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Social Network Analysis and Crime Prevention

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Abstract Social network analysis (SNA) has proven its value in refining criminological concepts and theories to aid the understanding of social processes behind crime problems and to assist law enforcement agencies in enforcing crime. Social network methods and techniques have a great value for crime prevention as well. SNA can be adopted to study crime epidemics and gang-related violence to identify proper violence reduction strategies. Furthermore, the adoption of a network approach can help understand the etiology and dynamics of criminal groups and assess the implications of different disruption strategies, thus limiting network reorganization. This chapter discusses the network approach in criminology and its value for crime prevention.

Introduction

Social network analysis (hereafter SNA) has been increasingly adopted by both criminologists and law enforcement agencies to study crime. It refers to the analysis of the patterns of social interactions among actors and how these patterns influence individual behaviors (Wasserman & Faust, 1994). In criminology, SNA has proven to be a valuable tool for the study of personal and neighborhood networks and their influence on crime and for the analysis of criminal groups.

This chapter discusses the network approach in criminology and the various areas of the application of SNA in the criminological context. It describes how SNA is a valuable tool not only for research but also for law enforcement purposes. Within law enforcement agencies, SNA methods and techniques have mainly been used for the purpose of crime enforcement. In the context of this contribution, it is argued that social network methods and techniques have great value for crime prevention as well.

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Crime and Social Network Analysis

Less than two decades ago, Nigel Coles (2001) suggested that it's not what you know, but who you know that counts (emphasis in the original). Coles was convincingly arguing for the adoption of SNA in the study of crime and, in particular, of criminal groups. Indeed, "social network analysis has the very real potential to uncover the complexities of criminal networks" (Coles, 2001, p. 581). This potential exists, according to the author, not only in a set of methodological techniques but also in two valuable insights: (1) every individual is part of a larger social system whose participants infl uence his behavior and (2) the pattern of interaction with other actors often follows certain rules or regularities (Coles, 2001; see also Galaskiewicz & Wasserman, 1994; Knoke & Kuklinski, 1991). Analyzing such regularities could help unpack criminal groups, their activities, and organizations.

While suggesting the great potential of SNA for studying organized crime, Coles (2001) complained about the failure of criminologists to adopt SNA's concepts and methods to better understand criminal groups. Ten years later, in a review of the applications of SNA in criminology, Papachristos (2011) sadly acknowledged that only a very limited number of papers adopting network analysis had been published in criminology journals, compared to sociology and public health papers. This neglect was even more striking considering the number of network-related concepts and images that permeate criminological theories (e.g., social control, peer influence).

The skepticism by criminologists towards SNA may be partially due to the fact that it implies a departure from most traditional regression-oriented approaches that assume independence among the variables (Emirbayer, 1997; Papachristos, 2011). SNA considers social actors as interacting units. Furthermore, these interactions shape individuals' behaviors, including deviant ones. Therefore, from a theoretical point of view, SNA emphasizes the interdependence among actors rather than their independence. As a consequence, the independence assumption as the basis of most causal analyses using regression models is no longer valid and new methods have to be applied (Papachristos, 2011).

From a methodological point of view, SNA encompasses a range of techniques rooted in mathematical graph theory (Carrington, Scott, & Wasserman, 2005; Wasserman & Faust, 1994). Social networks consist in a set of nodes (or vertices) and the edges (or lines) among them. The former can be represented by individuals, groups, or even countries, while the latter exist when a relation is present between two nodes. Edge connecting nodes may have different meanings (e.g., friendship, exchange of information, co-offending) and may have various properties. Indeed, the weight or the direction of the edges may be specified, for example, by counting the number of telephone calls between two actors or by recording the sender and the receiver of the call (Scott, 2000; Wasserman & Faust, 1994).

In their reviews of studies applying SNA in criminology and its methods and data collection strategies, various authors have demonstrated the versatility of this approach (Calderoni, 2014b; Carrington, 2011; Grannis, 2014; Haynie & Soller, 2014; McGloin & Kirk, 2010; Papachristos, 2006, 2011; Piquette, Smith, & Papachristos, 2014; Radil, 2014). Carrington (2011) identifies three main areas of application of SNA in criminological research.

First, SNA can be adopted to research the influence of personal networks on crime and, more generally, on delinquent behavior. This category includes studies on the consequences that personal networks may have on juvenile delinquency or, in fewer cases, on adult criminality (e.g., Ennett et al., 2006; Haynie, 2001, 2002; Kreager & Haynie, 2011; McGloin, 2009; Payne & Cornwell, 2007). Such analyses use social networks as independent variables to explain crime across the population. Indeed, the structure of social relations (i.e., the attributes of personal networks) is considered an explanatory variable of crime and delinquent behavior in addition to individual characteristics (Haynie & Soller, 2014; Papachristos, 2011).

A second category of studies adopting SNA in criminological research encompasses the analyses of neighborhood networks and their influence on crime (Carrington, 2011). Recognizing the importance of the "neighborhood effects" on crime (Sampson, Morenoff, & Gannon-Rowley, 2002), these studies adopted SNA to assess the facilitating and deterring effects that the structural properties of neighborhood networks have on crime and delinquency rates (Soller & Browning, 2014). Recent studies also focused on interactions among neighborhoods and the effects of these interactions on crime by integrating spatial and social network methods. Drawing on the idea that "observable outcomes in one neighborhood are partly the product of social actions and activities that can stretch beyond local communities" (Radil, 2014, p. 4995; see also Morenoff, Sampson, & Raudenbush, 2001), some authors have started to model proximity not only in georaphical terms but also in social network terms (e.g., Tita & Radil, 2010). Levels of crime in a neighborhood are thus influenced by features of both geographically proximate locations and places connected by social ties (e.g., rivalries among gangs) (Radil, 2014).

Finally, SNA has been adopted to explore and model the organization of crime (Carrington, 2011). Street gangs (e.g., McGloin, 2007; Papachristos, 2006), terrorist groups (e.g., Krebs, 2001; Rothenberg, 2002), and organized crime groups (e.g., Bright, Caitlin, & Chalmers, 2012; Calderoni, 2012; Campana, 2011; Morselli, 2009; Natarajan, 2006; Varese, 2013), as well as illicit markets and co-offending networks (e.g., Bichler, Schoepfer, & Bush, 2015; Heber, 2009; Malm, Bichler, & Nash, 2011), have been analyzed through the lens of SNA. In recent years, scholars have also adopted SNA to study online networks (e.g., Décary-Hétu, 2014a; Décary-Hétu & Dupont, 2012). In this context, the network is analyzed as a dependent variable and social network techniques are adopted to describe the criminal group and its main structural properties (Papachristos, 2011). Indeed, SNA makes it possible to seek, rather than assume, the structure of a criminal group (Morselli, 2009). Therefore, within this approach, all types of organizations, from decentralized to hierarchical, are conceived as networks of collaborating criminals, and the structural properties of such networks are subject to analysis through social network measures.

As Carrington (2011, p. 244) notes, “this research tends to be exploratory and descriptive rather than theory-testing,” although SNA also allows scholars to test hypotheses from the literature and compare criminal networks across countries or markets (Calderoni, 2014b; Papachristos, 2011). For instance, the idea that hierarchy does not play a pivotal role in mafia associations in specific circumstances such as international drug trafficking can be tested and possibly supported by empirical studies (see Calderoni, 2012). In recent years, scholars have started to adopt statistic models for social networks to identify the social processes underlying illicit network formation and development as a consequence of both endogenous and exogenous factors (Bichler & Franquez, 2014; Boivin, 2014; Everton & Cunningham, 2014; Berlusconi, Aziani, & Giommoni, 2015). Therefore, SNA also fosters an understanding of the etiology and dynamics of criminal groups and illicit trade networks.

The adoption of SNA in criminology has proven to be a valuable tool for various reasons. First, it can help refi ne criminological theories founded upon the idea that personal—and neighborhood—networks play a role in the etiology of deviance and crime (Papachristos, 2014). Second, it helps understand complex organizations such as organized crime and terrorist groups. As a consequence, academics and law enforcement agencies have adopted SNA for crime enforcement purposes (Calderoni, 2014b).

Social Network Analysis and Crime Enforcement

If scholars were skeptical about the adoption of SNA to study crime, others directly involved in criminal intelligence recognized its potential for the analysis of criminal networks (Coles, 2001). In this context, SNA has been considered a valuable tool almost exclusively to study criminal groups for the purpose of crime enforcement.

Since the 1970s, law enforcement agencies have increasingly applied link analysis “to portray the relationships among suspected criminals, to determine the structure of criminal organizations, and to identify the nature of suspected criminal activities” (Harper & Harris, 1975, p. 157). Link analysis is adopted for both tactical and strategic intelligence analysis, as it allows the identification of connections among individuals using information on activities, events, and places (Sparrow, 1991a; Strang, 2014; Van der Hulst, 2009). The output of this type of analysis is a two-dimensional representation of actors and the relations among them. The stronger the relationship between two actors, the closer they will be displayed in the graph representing the network (McAndrew, 1999).

Link analysis has the advantage of visually representing criminal networks starting with the law enforcement data. However, this analysis is not interested in the mechanisms behind the formation and persistence of criminal networks. Furthermore, since it does not entail any mathematical computation, the way connections among actors are represented in the graph are likely to influence the understanding of the network under analysis. For instance, actors in the center or at the top of the graph may be interpreted as central actors or leaders regardless of their values of degree or betweenness centrality (Klerks, 2001; McGrath, Blythe, & Krackhardt, 1997; Van der Hulst, 2009).[1] Instead, SNA enables the analysis of the structural properties of criminal networks through a set of measures based on mathematical graph theory. Network properties are thus calculated rather than inferred from a graph representing the criminal group (Davis, 1981; McAndrew, 1999).

Since the 1980s, the adoption of SNA for strategic analysis and enforcement of criminal groups has been advocated by several authors, including law enforcement analysts (Davis, 1981; Lupsha, 1980, 1983). In the following years, the adoption of SNA to criminal intelligence was also promoted by scholars researching organized crime. A common argument for its adoption was that its techniques allow an in-depth analysis of the internal configuration of criminal groups and are thus valuable for research, intelligence, and investigation. However, in most cases, such claims were not supported by empirical analyses of criminal organizations (Ianni & Reuss-Ianni, 1990; McAndrew, 1999; Sparrow, 1991b; Van der Hulst, 2009).

Van der Hulst (2009) identified various fields of crime enforcement in which SNA could provide valuable insights. SNA could help identify the key actors to be removed from the network to achieve destabilization and predict the impact of their removal as a consequence of an arrest by law enforcement agencies. Social network techniques could also help identify aliases through the analysis of actors with similar patterns of connections, especially in the case of large investigations, and they could provide evidence for prosecution. Furthermore, SNA may help identify potential defectors according to their position in the network (Faulkner & Cheney, 2015). SNA is currently adopted by law enforcement agencies. Duijn and Klerks (2014) describe the Dutch experience and the benefits for intelligence and investigation. According to the authors, SNA is particularly useful in guiding operational intelligence projects with the aim to identify strategies to target and disrupt criminal networks. For instance, the analysis of the topology of a network enables to define the targeting strategy that is likely to lead to the maximum of network disruptions (Xu & Chen, 2008).

Despite evidence of positive experiences with the adoption of network techniques for intelligence and investigation, law enforcement analysts also show some skepticism towards SNA, mainly because they do not observe any significant advantage offered by current applications to crime enforcement, especially for long-term investigations in which police agencies managed to gather detailed knowledge on the suspects from different sources (e.g., wiretapping, background checks) (Calderoni, 2014b). Nonetheless, SNA can be useful for intelligence collection. In particular, it can aid ongoing investigations in identifying key individu-

[1] Degree and betweenness measure an actor's centrality within a network. Degree centrality measures the number of nodes with which each node is connected. Betweenness centrality measures the extent to which a node lies on the shortest path between any two other nodes (Wasserman & Faust, 1994).

als and subgroups within a larger network of co-offenders, and suggesting effective strategies for network disruption (Strang, 2014). For instance, Calderoni (2014a) described how SNA can be useful to identify mafia bosses with limited information. Contrary to most network studies on criminal groups, the author retrieved the network structure using information on meetings among co-offenders, which is easily accessible also at the preliminary stages of a criminal investigation and is not conditioned by a court order. In the context of a hierarchical organization such as the Italian 'Ndrangheta, individual positions within the network (e.g., degree and betweenness centrality scores) can help identify the leaders of the criminal group with limited information and resources (Calderoni, 2014a).

SNA also supports strategies to disrupt criminal organizations (Strang, 2014). The benefit of the adoption of network techniques is twofold: the vulnerabilities of criminal networks to different types of attacks can be identified, and destabilization strategies can be selected and tested through simulations. Indeed, not all networks are equally vulnerable to attacks. Disruption strategies cannot be similarly applied to all criminal organizations; rather, they should be established by considering the variations in the structure of criminal groups (Malm & Bichler, 2011; Malm, Bichler, & Van De Walle, 2010; Xu & Chen, 2008).

SNA enables analysts to assess the topological features of criminal networks and thus their vulnerability to attacks based on both network measures and individual characteristics. Through the simulation of different types of attacks, it has been demonstrated that the removal of bridges (i.e., actors with high betweenness centrality scores) is likely to cause more damage to criminal networks. Random attacks, i.e. the random removal of nodes, are instead not likely to cause the disruption, or even the fragmentation, of such networks (Keegan, Ahmed, Williams, Srivastava, & Contractor, 2010; Xu & Chen, 2008).

SNA has proven to be a useful tool for crime enforcement. Indeed, it provides a set of measures that enable law enforcement agencies to identify actors with a prominent position within a criminal network and assists them in selecting the best strategies for network disruption. Recent developments in the application of SNA in criminological research suggest that it can be a valid instrument for crime prevention as well.

Moving Forward: SNA and Crime Prevention

Besides favoring advancements in research on crime and supporting law enforcement agencies during criminal investigations, SNA can assist in preventing crime and emergent crime problems (Strang, 2014). Recent studies provide good examples of the value of SNA for crime prevention.

If we consider social networks as independent variables to explain crime and victimization across the population, SNA can be adopted to study crime epidemics and identify individuals who are more likely to be involved in gunshot episodes. If networks are analyzed as dependent variables, the adoption of a network approach can help understand the etiology and dynamics of criminal groups and networks. SNA enables analysts to predict leadership roles within criminal organizations, as well as the implications of disruption strategies, thus avoiding network reorganization and the committing of more crimes. Furthermore, the adoption of a network approach to gang-related violence can help to identify targeted prevention strategies to reduce homicides and nonlethal shootings.

SNA has been used to explain how personal networks influence delinquent behavior. Similarly, SNA can help identify individuals who are more likely to be a victim of gunshot injuries as a consequence of both personal characteristics and those of their social networks (Papachristos, Braga, & Hureau, 2012). The traditional criminological approach to crime epidemics—i.e., the dramatic increase in crime in a specific location and within a restricted period of time—evaluates an individual's risk of victimization based on a series of individual, situational, and community risk factors. However, crime is highly concentrated within populations and neighborhoods characterized by the presence of such risk factors (Papachristos, 2011).

Papachristos and colleagues (Papachristos et al., 2012; Papachristos, Wildeman, & Roberto, 2015) explored the relationship between social networks and the risk of gunshot injury and demonstrated how SNA can help assess an individual's risk of being a crime victim or an offender, by analyzing his/her personal network. Evidence of a relationship between social distance and gun victimization was found in a study conducted in Boston's Cape Verdean community. Indeed, "the closer one is to a gunshot victim, the greater the probability of one's own victimization, net of individual and other network characteristics" (Papachristos et al., 2012, p. 999). Another study conducted in Chicago confirmed the association between the presence of gunshot victims in one's social network and his/her probability of victimization (Papachristos et al., 2015).

These studies demonstrate the utility of SNA to understand the risk of gun violence in urban areas and identify proper prevention strategies. Recognizing that the risk of victimization is highly concentrated within communities and associated with specific behaviors such as co-offending allows to direct prevention efforts towards specific segments of the population, instead of targeting the population at large or high-risk neighborhoods. SNA may thus support violence reduction strategies by redirecting resources to specific locations and segments of the population (Papachristos et al., 2012, 2015).

SNA can also be adopted to predict an individual's future involvement in gang-related activities after his/her participation in a murder. McCuish, Bouchard, and Corrado (2015) studied a homicide co-offending network whose members were part of the Canadian BC gang and found that homicide offenders were not recruited within the co-offending network, but they had high-ranking positions after the homicides. Therefore, involvement in gang homicides appears to be relevant for the criminal career of gang members. Following the criminal trajectories of adolescents involved in homicides after their release could help concentrate investigative efforts and adopt preventive measures targeting these individuals.

The adoption of a network approach can also help in understanding the structural properties of criminal groups and networks, as well as their etiology and dynamics. SNA can be used not only to identify leadership roles within criminal groups but also to predict such roles at the early stages of an investigation. Calderoni expanded on a previous study (Calderoni, 2014a) and demonstrated how using only information on meeting attendance, which is more easily accessible than, for example, wiretap records, makes it possible to predict criminal leadership and thus prevent criminal groups from operating (Calderoni, 2015).

The author analyzed a criminal group belonging to the 'Ndrangheta through the network based on attendance at mafia meetings. The investigation was divided into four time periods of increasing duration. A logistic regression model was run for each of the four periods with leadership (leader=1) as the dependent variable and centrality measures as the independent variables, controlling for a prosecution bias and the number of meetings attended by each actor. The results showed that after the first year of investigation and only 34 meetings, it was possible to successfully identify the role of 75.6% of all actors involved in the criminal investigation (Calderoni, 2015).

SNA may thus assist law enforcement agencies in the early identification of relevant actors and in the selection of individuals to be wiretapped. It could also enable "the adoption of preventive measures with the aim of hindering the activities of criminal organizations" (Calderoni, 2015, p. 105). Indeed, by identifying the leaders in advance, it would be possible to concentrate investigative efforts and allocate resources for the electronic surveillance of a limited number of persons, as well as to adopt personal preventive measures or apply special surveillance orders.

The development of statistical models to study network evolution may help criminologists go beyond mere descriptive analyses and understand the dynamics of criminal groups. SNA is adopted to support ongoing criminal investigations with the purpose of identifying potential network vulnerabilities and strategies for disruption (Strang, 2014). However, little information is available on the consequences that different disruption strategies may have on the structure and activities of criminal groups (Duijn & Klerks, 2014). Traditional enforcement strategies targeting leaders are not always applicable, especially in the case of loose networks of collaborating criminals. Moreover, the removal of critical nodes does not automatically entail an increase in the vulnerability of a criminal organization, or its disruption, because network flexibility and high turnover may reduce the effects of law enforcement targeting (Bright, Greenhill, & Levenkova, 2014; Carley, Lee, & Krackhardt, 2002; Décary-Hétu, 2014b; Morselli, Giguere, & Petit, 2007). Hence, the impact of law enforcement interventions is not necessarily negative because it may result in better adaptation of the targeted criminal group rather than its disruption (Ayling, 2009).

SNA can identify the structural properties of criminal networks and their changes over time. By analyzing how criminal networks recover from arrests and other law enforcement interventions (e.g., drug or asset seizures), SNA can provide insights into the adaptation of criminal groups to law enforcement targeting.

Therefore, social network techniques may help assess the implications of different disruption strategies and select those that limit network reorganization and the resulting committing of more crimes (Berlusconi, 2014; Bright, 2015). Indeed, analyzing criminal networks and their changes over time as a consequence of law enforcement interventions enables analysts to predict the impact of the arrest of key actors on the structure and activities of such networks (Ianni & Reuss-Ianni, 1990).

Recently, longitudinal modeling techniques have been applied to analyze the relationship between the structure and resilience of criminal networks and law enforcement strategies. Everton and Cunningham (2014) demonstrated how approaches that use non-coercive means can shape the structure of criminal networks and make them more vulnerable to further attacks which target critical nodes. Similarly, dynamic modeling has been applied to illicit trade networks, such as the gun trade (Bichler & Franquez, 2014). Indeed, SNA can help identify the consequences of various strategies to disrupt criminal groups and other types of illegal networks, such as online child exploitation networks and other clandestine online networks (Keegan et al., 2010; Kila & Bouchard, 2015).

Finally, SNA can help map the rivalries among gangs and the related violence for the purpose of understanding the patterns of gang-related violence and predicting future conflicts (Piquette et al., 2014). For instance, Descormiers and Morselli (2011) analyzed how gang-level attributes (e.g., ethnicity) and other factors (e.g., proximity of gang turf) help to anticipate conflicts among gangs in Montreal. Similarly, Papachristos (2009) focused on retaliation among gangs in Chicago and described how patterns of gang-related violence can be explained by prior conflict relations and the position of the gangs within rivalry networks.

Other studies modeled the effects of both geographic and network processes on gang violence. They found that both spatial proximity and prior conflicts (i.e., rivalries among gangs) influence the patterns of gang violence (Brantingham, Tita, Short, & Reid, 2012; Papachristos, Hureau, & Braga, 2013; Radil, Flint, & Tita, 2010; Tita & Radil, 2011). These studies consider networks as the dependent variable, whereas explanatory variables include properties of the network (e.g., reciprocity), of the nodes (e.g., size of the gang, ethnicity), and of the location (e.g., poverty level in a neighborhood), as well as spatial proximity of gangs' turfs and other social processes (Papachristos, 2011).

Analyses of gang-related violence adopting a network approach may suggest interventions at the gang level that could prevent specific groups from perpetrating violence against rival gangs (Papachristos, 2009). For instance, gang injunction policies may be revisited to incorporate the results from the network analysis of gang rivalries and alliances and to consider the event of a reorganization of the gangs targeted by injunctions. Insights into the effects of intervention strategies may also be acquired through the adoption of network models that simulate gang-related violence and predict future events (Hegemann et al., 2011; Tita, Butts, Valasik, & Brantingham, 2012).

Conclusions

Criminological studies adopting a network approach suffer from a number of limitations and methodological problems. Much research is still exploratory or descriptive in nature. Furthermore, scholars often rely on law enforcement data characterized by missing information and fuzzy network boundaries (Berlusconi, 2013; Carrington, 2011; Malm et al., 2010; McGloin & Kirk, 2010; Morselli, 2009; Von Lampe, 2009).

Nonetheless, SNA has proven its value in refining criminological concepts and theories to aid the understanding of social processes behind crime problems, and to assist law enforcement agencies in enforcing and preventing crime. Future developments will hopefully go beyond a descriptive approach and will rely on more complete and new data sets, thus being able to guide policy decisions and crime prevention programs.

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References

Ayling, J. (2009). Criminal organizations and resilience. *International Journal of Law, Crime and Justice*, 37 (4), 182–196.

Berlusconi, G. (2013). Do all the pieces matter? Assessing the reliability of law enforcement data sources for the network analysis of wire taps. *Global Crime*, 14 (1), 61–81.

Berlusconi, G. (2014). *Law enforcement and criminal network resilience: The impact of law enforcement action on the structure of mafia-related drug trafficking networks* (PhD Thesis). Università Cattolica del Sacro Cuore, Milano. Retrieved from http://hdl.handle.net/10280/2457

Berlusconi, G., Aziani, A., & Giommoni, L. (2015). *Does size matter? The determinants of heroin flows in Europe*. Presented at the 7th Annual Illicit Network Workshop, Montreal.

Bichler, G. M., & Franquez, J. (2014). Conflict cessation and the emergence of weapons supermarkets. In A. J. Masys (Ed.), *Networks and network analysis for defence and security* (pp. 189–215). Cham: Springer.

Bichler, G. M., Schoepfer, A., & Bush, S. (2015). White collars and black ties: Interlocking social circles of elite corporate offenders. *Journal of Contemporary Criminal Justice*, 31 (3), 279–296.

Boivin, R. (2014). Risks, prices, and positions: A social network analysis of illegal drug trafficking in the world-economy. *International Journal of Drug Policy*, 25 (2), 235–243.

Brantingham, P. J., Tita, G. E., Short, M. B., & Reid, S. E. (2012). The ecology of gang territorial boundaries. *Criminology*, 50 (3), 851–885.

Bright, D. A. (2015). Identifying key actors in drug trafficking networks. In G. M. Bichler & A. E. Malm (Eds.), *Disrupting criminal networks: Network analysis in crime prevention* (pp. 66–88). Boulder, CO: FirstForumPress, a division of Lynne Rienner Publishers.

Bright, D. A., Caitlin, E. H., & Chalmers, J. (2012). Illuminating dark networks: A social network analysis of an Australian drug trafficking syndicate. *Crime, Law and Social Change*, 57 (2), 151–176.

Bright, D. A., Greenhill, C., & Levenkova, N. (2014). Dismantling criminal networks: Can node attributes play a role? In C. Morselli (Ed.), *Crime and networks* (pp. 148–162). New York and London: Routledge.
Calderoni, F. (2012). The structure of drug trafficking mafias: the ‘Ndrangheta and cocaine. *Crime, Law and Social Change*, 58 (3), 321–349.
Calderoni, F. (2014a). Identifying mafia bosses from meeting attendance. In A. J. Masys (Ed.), *Networks and network analysis for defence and security* (pp. 27–48). Cham: Springer.
Calderoni, F. (2014b). Network analysis of organized criminal groups. In G. Bruinsma & D. Weisburd (Eds.), *Encyclopedia of criminology and criminal justice* (pp. 4972–4981). New York, NY: Springer.
Calderoni, F. (2015). Predicting organised crime leaders. In G. M. Bichler & A. E. Malm (Eds.), *Disrupting criminal networks: Network analysis in crime prevention* (pp. 89–110). Boulder, CO: FirstForumPress, a division of Lynne Rienner Publishers.
Campana, P. (2011). Eavesdropping on the Mob: The functional diversification of Mafi a activities across territories. *European Journal of Criminology*, 8 (3), 213–228.
Carley, K. M., Lee, J.-S., & Krackhardt, D. (2002). Destabilizing networks. *Connections*, 24 (3), 79–92.
Carrington, P. J. (2011). Crime and social network analysis. In J. Scott & P. J. Carrington (Eds.), *Sage handbook of social network analysis* (pp. 236–255). London: SAGE Publications.
Carrington, P. J., Scott, J., & Wasserman, S. (Eds.). (2005). *Models and methods in social network analysis*. Cambridge: Cambridge University Press.
Coles, N. (2001). It’s not what you know - it’s who you know that counts: Analysing serious crime groups as social networks. *British Journal of Criminology*, 41 (4), 580–594.
Davis, R. H. (1981). Social network analysis: An aid in conspiracy investigations. *FBI Law Enforcement Bulletin*, 50 (12), 11–19.
Décary-Hétu, D. (2014a). Information exchange paths in IRC hacking chat rooms. In C. Morselli (Ed.), *Crime and networks* (pp. 218–230). New York, NY: Routledge.
Décary-Hétu, D. (2014b). Police operations 3.0: On the impact and policy implications of police operations on the Warez scene. *Policy & Internet*, 6 (3), 315–340.
Décary-Hétu, D., & Dupont, B. (2012). The social network of hackers. *Global Crime*, 13 (3), 160–175.
Descormiers, K., & Morselli, C. (2011). Alliances, conflicts, and contradictions in Montreal’s street gang landscape. *International Criminal Justice Review*, 21 (3), 297–314.
Duijn, P. A. C., & Klerks, P. (2014). Social network analysis applied to criminal networks: Recent developments in Dutch law enforcement. In A. J. Masys (Ed.), *Networks and network analysis for defence and security* (pp. 121–158). Cham: Springer.
Emirbayer, M. (1997). Manifesto for a relational sociology. *American Journal of Sociology*, 103 (2), 281–317.
Ennett, S. T., Bauman, K. E., Hussong, A., Faris, R., Foshee, V. A., Cai, L., et al. (2006). The peer context of adolescent substance use: Findings from social network analysis. *Journal of Research on Adolescence*, 16 (2), 159–186.
Everton, S. F., & Cunningham, D. (2014). Terrorist network adaptation to a changing environment. In C. Morselli (Ed.), *Crime and networks* (pp. 287–308). New York and London: Routledge.
Faulkner, R. R., & Cheney, E. R. (2015). Defection from a fraud network. In G. M. Bichler & A. E. Malm (Eds.), *Disrupting criminal networks: Network analysis in crime prevention* (pp. 111–128). Boulder, CO: FirstForumPress, a division of Lynne Rienner Publishers.
Galaskiewicz, J., & Wasserman, S. (1994). Advances in the social and behavioural sciences from social network analysis. In S. Wasserman & J. Galaskiewicz (Eds.), *Advances in social network analysis: Research in the social and behavioural sciences* (pp. xi–xvii). London: SAGE Publications.
Grannis, R. (2014). Social network analysis and the measurement of neighborhoods. In G. Bruinsma & D. Weisburd (Eds.), *Encyclopedia of criminology and criminal justice* (pp. 4964–4972). New York: Springer.

Harper, W. R., & Harris, D. H. (1975). The application of link analysis to police intelligence. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 17 (2), 157–164.

Haynie, D. L. (2001). Delinquent peers revisited: Does network structure matter? *American Journal of Sociology*, 106 (4), 1013–1057.

Haynie, D. L. (2002). Friendship networks and delinquency: The relative nature of peer delinquency. *Journal of Quantitative Criminology*, 18 (2), 99–134.

Haynie, D. L., & Soller, B. (2014). Network analysis in criminology. In G. Bruinsma & D. Weisburd (Eds.), *Encyclopedia of criminology and criminal justice* (pp. 3265–3275). New York: Springer.

Heber, A. (2009). The networks of drug offenders. *Trends in Organized Crime*, 12 (1), 1–20.

Hegemann, R. A., Smith, L. M., Barbaro, A. B. T., Bertozzi, A. L., Reid, S. E., & Tita, G. E. (2011). Geographical influences of an emerging network of gang rivalries. *Physica A: Statistical Mechanics and its Applications*, 390 (21–22), 3894–3914.

Ianni, F. A. J., & Reuss-Ianni, E. (1990). Network analysis. In P. Andrews & M. B. Peterson (Eds.), *Criminal intelligence analysis* (pp. 67–84). Loomis, CA: Palmer Enterprises.

Keegan, B., Ahmed, M. A., Williams, D., Srivastava, J., & Contractor, N. (2010). Dark gold: Statistical properties of clandestine networks in massively multiplayer online games. In *Proceedings of the Second IEEE International Conference on Social Computing* (pp. 201–208). Minneapolis, MN.

Kila, J., & Bouchard, M. (2015). Vulnerabilities in online child exploitation networks. In G. M. Bichler & A. E. Malm (Eds.), *Disrupting criminal networks: Network analysis in crime prevention* (pp. 153–176). Boulder, CO: FirstForumPress, a division of Lynne Rienner Publishers.

Klerks, P. (2001). The network paradigm applied to criminal organizations: Theoretical nitpicking or a relevant doctrine for investigators? Recent developments in the Netherlands. *Connections*, 24 (3), 53–65.

Knoke, D., & Kuklinski, J. H. (1991). Network analysis: Basic concepts. In G. Thompson, J. Frances, R. Levacic, & G. Mitchell (Eds.), *Markets, hierarchies and networks: The coordination of social life* (pp. 173–182). London: SAGE Publications.

Kreager, D. A., & Haynie, D. L. (2011). Dangerous liaisons? Dating and drinking diffusion in adolescent peer networks. *American Sociological Review*, 76 (5), 737–763.

Krebs, V. E. (2001). Mapping networks of terrorist cells. *Connections*, 24 (3), 43–52.

Lupsha, P. A. (1980). Steps toward a strategic analysis of organized crime. *The Police Chief*, (May 1980), 36–38.

Lupsha, P. A. (1983). Networks versus networking: Analysis of an organized crime group. In G. P. Waldo (Ed.), *Career criminals* (pp. 59–87). Beverly Hills, CA: SAGE Publications.

Malm, A. E., & Bichler, G. M. (2011). Networks of collaborating criminals: Assessing the structural vulnerability of drug markets. *Journal of Research in Crime and Delinquency*, 48 (2), 271–297.

Malm, A. E., Bichler, G. M., & Nash, R. (2011). Co-offending between criminal enterprise groups. *Global Crime*, 12 (2), 112–128.

Malm, A. E., Bichler, G. M., & Van De Walle, S. (2010). Comparing the ties that bind criminal networks: Is blood thicker than water? *Security Journal*, 23 (1), 52–74.

McAndrew, D. (1999). The structural analysis of criminal networks. In D. Canter & L. Alison (Eds.), *The social psychology of crime: Groups, teams and networks* (pp. 51–94). Aldershot: Ashgate Publishing.

McCuish, E. C., Bouchard, M., & Corrado, R. (2015). The search for suitable homicide co-offenders among gang members. *Journal of Contemporary Criminal Justice*, 31 (3), 319–336.

McGloin, J. M. (2007). The organizational structure of street gangs in Newark, New Jersey: A network analysis methodology. *Journal of Gang Research*, 15 (1), 1–34.

McGloin, J. M. (2009). Delinquency balance: Revisiting peer influence. *Criminology*, 47 (2), 439–477.

McGloin, J. M., & Kirk, D. S. (2010). Social network analysis. In A. R. Piquero & D. Weisburd (Eds.), *Handbook of quantitative criminology* (pp. 209–224). New York: Springer.
McGrath, C., Blythe, J., & Krackhardt, D. (1997). The effect of spatial arrangement on judgments and errors in interpreting graphs. *Social Networks*, 19 (3), 223–242.
Morenoff, J. D., Sampson, R. J., & Raudenbush, S. W. (2001). Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence. *Criminology*, 39 (3), 517–558.
Morselli, C. (2009). Inside criminal networks. New York, NY: Springer.
Morselli, C., Giguere, C., & Petit, K. (2007). The efficiency/security trade-off in criminal networks. *Social Networks*, 29 (1), 143–153.
Natarajan, M. (2006). Understanding the structure of a large heroin distribution network: A quantitative analysis of qualitative data. *Journal of Quantitative Criminology*, 22 (2), 171–192.
Papachristos, A. V. (2006). Social network analysis and gang research: Theory and methods. In J. F. Short & L. A. Hughes (Eds.), *Studying youth gangs* (pp. 99–116). Lanham, MD: AltaMira Press.
Papachristos, A. V. (2009). Murder by structure: Dominance relations and the social structure of gang homicide. *American Journal of Sociology*, 115 (1), 74–128.
Papachristos, A. V. (2011). The coming of a networked criminology? Using social network analysis in the study of crime and deviance. In J. McCord (Ed.), *Beyond empiricism: Institutions and intentions in the study of crime* (pp. 101–140). New Brunswick, NJ: Transaction Publishers.
Papachristos, A. V. (2014). The network structure of crime. *Sociology Compass*, 8 (4), 347–357.
Papachristos, A. V., Braga, A. A., & Hureau, D. M. (2012). Social networks and the risk of gunshot injury. *Journal of Urban Health: Bulletin of the New York Academy of Medicine*, 89 (6), 992–1003.
Papachristos, A. V., Hureau, D. M., & Braga, A. A. (2013). The corner and the crew: The influence of geography and social networks on gang violence. *American Sociological Review*, 78 (3), 417–447.
Papachristos, A. V., Wildeman, C., & Roberto, E. (2015). Tragic, but not random: The social contagion of nonfatal gunshot injuries. *Social Science & Medicine*, 125 (Jan. 2015), 139–150.
Payne, D. C., & Cornwell, B. (2007). Reconsidering peer influences on delinquency: Do less proximate contacts matter? *Journal of Quantitative Criminology*, 23 (2), 127–149.
Piquette, J. C., Smith, C. M., & Papachristos, A. V. (2014). Social network analysis of urban street gangs. In G. Bruinsma & D. Weisburd (Eds.), *Encyclopedia of criminology and criminal justice* (pp. 4981–4991). New York, NY: Springer.
Radil, S. M. (2014). Spatial models and network analysis. In G. Bruinsma & D. Weisburd (Eds.), *Encyclopedia of criminology and criminal justice* (pp. 4991–4997). New York, NY: Springer.
Radil, S. M., Flint, C., & Tita, G. E. (2010). Spatializing social networks: Using social network analysis to investigate geographies of gang rivalry, territoriality, and violence in Los Angeles. *Annals of the Association of American Geographers*, 100 (2), 307–326.
Rothenberg, R. (2002). From whole cloth: Making up the terrorist network. *Connections*, 24 (3), 36–42.
Sampson, R., Morenoff, J., & Gannon-Rowley, T. (2002). Assessing "Neighborhood Effects": Social processes and new directions in research. *Annual Review of Sociology*, 28, 443–478.
Scott, J. (2000). Social network analysis: A handbook (2nd ed.). London: SAGE Publications.
Soller, B., & Browning, C. R. (2014). Neighborhood effects and social networks. In G. Bruinsma & D. Weisburd (Eds.), *Encyclopedia of criminology and criminal justice* (pp. 3255–3265). New York, NY: Springer.
Sparrow, M. K. (1991a). Network vulnerabilities and strategic intelligence in law enforcement. *International Journal of Intelligence and Counterintelligence*, 5 (3), 255–274.
Sparrow, M. K. (1991b). The application of network analysis to criminal intelligence: An assessment of the prospects. *Social Networks*, 13 (3), 251–274.
Strang, S. J. (2014). Network analysis in criminal intelligence. In A. J. Masys (Ed.), *Networks and network analysis for defence and security* (pp. 1–26). Cham: Springer.

Tita, G. E., Butts, C. T., Valasik, M., & Brantingham, P. J. (2012). *Rivalries and reciprocity: A relational event model of gang violence*. Presented at the 68th American Society of Criminology Annual Meeting, Chicago.

Tita, G. E., & Radil, S. M. (2010). Making space for theory: The challenges of theorizing space and place for spatial analysis in criminology. *Journal of Quantitative Criminology*, 26 (4), 467–479.

Tita, G. E., & Radil, S. M. (2011). Spatializing the social networks of gangs to explore patterns of violence. *Journal of Quantitative Criminology*, 27 (4), 521–545.

Van der Hulst, R. C. (2009). Introduction to social network analysis (SNA) as an investigative tool. *Trends in Organized Crime*, 12 (2), 101–121.

Varese, F. (2013). The structure and the content of criminal connections: The Russian Mafi a in Italy. *European Sociological Review*, 29 (5), 899–909.

Von Lampe, K. (2009). Human capital and social capital in criminal networks: Introduction to the special issue on the 7th Blankensee Colloquium. *Trends in Organized Crime*, 12 (2), 93–100.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. New York, NY: Cambridge University Press.

Xu, J. J., & Chen, H. (2008). The topology of dark networks. *Communications of the ACM*, 51 (10), 58–65.