & Gravel, 2018).

Surveys provide researchers with the flexibility to specify the number, type, and characterization of relationships. The control that researchers have over the data collection procedure is a major strength of this approach, especially when compared to police or archived records. Survey data of complete networks – where all members within a bounded population have been sampled – has been
used to study the social structure of peer friendship groups (Kreager et al., 2011), gang networks (Hughes, 2013), and inmate groups (Schaefer, Bouchard, Young, & Kreager, 2017). However, the use of survey data to study criminal groups is limited to the degree that all members of a bounded population can be sampled. Bounded populations may be more clearly defined in some samples, such as high school students, but more ambiguous in others, such as gangs where fluid boundaries preclude the existence of a roster or even be known to all members.

Further, network studies may rely on data collection tools already in the criminologist repertoire, such as snowball sampling of hidden populations (e.g., Decker, 1996). An extension of this technique, respondent-driven sampling, relies on patterns in repeated waves of recruitment to make statistical inferences about the full population under study, and help infer group boundaries (e.g., Heckathorn, 1997; Heckathorn & Cameron, 2017). In addition, the rise in social media provides additional sources for extending the pool of available data, by reaching populations that would be too difficult to study with traditional methods. Social media has already proven to be a valuable source to understand group dynamics with social networking platforms like Twitter (e.g., Patton, Lane, Leonard, MacBeth, & Smith Lee, 2017) and Facebook (e.g., Lane, 2019), along with email records (e.g., Palla, Barabási & Vicsek, 2007), mobile phone data (e.g., Eagle, Pentland, & Lazer, 2009; Morselli, 2009; Sugie, 2018) and other electronic tools such as the Global Positioning System (Schmidt, 2012), tracking and recording information on the ways in which groups interact and organize themselves in the “online” versus “offline” world. With this comes an unprecedented opportunity to adopt an interdisciplinary approach and employ computational techniques to mine network data. The impact of media communication and its capability to reach others by decreasing both social and spatial distance allows individuals to establish new forms of social ties and creates new forms of group structure (Castells, 2000).

The selection of a data source is the fundamental building block to design reliable and valid network studies, as it guides who will and will not be included in the network, along with the types of relationships to be considered. The various data collection strategies are not mutually exclusive, and there is ample evidence of scholars merging multiple sources (e.g., Malm et al., 2011; Stevenson & Crossley, 2014). Some works have been done to examine the validity of structural inferences across official records and self-reports (e.g., Ouellet & Bouchard, 2018; Sarnecki, 2001); however, these have focused on case studies, and more systematic efforts on the precise measurement biases, including how network data converges (or diverges) across sources is needed.

Additionally, an often-overlooked step is the time-varying nature of relations. To date, much research has focused on static networks, directing their attention to a single time snapshot or an aggregate view over time, yet networks are dynamic. Ties form, grow stronger and weaker, and eventually dissolve, with change being dependent on the characteristics of those that make up the network along with the structure of the network itself. As such, periods on which group-level data are sampled are essential. Data aggregated across extended periods may misconstrue
the true group structure at any one-time point. Klein and Crawford (1967) highlighted this point when discussing the scope of gangs, finding that some numbered over a few hundred when data were aggregated across multiple time points, but in reality, only consisted of 30–40 members at any single point in time. This is particularly important for network studies, where many metrics depend on the number of actors. Just like inaccuracies in network data can lead to fundamentally different representations of the same group, so can a singular snapshot at an arbitrary time point.

A NETWORK APPROACH TO DELINEATING GROUP BOUNDARIES

The available relational data provides cues for researchers looking to design network-based studies of criminal groups. While relational data may provide information on the relationships between individuals in the dataset, they are not necessarily telling of established boundaries amongst groups. We may know, for instance, the full set of interactions between students in a school, inmates in a prison, or offenders in a police district, but not much about the social groups that these actors belong to. Network methods provide a unique approach to resolve this issue, offering a set of methodological techniques to partition network data into groups according to patterns of social relations. Techniques such as block modeling, hierarchical clustering, and community detection have largely been applied by scholars grounded in computer science, physics, as well as the biological and social sciences.

In the study of crime, scholars have primarily relied on community detection techniques to delineate groups from relational data. The overall aim of community detection is to extract subgroups from the larger network that correspond with meaningful conceptualizations of social groups. Theoretically, community detection draws on suggestions by early scholars, such as Simmel (1955) who emphasized that while individuals are embedded in various webs of affiliations, strong(er) social ties are more likely to form with those who are in one’s immediate vicinity; their local “circle” as opposed to their larger social environment. It is through these immediate, local ties that larger heterogeneous networks of individuals filter into smaller homogenous groups. Methodologically, community detection aims to quantify the “intuitive concept of community structure” by arranging edges (ties between actors) into groups (Newman, 2006, p. 8578) – thus, identifying areas of structural homogeneity within the larger heterogeneous network graph. Community detection methods can be broadly divided into two classes of techniques: modularity- and clique-based approaches.

Modularity-based approaches partition network graphs into densely connected sub-groups with loose connections between groups. This approach takes into account both the proportion of within-group edges (high within-group connectivity) and between-group edges (low between-group connectivity) (e.g., Girvan & Newman, 2002; Newman & Girvan, 2004). The degree to which a network graph can be partitioned into subgraphs is assessed via a modularity score,
which represents a weighted function of within- as compared to between-group ties. The modularity score ranges from 0 to 1, with scores closer to 1 representing a better fit. There are multiple modularity-maximization techniques; some of the most popular include the Girvan–Newman (Girvan & Newman, 2002); Newman (Clauset, Newman, & Moore, 2004), and Louvain (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). The selection of the appropriate method often depends on the solution with the highest modularity score and greatest face validity, as compared to other solutions.

Modularity-based techniques provide a flexible approach to detect group boundaries; they can be used for weighted, directed, and longitudinal graphs (e.g., Mucha, Richardson, Macon, Porter, & Onnela, 2010). Kreager et al. (2011) demonstrated the utility of a modularity-based approach to discern peer friendship groups across students in 27 Iowa and Pennsylvania high schools. Relying on friendship nominations across 9,385 ninth-grade students, the authors delineated 897 distinct peer groups. These groups formed the unit of analysis for the study, which examined the link between a group’s delinquency and structural features. Scholars have since applied modularity-based approaches to extract groups of co-offenders (e.g., Lantz & Hutchison, 2015; Ouellet, Charette, & Bouchard, 2019), gangs (e.g., van Gennip, Hu, Hunter, & Porter, 2012), inmates (e.g., Schaefer et al., 2017), criminal organizations (e.g., Calderoni, Brunetto, & Picardi, 2017), and cryptomarket vendors (e.g., Duxbury & Haynie, 2018). Though widely used, modularity-based approaches have been critiqued for being limited in nature and scope. Methodologically, modularity-based techniques suffer from degeneracy, where a high number of alternative high scoring partitions may be extracted from the full network graph (Good, de Montjoye, & Clauset, 2010), and resolution limits, where subgroups are unable to be detected if they are too small relative to the overall size of the network (Fortunato & Barthélemy, 2007). Theoretically, modularity-based techniques have been critiqued for limiting membership to a single group, imposing “an artificial constraint on the groupings they are seeking to uncover” (Everett & Borgatti, 1998, p. 49).

Clique-based approaches distinguish themselves from modularity-based techniques primarily by their ability to produce overlapping groups, where group membership is not mutually exclusive (also see mixed membership stochastic blockmodels, Airoldi et al. (2008)). Cliques represent the most fundamental notion of a subgroup where each actor is connected to every other actor, with triads – a set of three actors who are all connected – the simplest notion of a clique. The clique percolation method (CPM) represents a clique-based technique to detect subgroups from relational data (Palla, Derényi, Farkas, & Vicsek, 2005). The CPM works by first identifying all cliques of size $k$ in a network graph. It then generates a new graph where each vertex represents one of the $k$-cliques. Vertices (i.e., $k$-cliques) are then clustered into larger groups if they are adjacent to other vertices, where adjacency is defined by any $k$-cliques that share $k-1$ members. Because an actor can belong to more than one $k$-clique, these groups can overlap.

In contrast to modularity-based approaches, the number of optimal groups is selected by the researcher who determines the size of the initial $k$-clique. Consequently, individuals may be excluded from any grouping as not all individuals in a network graph may belong to a clique of size $k$ though, solutions of $k$-size
should aim to maximize coverage of the actors within the graph (Palla et al., 2005). Although CPM offers clear advantages for delineating group boundaries, it is not without its limits, performing poorly in network graphs with few cliques (see Newman, 2018).

Schaefer et al. (2017) applied the CPM to delineate subgroups of residents housed in a medium-security prison. Relying on “get-along” nominations, the authors uncovered 12 social groups among the residents. Representing one of the few studies to compare modularity and clique-based social groupings, the authors showed that modularity-based approaches identified eight groups. Rather than pit the two approaches, the authors demonstrated how they offered complementary information and reinforced the finding that residents were organized into racial and religious heterogeneous social groups. The study also highlighted how the two approaches created important differences in the distribution of groups, with the modularity-based groups ranging from 8 to 26 residents, and the clique-based groups uncovering one larger social grouping of 61 residents, followed by several smaller ones.

Important methodological advances have been made to delineate group boundaries from relational data, including the ability to account for the frequency and duration of interactions, as well as more advanced methods such as the mixed-membership stochastic block model (Airoldi et al., 2008). However, there have been limited efforts to validate these groups. One of the rare examples to validate groups extracted using these techniques in criminology includes van Gennip et al.’s (2012) validation of algorithmically detected communities extracted from the networks of individuals as recorded in field incident cards by the Los Angeles Police Department. Indeed, studies may also rely on methodological approaches to validate the extracted partitions, such as similarity and dissimilarity measures that can be used to assess the effect of different distance measures on the quality of community detection algorithm results (Shirkhorshidi, Aghabozorgi, & Wah, 2015).

RESEARCH ON CRIMINAL GROUP DYNAMICS

Studies equipped with criminal network data are uniquely positioned to revisit and extend theories of crime and delinquency. Early applications of network analysis provided descriptive accounts of the social structure of criminal groups, challenging dominant perspectives that gangs and other criminal entities flowed vertically in a hierarchical structure (e.g., McGloin, 2005; Morselli, 2009), while also examining the sources of this structure (e.g., Bright, Koskinen, & Malm, 2018; Crossley et al., 2012; Morselli, Giguère, & Petit, 2007), and its impact on offending pathways (e.g., Haynie, 2001; McGloin & Piquero, 2010; Morselli & Tremblay, 2004; Morselli, Tremblay, & McCarthy, 2006). The underlying premise of these studies was that the etiology of crime was inherently a social phenomenon that shaped the emergence and evolution of delinquent activity. More recent studies have aimed to test these premises on collective trajectories, by providing explanatory accounts of how group dynamics influence behavior. These studies
can be broadly categorized into two classes: studies that examine *intra*-group dynamics (within-group structure), and studies that examine *inter*-group dynamics (between-group structure).

**Intra-group Network Dynamics**

Intra-group explanations make use of within-group interactions to account for group behavior. Much of this work has focused on the internal connectivity – or *cohesiveness* – of a group. Cohesion has long been central to theorizing about criminal group processes, often viewed as a key governing force of group behavior, influencing patterns in group delinquency and violence (e.g., Decker, 1996; Jansyn, 1966; Short & Strodtbeck, 1965; Vigil, 1988). Conceptually, cohesion refers to the degree of solidarity and unity between members within a group (e.g., Collins, 1988; Decker & Curry, 2002). However, challenges in directly measuring cohesion have meant that many theories of cohesion have remained largely untested (see Papachristos, 2013). Network methods have aimed to fill this gap by providing a set of measures to quantify group cohesion, based on patterns in members’ social interactions, and the degree to which groups are structured into tightly knit entities.

A classic study of gangs by Klein & Crawford (1967) made direct connections between a group’s cohesion and delinquency. Its key concept – cohesion – was defined as the “mutual liking or acceptance, attraction to group, degree of shared norms or values, and resistance to disruptive forces” (Klein & Crawford, 1967, p. 69). However, the authors rejected traditional approaches to operationalizing cohesion in favor of a network approach that directly measured member interactions. Relying on detached worker contact cards, which recorded workers’ daily observations of gang members and who they were seen with, the authors mapped out the interactions between 576 gang members across four gang clusters. The cohesiveness of each gang cluster was operationalized as the degree to which members formed tightly connected groups, according to nine different network indices, including a measure of the overall density of the group (i.e., the number of connections between gang members as a proportion of all possible connections). Comparing a group’s cohesiveness with their delinquency, the authors found a positive association between cohesiveness and delinquency, with the most cohesive groups being the most delinquent.

Despite the important contribution of network methods to operationalize cohesion, it would be nearly half a century before scholars would re-test the cohesion–delinquency link with statistical models across samples of delinquent and non-delinquent groups. Kreager et al. (2011) examined the sources of a group’s cohesion across 897 peer friendship groups with varying levels of delinquency. Cohesion in this study reflected measures of: transitivity (degree to which groups consisted of triads), reciprocity (the percent of friendship nominations within a group that were reciprocated), and structural cohesion (the mean number of node independent paths). However, in contrast to Klein and Crawford (1967), the findings did not support a consistent relationship between a group’s cohesiveness and delinquency. Once behavioral and attitudinal measures were controlled for, only transitivity was found to be positively associated with a group’s overall delinquency.
The relationship, or better yet, a lack thereof, of relationship between a group’s delinquency and cohesion was also supported by Hughes (2013) study of Chicago gangs. Resurrecting relational data embedded in surveys of 248 gang members conducted during Short and Strodtbeck’s (1965) field research in Chicago, she examined variation in delinquency and cohesion across 11 gangs. Measuring cohesion as the average number of friends nominated by each gang member within the gang, results showed that a group’s cohesion did not predict its general delinquency levels, but it did negatively predict a group’s violence.

Network approaches have provided meaningful advances in unpacking the cohesion–delinquency relationship – allowing us to look at cohesion across large samples of delinquent and non-delinquent groups and forcing us to revisit assumptions about the impact of a group’s structure on collective behavior. However, the relationship between a group’s cohesion and delinquency is far from conclusive. One way forward would be to extend these examinations to focus on the temporal order of the cohesion–delinquency relationship. Scholars working on cohesion and delinquency typically focus on one strategy and point the causal arrow in a single direction. However, the direction of the relationship is unclear. Cohesion ebbs and flows across a group’s life cycle, and the relationship with delinquency may not be linear, but rather reflect dynamic, reciprocal, or cumulative processes. In some contexts, non-cohesive groups are more likely to engage in delinquent acts bringing members together for a singular event (e.g., Jansyn, 1966). In other contexts, cohesive groups are more likely to engage in delinquency, such that, members are embedded in tightly knit structures that facilitate the transfer of norms and behaviors (e.g., Klein, 1969; Thornberry, Krohn, Lizotte, & Chard-Wierschem, 1993). As part of this research agenda, it would be meaningful to investigate whether sources of cohesion change across a group’s evolution. It may be that cohesion is important when the group is still forming, but its effect dwindles as group activities shift or exhibit greater mobility.

Efforts to look at the flow of cohesion over time may draw from research in the social movement literature, which has conducted detailed accounts of a group’s evolution over time. Focusing on a case study of the Provisional Irish Republican Army, Stevenson and Crossley (2014) demonstrated that despite high turnover, the group remained structurally stable. The group maintained a core set of members who became more central over time and connected the group as it evolved. This study suggests that subgroups within the criminal group were just as important as the overall structure of the group itself.

**Inter-group Network Dynamics**

Groups, criminal or otherwise, are rarely isolated entities but embedded in webs of relations. Decades of research have shown that neighboring groups play important roles in shaping a group’s own identity and behavior, influencing group-based identities, serving as reference points, and structuring the spread of behaviors (e.g., Decker, 1996; Decker & Curry, 2002; Klein, 1971; Sanchez-Jankowski, 1991; Thrasher, 1927). Although these studies did not explicitly rely on formal network methods or terminology, their early insights into inter-group
social processes shaped the network agenda. Network scholars have since mapped out the networks of collaboration and conflict between groups as a means to explicitly test these early perspectives and their implications for group behavior.

In a study of Chicago gangs, Papachristos (2009) provided an influential demonstration of the relevance of network methods for understanding the spread of gang violence. Defining gang conflict, as “first and foremost an interaction” (p. 75) he mapped out the network of conflict between all gangs who had been involved in a homicide, either as a perpetrator or a victim, for nearly two decades in Chicago. Extracted from law enforcement records, these data provided the full network of lethal rivalries between gangs. From this network, Papachristos (2009) estimated the likelihood that any two gangs would engage in lethal conflict with one another based on previous patterns of conflict. The results highlighted a social contagion process, such that the likelihood of violence was governed by cycles of reciprocal murders – cases where gangs were more likely to target gangs that they had targeted or had been targeted by in the past – creating institutionalized patterns of violence (p. 118).

Extending this research, Papachristos, Hureau, and Braga (2013) tested claims that violence served as a means for gangs to assert their social standing, creating the presence of dominance hierarchies. Specifically, they drew from a body of literature that observed the consequences of dominance hierarchies through interchanges of aggression (see Chase, 1980). Drawing analogies with the gang dominance literature, Papachristos et al. (2013) tested whether gangs that successfully use violence to settle disputes, or retaliate, were less likely to become victims such that they have asserted their dominance. And whether the converse was equally true, where a failure to react to violence was detrimental to the reputation of the gang, given that others within their network perceive their lack of action as a sign of weakness, making the gang and its members susceptible to future aggressors (Gould, 2003, p. 118; Papachristos, 2009). The main construct – dominance hierarchies – was measured as a network variable, whereby more aggressive gangs (more out-group ties) were presumed to have a higher status than victimized gangs (more in-group ties). Specifically, a transitive triad term allowed them to test for whether gangs exhibited different status rankings according to their violence profiles. Findings from exponential random graph models showed that dominance hierarchies were not associated with gang conflict; rather, results bolstered earlier findings: lethal violence between gangs was primarily a function of reciprocal violence, where gangs were more likely to engage in conflict if a member of their gang had previously been targeted.

Since Papachristos’s (2009) seminal study, scores of research findings have affirmed that gang violence spreads through a social contagion process in Boston (Papachristos et al., 2013), Chicago (Papachristos, 2009; Papachristos et al., 2013), and Los Angeles (Radil, Flint, & Tita, 2010; Tita & Radil, 2011). These studies provide important insights, and shed light on ways forward. For instance, studies of violence have primarily focused on the role of “conflict” ties rather than “collaborative” ties between gangs. We know from earlier studies that network rivalries are not necessarily independent. Alliances have been shown to form between gangs that share a common enemy, rival, or exhibit a similar
gang-related motive. These alliances are responsible for how gangs respond to conflict, shaping retaliatory patterns of conflicts that may not have been there otherwise (see Bouchard & Hashimi, 2017; Morselli, Tanguay, & Labalette, 2008; Papachristos et al., 2013). In extreme cases, it may even create a polarized state whereby participants who otherwise would not have been involved in the conflict, or those located on the periphery of the network, may be inclined to choose a side (Morselli et al., 2008).

Relatedly, other studies emphasize that rivalries and alliances are not mutually exclusive categories. For instance, in Montreal, Canada, focus group interviews with 20 gang members belonging to 15 different gangs found that many gang members count their friends among their enemies; reporting instances of conflict between members of allied gangs (Descormiers & Morselli, 2011). Similarly, in Newark, New Jersey, McGloin (2005) found that gang members did not display a homogenous set of allegiances or “gang networks” per se, rather they operated in a series of loosely knit cliques, maintaining associations with individuals outside of their “explicit named sets” and members of other gangs (p. 619). This perspective underlies the main demonstration of Morselli’s (2009) examination of drug distribution networks, namely that the modal form of criminal entities are ephemeral groups, where collaborations develop between groups opportunistically, to facilitate the commission of crimes and increase profitability (also see Bouchard & Morselli, 2014).

CONCLUSION

In many ways, network studies of criminal group dynamics are just getting started. This chapter provides an overview of prior research aimed at integrating group dynamics and also points to future directions for expanding such efforts. Here, we review three promising areas for moving the area forward.

A hybrid approach to group dynamics. The bulk of research on criminal group dynamics considers either a group’s internal connectivity (i.e., intra-group) or external connectivity (i.e., inter-group), but rarely merges the two. Both perspectives can create important shortcoming in our understanding of group dynamics; groups are considered independent entities, in the former, or as unitary actors lacking variation in their structural features, in the latter. Yet, from the earliest studies of criminal groups we know this is not the case. Early theories emphasized that the main source of criminal groups’ internal cohesion was due to this “group effect” whereby conflicts sustained with other groups increased within-group ties. Conversely, a group’s cohesion has been viewed to be threatened by alliance structures that may pull members to other groups. Indeed, a hybrid approach – looking at both a group’s internal and external network structure – may help explain discrepancies in whether a group elects to engage, or not engage in violence, with scholars emphasizing that a group’s cohesiveness and solidarity moderates whether inter-group violence escalates or desists (see Gould, 2003; Morselli et al., 2008).

Advances in network modeling suggest there is much to be gained from looking at the intersection of these categories. For instance, Shi, Fedor, Genkin, and
Brashears (2017) demonstrated that a group’s ability to persist depended on bridging internal, and external structures, maintaining cohesiveness to retain members, and creating ties to other organizations to facilitate recruitment (also see Vedres & Stark, 2010). Drawing from this literature, Ouellet et al. (2019) examined the network dynamics of criminal group persistence with an explicit focus on a group’s internal and external connections. Results showed that groups at different stages in their evolution required distinct network structures to survive. More established groups, with high levels of membership, profited from adopting closed structures to maintain their existing position. Whereas, smaller groups, in their early stages of formation, benefited from more versatile structures, opening up to outside associates to expand their access to illicit opportunities. Importantly it was the balance between how a group structured its internal- and external-connectivity that shaped how the group was able to persist over time.

Beyond delinquency. Another important direction would be to extend research on criminal groups to look over and beyond delinquent activities. Even among the most delinquent groups, only a fraction of social activities is spent in the commission of the actual criminal act. Similarly, many of the individuals who may be considered members of a criminal group, may or may not participate in criminal incidents. A focus purely on the delinquent aspects of a group may cloud the more peripheral, but equally important factors that bring together groups, allowing them to forge bonds, and eventually shift into collective actions. For instance, Ouellet and Bouchard’s (2018) study of a domestic terrorist organization demonstrated that only a minority of the participants interacting with the group were charged for a crime. Yet, it was the majority who had an impact on the group’s evolution into violence. Network methods provide a means to look beyond delinquent acts and shed light on the factors that allow groups to emerge and evolve (see Bright et al., 2018; Fitzhugh & Butts, 2018), and stress the importance of non-delinquent actors that bring together their delinquent counterparts (Morselli, 2009). These insights could assist in explaining a host of group-level outcomes, including the distribution of criminal groups, their resiliency to interdictions, and changes in group activity over time.

Cross-level analysis. Network methods are not just an opportunity for advancing our understanding of collective trajectories. More importantly they provide a path for bridging the divide between how individual- and group-level pathways intersect (see Matsueda, 2017).

Although the focus of this chapter was on the group-level dynamics associated with crime, it also advances an individual-level research agenda that suggests individual-level variation can only be understood within the context of a group’s overall trajectory (see Tremblay et al., 1989). From this perspective, we view individual- and group-level research as complementary fields of inquiry. Notably, one of the strengths of social network analysis is in its ability to seamlessly move between different levels of while work has been done on investigating how group membership structures an individual’s offending pathway, group membership is often designated as a static or binary variable, creating binary cleavages between individuals who belong to a group, and those who do not. Here, we propose nesting individuals within these groups, and
distinguishing between different types of groups. For instance, individuals who belong to highly cohesive gangs may have distinct offending pathways, as compared to individuals who belong to more decentralized, opportunistic entities. The same could be said for individuals who join a gang as it is just forming, in comparison to those who join a gang after it has been established. This perspective is consistent with a long line of research that considers offending pathways as structured by opportunities (e.g., Conway & McCord, 2002; McGloin & Piquero, 2010) and the underlying premise of Tremblay et al.’s (1989) work on the collective trajectories of organized crime groups.

Relatedly, cross-level analysis disentangles social interaction effects by representing network dependencies in statistical models. Analytical approaches such as stochastic actor-oriented models help transition from the macro- to the micro-level by teasing exogenous (individual level effects), endogenous (structural network effects) from non-effects, longitudinally (Snijders, 2011). Alternatively, analysis of multilevel data with statistical techniques, such as hierarchical linear modeling, incorporates effects at various hierarchical levels, modeling cross-level interactions while controlling for their shared variance (Bryk & Raudenbush, 1992). When supplemented with community detection techniques, statistical models used to deal with complex network dependencies pave the way forward to generate statistical inference, causality, and spillover effects.

NOTES


2. The authors also estimated models where cohesion was operationalized as the mean number of friendship nominations received, the proportion of intra-gang nominations (i.e., density) with a control for size, and the maximum $k$-core (based on undirected ties). All substantive results remained the same.

3. To identify the presence of gangs: (a) high in status, perpetrated violence against other gangs, but were not the targets of violence; (b) low in status, did not perpetrate violence, but were the targets of violence; and (c) gangs in the middle of the hierarchy who were both perpetrators and targets of gang violence.

REFERENCES


