“On to the next one:”
Using social network data to inform police target prioritization

by
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Abstract

As part of the portfolio of strategies used to achieve crime reductions, law enforcement agencies routinely establish a list of offenders to be targeted as priorities. Rarely considered, however, is the fact that targets are embedded in larger social networks. These networks are a rich resource to be exploited as they facilitate: 1) efficient prioritization by understanding which offenders have access to more resources in the network, and 2) assessments of the impact of intervention strategies. Drawing from law enforcement data, the personal networks of two mutually connected police targets from a mid-size city in British Columbia, Canada were constructed. Results show that of the 101 associates in their combined network, 50 percent have a crime-affiliated attribute. The network further divides into seven distinct communities, ranging from four to 25 members. Membership to these communities suggests how opportunities, criminal and non-criminal, form and are more likely to occur within one’s immediate network of associates as opposed to the larger network. As such, seven key players that have the highest propensity to facilitate crime-like behaviours are identified via a measure of “network capital,” and located within the communities for informed target selection.

Keywords: Social network analysis; intelligence-led policing; law enforcement priorities; key players; deterrence; community structure
Dedication

To my constants, my rocks, who have been through it all with me: the good, the bad, and the uncertainties. I am grateful for your support, patience, and unconditional love. Thank you for teaching me the importance of balance while allowing me to get lost in the process. You are *my* irreplaceables and I owe everything to you.

Love and respect, always

xxx
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“Everyone you will ever meet knows something you don’t” – Bill Nye

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Chapter 1.

Introduction

Individuals operate within overlapping networks of family, close friends, coworkers, and acquaintances. These social relations, in return, set forth different types of resources and constraints. Social network analysis is oriented towards the understanding of human behaviour, particularly the process in which actors become embedded, stay embedded, and are influenced by their social surroundings (Granovetter, 1985; McGloin & Kirk, 2010). As many forms of criminal behaviour rely on social interactions, where individuals co-offend with a network of friends, family, and/or associates, there is a transference of attitudes, norms and activities (Reiss & Farrington, 1991; Warr, 1993; Weerman, 2003). A network approach provides a conceptual framework for better understanding these interactions, exploiting the fact that offenders may not necessarily operate as individual units, but are interconnected with one another (Morselli, 2009; Kennedy, 1997). To contextualize social interactions, and the diffusion of behaviours in criminal (co-offending networks, peer delinquent networks, drug trafficking networks, criminal organizations), and/or non-criminal (adult networks, family networks, friendship networks) environments, researchers have historically drawn from traditional theories such as social learning theory (Cressey, 1952; Kissner & Pyrooz, 2009; Reiss & Farrington, 1991) and social control theory (Gallupe & Bouchard, 2013; Morselli, Tremblay & McCarthy, 2006) to supplement network analysis.

Beyond theoretical inquiries into the understanding of human behaviour, network analysis has proven to be a powerful tool for law enforcement investigations. An objective of policing agencies and law enforcement officials is to prevent and control crime. Their level of success, however, is largely based on their ability to identify criminals and their associates, detect the nature and structure of organizations bounded in criminal settings,
and predict the movement of individuals who pose a risk to the community (Harper & Harris, 1975). The challenge that resides with meeting these objectives is in the ability to organize, manage, and utilize criminal intelligence. Not all police data are useful. This was recognized by Sparrow (1991b) when he noted that law enforcement officials “typically have plenty of data” but “comparatively little capability for extracting useful intelligence from it” (p. 257). Network analysis provides an analytical framework to organize and contextualize police data and criminal intelligence (Harper & Harris, 1975; Sparrow, 1991a; Sparrow, 1991b; Carley, Jung-Sung, & Krackhardt 2002). The types of questions sought by networks, such as assessing the organization and structure of a criminal group, the need to link criminals to events and or to each other, the roles of key individuals in criminal events, and the need to proactively seek patterns in the movements of offenders naturally coincides with the goals of law enforcement officials, and criminal investigations (Sparrow, 1991a, 1991b; Carley et al., 2002). Realising the effectiveness of this partnership, researchers have synthesized the two fields, applying network analysis to law enforcement data on co-offending groups (Bouchard & Konarski, 2014) criminal organizations (Morselli, 2010), drug networks (Morselli & Petit, 2007; Malm & Bichler, 2011), and gang networks (McCuish, Bouchard, and Corrado, 2015; Morselli, 2009). Additionally, this partnership has led to the development of intervention strategies and crime control policies (Braga, Kennedy, Waring & Piehl, 2001; Engel, Tillyer & Corsaro, 2011; Papachristos, Meares & Fagan, 2007).

The current study builds on this collaboration in three ways. First, it maps the social environment of two police targets using law enforcement data. These targets were the top priorities in a specific jurisdiction based on their criminal connections. We account for the fact that most police targets are embedded in a larger network of family, friends, criminal and non-criminal associates. This leads us to the second objective, that is, to advance the understanding of network structures that contain both criminal and non-criminal elements. Doing so is useful on a theoretical level as it allows us to understand more about the targets and their decision-making behaviours. The final objective is more practical: provide a framework to detect key players (or sets of key players) who contribute most to the network based on an intersection of factors meeting the crime reduction objectives of law enforcement agencies. We hone in on these network members via a measure of network
capital (see Schwartz & Rouselle, 2009; Westlake, Bouchard & Frank, 2011), which combines an associate’s importance to the network and their propensity to facilitate serious criminal behaviours (e.g. gang ties). Doing so allows us to make specific recommendations as to who the next round of targets could be, once the two initial targets have been sought.
Chapter 2.

Theory and literature review

2.1. Embeddedness in social and criminal networks

Of particular importance to “social networks,” are the environment and purpose for which individuals organize their social relations around (Feld, 1981). Understanding the relationship between the structure of networks and aspects of social structure is important for understanding network constraints - particularly the ways in which people become “associated with, stay associated with, and become disassociated” (Feld, 1984, p. 642).

Social networks provide different avenues for the acquisition of social and capital resources. Networks, contingent on their foci, vary in their social, economic, and cultural influences. Most importantly, however, they vary in types of relations, and the strength of ties that form (Granovetter, 1973, 1985; Krohn, 1986; Moody & White, 2003). For instance, in adult networks, adults develop and maintain relationships in three particular ways (Verbrugge, 1979). First, Verbrugge (1979) noted the frequency of contact adults have with one another. Spatial proximity encouraged frequency of contact. When adults lived in the same community, or were readily accessible to one another they were more likely to interact. These interactions in return enhanced opportunities for face-to-face contact and intimate ties. Second was a preference for special similarities. Shared experiences and similarities in cultures and norms were likely to encourage relationships. Particularly similarities in age, attitude, behaviours, social status and activities increased the likelihood of close relations (Feld, 1982; Verbrugge, 1979). Finally, Verbrugge noted the desirability of diffusion and holistic ties, that is, the quality of emotional and instrumental exchanges between two people that form through common events, or foci. He noted that family, neighbours, co-workers and friends provided different types of support and services. Relatives and close friends were expected to be a source of social, emotional, and at times financial support whereas co-workers were a source of help and service in the workplace (Fischer, 1982; Verbrugge, 1979). When relations converged,
they established multiple types of bonds affecting the quality of exchange amongst individuals. Verbrugge (1979) referred to these relations as multiplex. Multiplex relations create “multiple bases for interaction” (Verbrugge, 1979, p. 1787). They are attributed to individuals playing dual roles in one another’s lives, or sharing multiple focal nodes. For instance, a neighbor who is a co-worker, or a friend who belongs to the same sports team. Multiplex relationships, in comparison to other types of relations, were important in that they strengthened bonds; accelerating norm acceptance and role accretion (Verbrugge, 1979).

Moreover, extant research (see Battin, Hill, Abbott, Catalano, & Hawkins, 1998; Cook, Deng, & Morgano, 2005; Crosnoe, Cavanagh, & Elder, 2003; Frank, Muller, & Mueller, 2013; Haynie, 2001; Kreager, Rullison & Moody, 2011; Stanton-Salazar & Spina, 2005) have established the social benefits of friendships, and diffusion of behaviour in adolescent networks. Similar to adult networks, these studies have suggested two ways in which adolescents were likely to behave in a manner that is consistent with their friends. First is conformity. Adolescents were likely to conform to the norms, attitudes and behaviours of those they considered friends. Carbonaro and Workman (2013) stated that in school, “students view their close friend’s actions as an outgrowth of their individual circumstances and personality” (p.1266). Cook et al. (2005) found that GPA, drug use and crime-like behaviours, net of causal effects such as demographic, family and cognitive attributes, matched between friends. Second is resource exchange. Cook et al. (2005) found exchanges in social capital and resources between friends within the networks. Adolescents were likely to provide support, resources and opportunities to those they considered friends. These ties were powerful in that adolescent friendships, like adult friendships, became social resources, providing an exchange of emotional and social support (Carbonaro & Workman, 2013; Cook et al., 2005; Crosnoe et al., 2003; Fischer, 1982; Stanton-Salazar & Spina, 2005).

Criminal networks, on the other hand, have their own set of distinct features. While similar to their non-criminal counterparts, Morselli (2009) argued that “criminal networks are not simply social networks operating in criminal contexts” (p. 8). Rather, the “covert” nature of these networks necessitates different interactions and relational features
First, criminal networks, unlike conventional social networks, operate illegally, constraining the interactions of network participants. Morselli (2009) noted that, internally, participants within criminal networks have to adjust and control their behaviours as conflicts cannot be settled by legitimate social means (law enforcement etc.). Externally, criminal networks have to build and establish resilience, adjusting to legitimate formal social controls such as the police, the public, and the community that are hostile to their existence.

Second, this illegality, also influences the quality and types of relations formed within criminal networks. Embeddedness in criminal or deviant networks may facilitate important relationships (ties) amongst network participants (Granovetter, 1985). Embeddedness in criminal networks provides participants with the opportunity to learn, share and partake in criminal and deviant behaviours with one another. The learning process ties in with Sutherland’s differential association theory which postulates that criminality and delinquency is learned through social interactions as opposed to biological or psychological conditions (Cressey, 1952). A central component of social learning theory is instrumental conditioning, in that, the attitudes of friends are interconnected, and that “delinquent behaviour is learned through associations with patterns of delinquent behaviour” (Reiss & Farrington, 1991, p. 363; Winfree, Bäckström & Mays, 1994a; Winfree, Bäckström, & Mays, 1994b). For instance, in a study of 1,726 youth, Warr and Stafford (1991) found that the attitude of one’s peers affects an individual’s propensity to commit delinquent acts such as cheating, smoking marijuana, and larceny. Hochstetler, Copes and DeLisi (2002) found similar results in their study of 1,492 youths. When controlling for the respondent’s attitude, the behaviours of one’s friends was significantly associated with their propensity to commit theft, assault, and vandalism. Consequently, individuals were more susceptible to crime if they associated with peers who condoned and participated in criminal activity (Hochstetler et al., 2002, p. 559)

Kissner and Pyrooz (2009) applied differential association theory to examine former and current gang membership. They tested whether having a parent, older sibling(s), older relative, or friends in a gang affected gang membership. Controlling for age, sex, ethnicity, household stability, and low self-control, Kissner and Pyrooz (2009)
found that having friends in a gang had a significant impact on former gang membership, whereas, having a parent, older sibling and gang friends had the largest positive effect on current gang membership. It was suggested that having peers or family members in gangs might expose individuals to certain types of behaviours, facilitating crime, and promoting gang membership.

Finally, access to criminal networks may facilitate social capital and greater access to criminal resources. Such opportunities may be generated through mentorship (Morselli et al., 2006), or the use of networks to select suitable co-offenders. (Tremblay, 1993; Weerman, 2003). Morselli et al. (2006) extended the discussion on mentorship by exploring the relationship between criminal achievement, self-control and mentorship. Relying on data from 193 inmates from a Quebec prison, they found that 39 percent of inmates reported having a mentor, that is, someone who introduced them to the “criminal milieu” at some point (Morselli et al., 2006, p. 26). They defined mentors as “a partner in crime, a supplier,” or individuals who played a role in the criminal career (Morselli et al., 2006, p. 26). Amongst their sample of inmates, they found that those with lower self-control were most likely to attract mentorship. In fact, the presence of a criminal mentor facilitated their criminal earnings. Criminal mentors improved their “protégés” social capital, size of network, and reduced the risk of incapacitation. Those with mentors had greater indirect access to others, such as criminals in their mentor’s networks, which indirectly lead to the accumulation of social capital.

In finding a potential accomplice, Weerman (2003) suggested that offenders were likely to utilize their existing criminal relationships to facilitate such ties. When looking for suitable co-offenders, offenders use their contacts and their connections to enable criminal activities. For instance, offenders may utilize their network as a whole, such as in drug trafficking networks, or hierarchal criminal organizations. Alternatively, offenders may be constrained to selecting potential co-offenders from their gang, or group of delinquent friends (McCuish et al., 2014; Reiss, 1988; Weerman, 2003). Nevertheless, offenders embedded in delinquent networks utilize their ties, co-offending with others in their immediate network, most of whom they share similarities and have existing relationships with (McCuish et al., 2014; Morselli, 2009; Tremblay, 1993).
2.1.1. The emergence of communities and groups within networks

Within networks, clusters, or cohesive sub pockets that localize into groups (communities), emerge. These communities are densely interconnected to one another, and are less densely connected from the larger milieu. Given the nature of group ties, and the socialisation process that follows, membership within these groups leads to the transmission of influences as it 1) facilitates norms and values across members; 2) leads to internal controls, where members are monitored and can be sanctioned; and 3) generates a sense of conformity between homogenous groups (Kreager et al., 2011). Communities are often formed on the bases of cohesion, shared interactions, and intimacy. This, overtime, leads to the transmission and enforcement of norms, cultures and shared beliefs, all of which is grounded upon the principle of homophily.

Homophily is present amongst people who are more similar than dissimilar (Lazarsfeld & Merton, 1954; Mcpherson, Smith-Lovin & Cook, 2001). These similarities can be in age, sex, ethnicity, social proximity, and or criminal experience (Carrington & van Mastroigt, 2013; McCuish et al., 2014; van Mastroigt & Farrington, 2011). For instance, McPherson and Smith-Lovin (1987) found that members of close peer groups, or social groups, tend to be similar, as they adjusted their opinions and beliefs based on the opinions and attitudes of their close associates. Particularly, they found that homophily was greater in larger groups. Larger groups provided more people, who were characteristically alike, thus expanding the pool of peers to choose from (McPherson & Smith-Lovin, 1987). Within the context of networks “homophily implies that distance in terms of social characteristics translate into network distance” (Mcpherson, Smith-Lovin & Cook, 2001, p. 416). In other words, social characteristics influence the quality and frequency of contact. Reiss and Farrington (1991), in their analysis of the Cambridge Study of Delinquent Development, found that co-offenders often lived in close geographical proximity to each other, and were likely to commit crimes close to their residence (p. 394). Additionally, they found co-offenders were “similar in age, sex, race, and criminal experience” (Reiss & Farrington, 1991, p. 394). The formation of such cliques, within the larger structure of networks, provides insight into the diffusion of opinions and beliefs.
To detect communities, researchers have utilized algorithms such as the Girvan and Newman on a variety of networks. In lieu of hierarchal clustering methods, the Girvan and Newman algorithm divides network nodes within groups, focusing on edges with the highest betweenness scores to determine community peripheries (Girvan & Newman, 2002). The number of minimum paths, connecting pairs of nodes that go through that edge, defines the betweenness of an edge. Highly connected actors are responsible for connecting many others, thus, the removal of these edges fragments the network, revealing the underlying structure. To test the performance of their algorithm, Girvan and Newman (2002) applied it to computer-generated graphs and real world networks, where the community structure algorithm was known beforehand. In both cases, the Girvan and Newman (2002) algorithm proved to be an accurate method for extracting community structure. Additionally, they tested their algorithm on two networks, the collaboration network of scientists in Santa Fe, New Mexico, and a food web of organisms living in Chesapeake Bay, both of which the structure was unknown. Amongst the collaboration network, the algorithm split the network of 271 scientists into one community of 118 scientists, and a few peripheral communities all based on the scientists area of research, and the methodology they used. In the food web of marine organisms, the Girvan and Newman (2002) algorithm partitioned organisms that made up the network into two communities that were classified by their ecological subsystems.

Guimera, Danon, Diaz-Guilera, Giralt and Arenas (2006) further validated the Girvan and Newman algorithm by exploring the exchange of emails between employees in a university. Using email logs, they were able to reconstruct the network of interactions, identifying and accurately partitioning individuals within the university into working research teams, departments, faculties, and colleges (centres) within the university while identifying the interrelations between them (Guimera et al., 2006, p. 666). Email logs exposed the real networks of interactions within the university, grouping individuals into a hierarchy of communities at all levels. Furthermore, Athey and Bouchard (2013) explored the presence of communities in their analysis of the Bay Area Laboratory Cooperative (BALCO) scandal. The BALCO scandal involved the production and distribution of illegal steroids to professional athletes in a facility in California. The study’s objective was to see whether shared interests in performance-enhancing drugs created an opportunity for
individual actors and groups involved in the investigation to unify. Their network of 97 participants comprised athletes, BALCO associates and employees, athletic coaches, trainers, and “others”, with little to no affiliation, other than their mutual interest in performance enhancing drugs. The Girvan and Newman algorithm was performed to determine whether distinct communities formed around specific sporting communities, or whether the BALCO network was a single, large community in and of itself. The authors found a core group of athletes centralized around one focal actor, surrounded by five peripheral communities that formed around athletic interests (Athey & Bouchard, 2013, p. 227). These studies empirically demonstrate the utility of identifying communities for understanding network structure and interactions amongst sub-groups of individual’s embedded in larger networks.

2.2. Applying social networks to law enforcement data

Given the group nature of crime, and the diffusion of information through actors, networks are useful in exploring social structure, the role of actors, and the patterns of relations that follow. Law enforcement officials have previously used simpler forms of network analysis, like link analysis, as a starting point for investigating criminal organizations, terrorism, and narcotic related offences (Sparrow, 1991a, 1991b; van der Hulst, 2009). Link analysis was developed to assist law enforcement officials in portraying the complex set of relationships amongst individuals and organizations (Harper & Harris, 1975). A conventional problem with link analysis lies with the fact that it “simply communicates the results” (Sparrow, 1991a, p. 254). The onus is on the investigator to generate their analyses first, based on their knowledge and expertise, and then produce a graphical portrayal of their data via link analysis (Sparrow, 1991a). Thus, a long-standing problem is that while police agencies have data, and access to investigative information, they may lack the ability to extract systematic results from it (Sparrow, 1991b). This is because 1) greater volumes of data do not necessarily lead to better policing tactics, quality intelligence files, or successful investigations; and 2) due to limited resources and time many agencies may lack a conceptual framework for implementing intelligence-led
strategies as opposed to conventional policing practices that are more reactive in nature (Ratcliffe, 2002, p. 64; Ratcliffe, 2007).

Law enforcement data can be derived from police databases, intelligence data, offender interviews, informants, crime patterns, and or socio demographic data (Ratcliffe, 2008, p. 7). When combined, network analysis supplements this type of data as there is a natural overlap in the questions posed by network analysts and enforcement officials (Sparrow, 1991a, 1991b). For instance, inquiries comprise, but are not limited to identifying leaders of criminal organizations, the roles of individuals, the effect of disruptions on the organization, and the context of relationships (Carley et al., 2002; Sparrow, 1991a, 1991b). In line with these goals, extant studies have shown the efficiency, and benefits of merging these approaches.

Morselli (2009) analysed the alleged street gang problem in Montreal, Canada by combining three independent investigations by the Montreal Police. Analyzing the three investigations together, he found that a single network was responsible for the drug distribution operation. Initially, a well-known street gang, the Bo-Gars were suspected of operating the drug distribution operations. The police intended to target the Bo-Gars and their affiliates without considering the context of the whole network, and the role of participants. The Montreal police were experiencing a typical challenge to this investigation. They were not able to use the history of relations between participants in planning its intervention – only the targets and evidence accumulated for the “current” investigations were allowed. The question Morselli (2009) put forth was whether members of the Bo-Gars or members of surrounding gangs implicated in the network were in control of the drug distribution operation as suggested by law enforcement officials (p.140). Of the 70 individuals who were identified as participants in the drug distribution, they found that 23 individuals were gang members, 11 being Bo-Gars members. Of the five key participants in the distribution, however, only one was a Bo-Gars member. Contrary to police suggestions, gang members were not “more central” to the network than non-gang members. The Bo-Gars while present across the investigations did not act as a collective entity. Members did not form cliques, rather non-gang participants, and members of smaller gangs formed clusters, interacting with one another.
Bouchard and Konarski (2014) drew on social network analysis to analyze the co-offending network of a street-level gang in British Columbia. The “856 gang” were on police radar as several criminal activities were attributed to the gang. Bouchard and Konarski (2014) analysed the validity of the decision made by law enforcement officials to target six individuals who they believed represented the core of the 856 gang. They found that members from the 856 gang whom police identified as “core members” only represented 22 percent of all offenders in the network (13 of the 60). Additionally, they examined the data to seek whether any densely connected subset of actors (core) could be significantly differentiated from the others (periphery) (Bouchard & Konarski, 2014, p. 88). The core periphery analyses revealed that the targeted six members only represented 38.5 percent of what the co-offending network analysis suggested was really the core of the 856 gang. Despite the allocation of police resources into arresting the original six members believed to be at the “core” of the gang, results indicated that only four of the chosen six were, in fact, part of the core. Findings by Bouchard and Konarski (2014) showed the importance in utilizing various social network analysis tools with law enforcement data.

Morselli and Petit (2007) studied the impact of law enforcement controls on Project Caviar, a drug importation network monitored by Montreal police for two years. Project Caviar was unique for two reasons. Law enforcement monitored the network, exerting some level of control, but followed a strategy where they would seize consignments of drugs without arresting the participants who were involved in the importations. Morselli and Petit (2007) incorporated targeting strategies used by law enforcement to seek how external controls influenced the structure and positioning of participates. The strategy showed the resilience and vulnerabilities of the criminal network as participants of the network were followed over the course of the two years. Findings revealed changes in the structure and composition of the drug importation network. As the volume of drugs seized accumulated, the central participant’s status within the network decreased. This, in return, coincided with an increase in the centrality of other participants who were trying to overcome the losses. The studies by Morselli (2009), Bouchard and Konarski (2014) and Morselli and Petit (2007) were conducted “post fact,” that is after the end of the investigation. In doing so, they used network analysis to highlight the importance of
demonstrating the structural positions of key network players within police investigations, rather than simply assuming importance.

Alternatively, researchers have used network approaches to actively disrupt the dynamic nature of violence, and particularly group crime before they occur. Initiatives such as the Operation Ceasefire in Boston (Braga et al., 2001), the Cincinnati Initiative to Reduce Violence (CIRV) (Engel et al., 2011) and Project Safe Neighborhoods (PSN) in Chicago, Illinois, (Papachristos et al., 2007) used focused deterrence strategies to reduce serious violence generated by street gangs, criminally active street groups, or repeat offenders. Focused deterrence strategies use the interconnectedness of offenders to “serve as a communication vehicle” and act as a “source of a control” for members of socially connected groups (Engel et al., 2011, p. 5). Thus, a common strategy amongst all three initiatives was in exploiting the group nature of crime. For instance, it is an established fact that criminal offending is “highly concentrated,” in 1) serial offenders; 2) criminal groups; and 3) hot spot areas within neighborhoods where crime is often committed by “many of whom associate with one another and work together” (Kennedy, 1997, p. 449; Tillyer & Kennedy, 2008). Thus, strategies were based upon the belief that 1) repeat offenders commit the majority of crime; and 2) these offenders are connected and operate to “some degree in gangs or groups” (Kennedy, 1997; Tillyer, Engel, & Lovins, 2010, p. 975). Applying this, they used the networks of offenders to diffuse a deterrence message across the community. Offenders were warned that if they failed to change their behaviour, officials would create consequences by “exploit[ing] lengthy criminal records” and “pulling” every lever legally available” to disrupt their networks (Braga, 2001; Tillyer et al., 2010, p. 975).

In one of the first focused deterrence initiatives, Operation Ceasefire, a problem oriented policing strategy, in Boston focused on reducing serious violence by street gangs, and gang members (Braga et al., 2001; Braga, Papachristos & Hureau, 2012; Papachristos et al., 2007; Kennedy, 1997). These gangs represented 1 percent of Boston’s youth aged 14 to 24, however, they were the cause of 60 percent of Boston’s youth homicides. The Boston Ceasefire was an interagency approach involving law enforcement officials, researchers, youth workers, probation, parole officers, and
community groups. Its objective was to deter serious violence among specified groups (Kennedy, 1997). They did so by spreading a message that violence was not acceptable, and that violent behaviour would evoke severe punishments. This message was voiced to gang members through notification meetings, probation and police contact with gang members, and inmate meetings in juvenile facilities. Boston’s Operation Ceasefire reduced youth homicides by 63 percent. There was also a 25 percent reduction in gun assaults, 32 percent reduction in shots fired called for services, and 44 percent reduction in youth gun assaults in a targeted high-risk district (Braga & Weisburd, 2012, p. 335).

Modeled after the Boston Ceasefire, the Cincinnati Initiative to Reduce Violence (CIRV) used a network-based approach to deliver a deterrence message for violent group members (Engel et al., 2011). As one of its strategies, the CIRV law enforcement team was tasked with systematically identifying victims and offenders who were most at risk of being perpetrators and/or victims of gun-related homicides. Due to the concentration of violent, chronic offenders in the city, the CIRV law enforcement team selected two violent groups for targeted enforcement (Engel et al., 2011). They mapped and explored the interconnectedness of group members, and identified key players via their propensity to commit crime (Engel et al., 2009). Law enforcement officials removed targeted individuals from the network resulting in a 95-count Grand Jury indictment (Engel et al., 2009), and were able to drastically reduce shootings, gun-related homicides and group homicides by 35 percent (Engel et al., 2011).

Project Safe Neighborhood (PSN), implemented in Chicago, aimed at reducing gun homicides in areas with the highest level of gun violence (Papachristos et al., 2007). Chicago’s PSN initiative was a multiagency taskforce that included law enforcement agencies, corrections, prosecutorial services, and local community based agencies. Representatives of each agency or organization met on a monthly basis to construct strategies to reduce gun violence in neighborhoods with the highest rates of gun violence. The PNS task force focused on a targeted group of violent repeat offenders, clustered in high crime neighborhoods. By focusing on targeted, repeat offenders, strategies relied on deterrence-based methods such as increasing federal prosecution, and sentence lengths for repeat offenders carrying or using guns, increasing the overall rate of gun seizures,
and voicing the consequences of committing crime to repeat offenders in offender notification meetings. In comparison to control neighborhoods, they found that homicide rates in targeted neighborhoods decreased by 37 percent, and there was a statistically significant reduction in aggravated assaults.

2.3. Target selection and network prioritization

Networks have conventionally been used as a means of social control to reduce crime. The promises offered by advanced social network analysis coincide with law enforcement and intelligence objectives. As a result, extant research has advanced the concept of informed strategic analysis. With guidance from network analysis, methods for extracting intelligence information from the mass data available to law enforcement agencies have been put forth. Of particular interest has been research on: 1) the role of network participants (Borgatti, 2006; McCuish et al., 2014; Carley et al., 2002; Everett & Borgatti, 2000; Morselli, 2009, 2010); 2) changes in network composition (Borgatti, 2006; Moody & White, 2003; Morselli, 2009; Morselli & Petit, 2007); and 3) the emergence of key players via their overall contribution to the network (Borgatti, 2006; Schwartz & Rouselle, 2009; Westlake, Bouchard, & Frank, 2011).

2.3.1. Identifying key players

Previous research has used traditional social network measurements to identify important network participants who are central to the network. This may be due to their relative position in the network (network importance) in comparison to all others, the role they play, or the quality/quantity of their resources. As such, there subsist distinct benefits in identifying key players from the overall network.

Three of the most common network strategies to detect key players have been measures of network centrality: closeness centrality, degree centrality, and betweenness centrality (Borgatti, 2006; Carley et al., 2002; Joffres & Bouchard, 2015; Morselli, 2010; Morselli, Giguère, & Petit, 2007; Schwartz & Rouselle, 2009). Closeness centrality
considers participants who minimize the longest path lengths to others in the network. Participants with high closeness values have the shortest connecting paths to others in the network. Degree centrality measures the number of direct contacts surrounding a participant. Betweenness centrality measures indirect connectivity, such as, the ability of the participant to connect participants that would otherwise not be connected. Centrality is not mutually exclusive as participants, for the most part, manage to balance their roles (how many contacts they have, and how many they connect), but each measure has a distinct meaning (Morselli, 2010).

Morselli (2010) explored “vulnerable” and “strategic” positions in a criminal network using degree and betweenness centrality. Considering the interplay between the two centrality measures, Morselli (2010) provided four possibilities of how participants could be positioned in network: 1) low degree centrality, and low betweenness centrality; 2) low degree centrality and high betweenness centrality; 3) high betweenness centrality and low degree centrality; and 4) high betweenness centrality and high degree centrality (Morselli, 2010, p. 388). Morselli (2010) analysed the network of 174 participants involved in a drug distribution activity that centred on the Hells Angels criminal organization in Quebec, Canada. Morselli (2010) found that the visibility that comes with high degree centrality was a sign of vulnerability as participants with high degree centrality were in the “thick of things” and were likely to be arrested (p. 390). On the other hand, participants with high betweenness centrality were described as the most strategic set of participants in the network. These participants were on the periphery, secure from the core and thus detection, yet still occupied intermediary roles. When participants were high on both centrality measures, the visibility that emerged from high degree centrality outweighed any strategic capital that came with high betweenness centrality (p. 389).

Borgatti (2006) strayed away from existing measures and algorithms (degree centrality, betweenness centrality, and closeness centrality) to seek which key players were important to a network. Rather than focusing purely on centrality measures, Borgatti (2006) also considered the roles of key players, or sets of key players within the network. Optimal selection of key players, he noted, was dependent on the composition of the network, and the goals of law enforcement officials. Borgatti (2006) identified two separate
conceptions of key players. First were key player(s) that played intermediary roles, acting as gatekeepers in the network. These key players, if removed, would decrease the cohesion of the network. In other words, they would fragment the network. If the goal of law enforcement was to disrupt the network then removing a participant(s) who acts as an intermediary, that is a participant who connects agents that would not otherwise be connected, would correspond with the goal of fragmentation (Borgatti, 2006; Schwartz & Rouselle, 2009). Second were key players(s) that were maximally connected to all others. These key players could reach others within the network, and were able to better utilize the resources flowing through the network (Borgatti, 2006, p.33). For instance, if the goal of law enforcement was to maximize the collection of investigative data then targeting participants who were most connected, with close ties to many, would correspond with that goal (reach) (Borgatti, 2006; Schwartz & Rouselle, 2009, p. 189). Fragmentation and reach reflect different goals of law enforcement, hence, requiring different optimization algorithms.

Joffres and Bouchard (2015) analysed the effectiveness of different network attack strategies on online child exploitation websites. They used three types of attack strategies to examine changes in density and reachability. Using 1) hub attacks, contingent on degree centrality, 2) fragmentation, and 3) random attacks where all nodes were equally likely to be targeted, they identified which types of removal strategies would be best in an intervention against the exploitation networks (Joffres & Bouchard, 2015, p. 10). They found that hub attacks centered towards the core of the network, whereas, fragmentation attacks diffused across the network. In terms of attack strategies, targeted attacks were uniformly more effective than random ones. In sum, however, they found that different strategies reflected different types of disruptions. For instance, if the goal of law enforcement was to eliminate cohesion in the network, hub attacks were more effective in reducing network density. If the goal was to isolate groups, or nodes from other parts of the network, fragmentation attacks were most effective at reducing reachability.

Bright, Greenhill, and Levenkova (2014) analyzed various strategies for dismantling criminal networks involved in the manufacturing, trafficking and/or distribution of methamphetamine. In particular, they used four different simulations to examine which
factors, or combination of factors were best for targeting participants in the criminal network. In contrast to previous studies, they incorporated the role of participants. Roles reflected the main set of activities and responsibilities of participants in the criminal network. They used four strategies to measure to the effectiveness of disruption: 1) centrality scores; 2) the roles of nodes in the network; 3) a mixed strategy comprising degree centrality and the roles of participants; and 4) a random strategy. In the random strategy, participants were targeted in a random order, where no knowledge of the structure of the network was required. Bright et al. (2014) found that targeting participants based on their degree centrality, and the mixed strategy were the most effective disruption strategies for law enforcement interventions.

2.3.2. From key players to network capital: Using multidimensional data to go beyond centrality

Schwartz and Rouselle (2009) advanced conventional methods of targeting strategies such as centrality, fragmentation, and reach. Moving beyond centrality measures, Schwartz and Rouselle (2009) adopted Borgatti’s approach to identify key players, but modified it to incorporate attribute and link weights. Attribute weights considered the strength of network actors, or any type of attribute that could be quantified such as drugs, money, weapons, information, and skills (p. 193). These actors added to network capital via their presence in the network. Link weights reflected the strength of the relationship between network actors, considering the potential for sharing resources within the network. In this instance, an actor’s resources may not be used only by the actor; rather it may be available for all other actors to whom it was connected with. With the addition of attribute and link weights, Schwartz and Rouselle (2009) put forth a formula for network capital, where network capital accounted for the cohesiveness of the network, and distinguished between the strength of actors, and the strength of association between actors.

Westlake, Bouchard and Frank (2011) adapted Schwartz and Rouselle’s (2009) network capital measure to identify key players in online exploitation networks. Westlake et al. (2011) used a combination of connectivity (exploitation websites’ direct connections
to one another) and severity (the characteristics of the websites content) to measure network capital. Combining the two measures, they considered two issues: 1) that the connectivity of a website is optimal to the circulation of information, content and exposure; and the fact that 2) the most connected website may not comprise the most harmful content. They found that websites with the highest severity scores were not necessarily the most connected, and websites with the highest connectivity scores did not necessarily have the highest severity scores. With the network capital measure, they were able to identify key players (websites) in child exploitation networks, and prioritize “hard-core key players,” that is, which website, if removed, would result in the greatest reduction of network capital. Overall, a unified measure such as network capital aided in maximizing the impact of efforts to disrupt online child exploitation networks, and reinforced the need for targeted, well-informed attacks on networks.

2.4. The current study

This study explores the social environment in which two police targets are embedded, and proposes a systematic framework to guide law enforcement officials in prioritizing key players. Particularly, within these networks targets form, maintain, structure, and re-structure their social relations in an environment where they are being observed by law enforcement, but still have the freedom and flexibility to move around and go about their daily routines. The study has three objectives. First, using law enforcement data, the social environment of police targets are mapped. Data on the networks of the two targets were obtained from a data management system, PRIME-BC, that records and manages all social and criminal interactions targets and their associates have had with law enforcement officials. Because this is a social network, ties within the egocentric networks of Target 1 and Target 2 ranged from family members, associates, business partners, and/or friends. The second objective is to advance the understanding of network structures that contain both criminal and non-criminal elements. Networks are considered via their size, cohesion, and number of interlinks amongst associates. Additionally, cohesive subgroups, referred to as communities, embedded within the larger social networks are identified. Finally, a framework to detect key players, that is,
associates who matter most, relative to all others, is put forth. Key players are identified via a measure of network capital. Network capital considers two things: network importance, that is, how linked an associate is, and severity, that is, their potential contribution to the criminal network. Combining these attributes, key players, within the networks of Target 1 and Target 2, are systematically located and prioritized for the next round of target selection. To further supplement the validity of the network capital measure and the efficacy in the target selection process, simulations are used to examine the differential impact of targeting key players, as opposed to random associates, on the network as whole.
Chapter 3.

Data and methods

3.1. Data source

Constructing a network in which police targets are embedded requires a meaningful starting point. Targets were obtained from the Provincial Target Enforcement Priority (PTEP) list, an official list generated amongst Royal Columbia Mounted Police (RCMP) detachments identifying key persons of interest. The RCMP is the Canadian national police service, and an agency of the Ministry of Public Safety Canada. It is unique as it is a national, federal, provincial and municipal policing body. The RCMP provides federal contract policing services to Canadians in three territories, eight provinces (excluding Ontario and Quebec), more than 150 municipalities, 600 Aboriginal communities, and three international airports. The PTEP list is a threat assessment list that scores individuals based on their propensity to commit violence and the risk they pose to society. All targets that are listed on the PTEP list are unique to the area. That is, each participating RCMP department within British Columbia lists individuals within their jurisdiction who are highly active and likely to pose problems. These individuals can be gang members, prolific offenders, or high-risk targets – but they have to pose some level of risk to society with a propensity to commit violence. Lists from each participating department are then gathered, and individuals are ranked based on the level of threat they pose to the province. In deciding which two targets to collect data on, law enforcement officials directed the starting point to two targets, Target 1 and Target 2, residing in the same mid-sized city in British Columbia, Canada.

1 http://www.rcmp-grc.gc.ca/about-ausujet/index-eng.htm
Table 1. Who are the PTEP targets?

<table>
<thead>
<tr>
<th></th>
<th>PTEP: Target 1</th>
<th>PTEP: Target 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>British Columbia, Canada</td>
<td>British Columbia, Canada</td>
</tr>
<tr>
<td>Sex</td>
<td>Male</td>
<td>Male</td>
</tr>
<tr>
<td>Age</td>
<td>32</td>
<td>38</td>
</tr>
<tr>
<td>Status</td>
<td>Escape risk, violent</td>
<td>Escape risk, violent</td>
</tr>
<tr>
<td>Criminal record</td>
<td>N/A</td>
<td>Yes</td>
</tr>
<tr>
<td>Gang status</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Firearm Status</td>
<td>Prohibited</td>
<td>Of Interest</td>
</tr>
</tbody>
</table>

Table 1 shows the attributes of the two targets. Both Target 1 and Target 2 are alleged drug dealers, suspected of drug-related offences such as trafficking in substances, and possession of substances for the purposes of trafficking. In particular, Target 2 at 38 years old has four criminal convictions, two of which are drug-related trafficking offences, and is of interest to firearm officers. Target 1 is 32 years old, six years younger than his counterpart. He does not have a criminal record but is prohibited from carrying a firearm.

Data on targets and their associates were obtained from two official law enforcement data management systems operated by the RCMP: Police Records Information Management Environment of British Columbia (PRIME-BC) and Canadian Police Information Centre (CPIC).

PRIME-BC is an information management system that collects, connects, and contributes to law enforcement data (RCMP, 2012). The server system integrates information received from RCMP detachments and municipal police departments, providing access to police files instantaneously. A file is created on PRIME anytime individuals encounter the police, or the police encounter individuals. These files are treated as incident reports, and recorded as an “event” in the Lower Mainland Record Management System. Listed within each queried event are the date, location, municipality,
a synopsis indicating the nature and details of the incident (officer synopsis), and any
offences committed. Also listed are entities. Entities can be businesses, cars, or any
persons involved and subsequently checked in the incident. If entities are linked to a file,
attributes shown in Table 2 are listed, additionally; the officer indicates the role of all
entities within each event.

<table>
<thead>
<tr>
<th>Entity</th>
<th>Attribute</th>
<th>Potential role in file</th>
</tr>
</thead>
<tbody>
<tr>
<td>Person</td>
<td>Name, date of birth, sex</td>
<td>Street check, registered owner, subject of complaint, charged, suspect chargeable, victim, property representative, passenger, driver, witness, registered owner, other suspect, of interest, pedestrian</td>
</tr>
<tr>
<td>Cars</td>
<td>Type of car, license plate, colour of car</td>
<td>Personal, street check</td>
</tr>
<tr>
<td>Business</td>
<td>Business name</td>
<td>Of interest, street check</td>
</tr>
</tbody>
</table>

In creating an event, police are able to flag files as “suspicious activity,” “gang
affiliation,” “intelligence,” “drug trafficking” etc., or entities as gang-associates, criminals,
etc. CPIC supplements PRIME-BC as it links the criminal justice system with law
enforcement agencies. CPIC provides officers with access to an individual’s criminal
record, in addition to convictions, pending charges, stay of charges, and any prohibitions
that the individual may have.

3.2. Network extractions: Associates and ties

The strategy chosen to construct the networks of the two targets were similar to
Sarnecki (2001) with the Angen gang in Stockholm, Sweden, and Bouchard and Konarski
(2014) with the 856 gang in British Columbia, Canada. Using various official and unofficial
sources, both studies identified sets of individuals as starting points (or “seeds”) for
creating the networks. Whereas Bouchard and Konarski (2014) were limited to the co-
offending patterns of six identified gang members, Sarnecki (2001) expanded by
extracting the networks of the initial six seeds, in addition to the networks of their co-
offenders.
In the current study, Sarnecki’s (2001) strategy was followed. The egocentric networks of Target 1 and Target 2 were constructed by querying all event files noting Target 1 and Target 2 from 2006 to 2013. In keeping networks relevant to the area of study, only files created in the Lower Mainland, and/or listed on PRIME-BC were included. To build the networks of the targets, exclusively, all persons listed as an entity in the targets’ files were extracted. That is, all persons linked to the target via an event file. Figure 1 (Layer 1) notes the presence of ties between targets and associates within Target 1 and Target 2’s files, exclusively. Police files involving any of the two targets associates (n=99) were individually queried on PRIME-BC. As such, all ties in which an associate may have been checked with another associate in Target 1 or Target 2’s network, independent of the targets, were recorded, forming the final network on the right side of Figure 1.

Figure 1. Layer 1 involving Target 1 and Target 2 exclusively with 97 events (left), and the final network with 199 events (right)

Given the range of police data, and variations in police encounters, the nature of ties varied. Associates were linked to targets in social settings where they were 1) checked in a non-criminal context such as restaurants, bars, clubs, and gyms; 2) in the context of investigation where ties were formed based on suspicious encounters with the police, or investigative-led policing; and 3) car-related events, where associates were stopped together in cars, or were registered owners of vehicles linked to the event. All ties were labelled as a “social tie” amongst the network of associates. The purpose of the study is to explore the social environment in which police targets are embedded. As a result associates who served roles as complainants, victims, registered owners of vehicles,
property owners, or witnesses etc., on police files, and had no other tie with Target 1 and Target 2 were excluded from the network. An exception to this was if an associate played a dual role. For instance, they were a victim in one event, and were subsequently checked in a social setting in another event (vice versa). All ties were dichotomized into two categories, the presence of a tie (1), and no tie (0).

Overall, 199 events were vetted from Target 1 and Target 2’s file. Extracted from the 199 events were 56 associates in Target 1’s network, and 54 associates in Target 2’s network. Both Target 1 and Target 2 were present in each other’s networks, and had nine associates in common. Figure 2 shows the combined network, highlighting common associates.
Figure 2. Combined egocentric networks of the two police targets, Target 1 and Target 2, 2006-2013 (n=101)
3.3. Associate attributes

To contextualizing the role of associates, attributes such their age, sex, gang status, criminal history, and firearm status were collected. Age, sex, and gang status were extracted from the event files on PRIME-BC. Associates were considered gang-related if they were noted on PRIME-BC as having any sort of a gang tie. These associates could be gang members, or associated with gangs. Regardless of the strength of association, their ties to a gang(s) were known to officers, that is, either through intelligence files or through the Gang Task Force list. Thus, their gang status was listed on their PRIME-BC file as a special indicator.

Alternatively, criminal history, and firearm status were collected from CPIC. In this instance, if an associate had a criminal record, CPIC listed the charge(s), along with the date of the charge. CPIC also noted any pending charges and all previous charges that led to an acquittal, or stay of proceedings. Firearm status indicated on CPIC comprised two categories: firearm prohibited, where the associate was prohibited from carrying a firearm, and firearm interest, where the associate was of interest to firearm officers.

3.4. Network measurements

Network-level measurements such as density, presence of ties, and degree centralization were examined. Density is defined as the degree to which a network is connected. Density is expressed by the total number of actual ties in a network divided by the total number of potential ties within that network. Network density is important in that in considers the make-up of the network, providing a better conceptual understanding of the interconnectedness of individuals. Ties, or edges, represent the presence of inter-links between common nodes. Given that associates were embedded in the social network of associates, ties illustrate the presence, for the most part, of social activity, or suspicious activity. Centralization, like density, is a property of the network as a whole (Hanneman & Riddle, 2005). Centralization measures the extent to which a network is dominated by a
single node. Measuring the variation of direct connectivity around one or a few central nodes, centralization coefficients vary between 0 to 100 percent. For instance, a clique like network in which all nodes are connected to each other will have a centralization of 0 percent, whereas a “star” like network where one node is the “vector” of connectivity amongst all other networks will have a centralization of 100 percent (Morselli & Petit, 2007, p. 119; Hanneman & Riddle, 2005). The standard approach used to measure centralization was Freeman’s degree centralization. Because these are egocentric networks, centralization is expected to be high, as both networks are contingent on ties to Target 1 and Target 2. In other words, higher centralization scores where the ego is the vector of connectivity amongst all other actors is expected.

Node-level measurements such as degree centrality and betweenness centrality were examined. Degree centrality is the number of ties an actor has. Individuals with high degree centrality may be in an advantageous position in that they know many people and thus may not have to rely on a select few. These individuals have access to many resources, and are thus able to better utilize the network as a whole. Betweenness centrality extends on degree centrality. In considering the quality of connections as opposed to quantity, it measures the shortest path between nodes within a network, incorporating indirect contacts that surround the node. It considers the extent to which a node connects others through the shortest path (geodesic). The greater an individual is situated along the geodesics in the network, the higher their betweenness centrality (Freeman, 1977). Betweenness is important in that it identifies individuals who have a “broker-like” position mediating relationships between others within the network. Individuals with high betweenness centrality are strategically placed in the network because they 1) connect individuals who otherwise would not be connected; and 2) have the greatest number of “paths” that go through them, hence controlling the flow of connectivity in the network (Everton, 2012; Hanneman & Riddle, 2005; Morselli, 2010).
3.5. Multiplexity and the duality of roles

Unlike traditional co-offending studies, this network is not a network of co-offenders. Rather it is a network of associates that hang out, socialize, and are embedded in each other’s lives. In other words, while they may not be formally detected of committing crimes together, associates may partake in multiple types of events. For instance, events that police officers deem as “suspicious activities,” in addition to more traditional, social events that associates, or friends, partake in, encouraging multiplex relations. Multiplexity implies that “individuals can be connected in multiple ways or through multiple types of relationships” (Papachristos & Smith, 2014, p. 99; Feld, 1981).

Multiplexity, within the contacts of Target 1 and Target 2’s networks, occurred when associates were checked in social activities, such as attending bars, restaurants, and or driving to locations etc., with a target, in addition to suspicious types of events, which includes events that fall short of a formal charge. In this instance, a suspicious activity would be any event where the police officer flagged the event on file as “suspicious activity,” “suspicious pers/veh/occurrence,” involving a “suspected criminal,” or a “suspected drug dealer.” These events were flagged at the discretion of the officer; however, the number of suspicious events in both Target 1 and Target 2's files were relatively low illustrating the rarity of these labels. Of the 97 events that involved Target 1 and Target 2, Target 1 was involved in 12 suspicious events, and 48 other social activities, whereas Target 2 was involved in 11 suspicious events (20%), and 26 other social activities (30%) (Table 3).
Table 3. **Suspicious vs. non-suspicious events involving Target 1 and Target 2 (n=97)**

<table>
<thead>
<tr>
<th></th>
<th>Target 1</th>
<th>Target 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of events</td>
<td>60</td>
<td>37</td>
</tr>
<tr>
<td>% Suspicious events</td>
<td>20</td>
<td>30</td>
</tr>
<tr>
<td>% Other social activities</td>
<td>80</td>
<td>70</td>
</tr>
</tbody>
</table>

Moving beyond the types of events to the roles of network participants, of the 101 associates in the combined network, 16 (16%) participants, including Target 1 and Target 2, had multiplex roles, involved in both suspicion and social activities. On the other hand, as show in Figure 3, 74 (73%) associates were checked in events deemed as suspicious, followed by 11 associates (11%) who were checked in pure social activities.

Of the 56 associates in Target 1’s network, 20 percent were involved in a suspicious activity (n=11), whereas 26 percent of associates in Target 2’s network were involved in suspicious activity (n=14). For a relationship to be multiplex, however, there needs to be an overlap in the types of relationships. For instance, associates that were involved in some type of a suspicious activity with Target 1 and Target 2 have to partake in another type of activity. Six associates in Target 1’s network and eight associates in Target 2’s network shared a multiplex relationship. That is, in addition to partaking in
suspicious types of activities, these associates also shared social ties, attending social activities such as clubs, bars, restaurant, and/or checked in cars together.

While the number of associates with multiplex relations was relatively low, these associates were repeatedly involved in the same types of activities. This could be due to two reasons: 1) Target 1 and Target 2 were partaking in suspicious activities with a selected few, increasing the “pressure” and number of checks placed on a selected number of associates. For instance, officers were aware of the relationship between the targets and the associate, therefore, they were being checked more often in the presence of each other, raising the probability of detection. Alternatively it may be related to, 2) officer discretion, and/or bias was influencing the frequency of checks. In other words, officers considered any event as “suspicious” when these individuals were involved together.

Table 4 shows the property of edges (ties) in the network, where edges represent the movement of associates who share multiplex relationships across events. For instance, the most common edge in the network was events in which associates were sequentially checked in social activities. In other words, even though associates, at one time, partook in some sort of suspicious activity, associates often moved from one social activity to another social activity together. Of the 45 edges in the network, in 13 instances (29%), associates moved from a suspicious activity to a social activity, followed by nine instances (2%) where associates moved from a social activity to a suspicious activity. The least occurring tie comprised events where associates were consecutively checked in a suspicious activity.
Table 4. Multiplex relationships, and the direction of edges in the network (n=45)

<table>
<thead>
<tr>
<th>Property of edges</th>
<th>Target 1’s network</th>
<th>Target 2’s network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nb. of edges</td>
<td>33</td>
<td>12</td>
</tr>
<tr>
<td>Suspicious activity - Other social activity</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>Suspicious activity - Suspicious activity</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Other social activity - Other social activity</td>
<td>19</td>
<td>2</td>
</tr>
<tr>
<td>Other social activity - Suspicious activity</td>
<td>6</td>
<td>3</td>
</tr>
</tbody>
</table>

Note: These edges indicate the movement of the 14 associates who shared a multiplex relationship with either Target 1 or Target 2.

3.6. Determining key players: Measuring network capital

Network capital is derived from Schwartz and Rouselle (2009). Measuring network capital, Schwartz and Rouselle (2009) considered the cohesiveness of the network, the relationships between nodes, and the resources available to them. Particularly, Schwartz and Rouselle (2009) integrated attribute weights (the strength of network actors) and link weights (the strength of these relationships). An actor with a combination of high attribute weights and link weights scores contributes most to network capital in two ways: 1) their mere presence; and 2) the potential resources they employ and potentially share.

To extract key players in Target 1 and Target 2’s network, the formula provided by Westlake et al. (2011) was adapted to the current study. Network capital is calculated as follows:
The first component of network capital, *associate severity*, is defined as the summation of three crime-affiliated attributes: criminal record, firearm status, and gang links. Each crime-affiliated attribute was treated as a dichotomous variable: (1) if the attribute was present and (0), if it was absent. The maximum sum for crime-affiliated attributes being three and minimum being zero. Scores were then standardized against the highest scoring node within the network. For instance, an associate with a criminal record, a firearm status, and gang ties would receive a perfect severity score of 1.0 with all other scores ranging from zero to 1.0. The formula for calculating *associate severity* is:

\[
\text{Associate Severity} = \sum_{i=1}^{NAW_i} \frac{AW_{ni}}{NAW_i}
\]

where
- \( AW_{1b} \), \( AW_{2b} \), \( AW_{3i} \): crime-affiliated attributes: criminal record (1), gang ties (1), and firearm status (1)
- \( NAW_i \): number of resources (3)

\[33\]
3.6.2. **Associate connectivity**

The second component of network capital is *associate connectivity*. *Associate connectivity* considers the contribution a node makes to the overall network based on its connections to other nodes and the resources it has available. *Associate connectivity* scores were multiplied by the percentage of resources made available by the associate to the rest of the network, and multiplied by link values. The resource sharing level (RSL) considers resource availability within a network, that is, the amount of resources that are made available for sharing by network actors. Schwartz and Rouselle (2009) do not suggest a particular measure for RSL. Rather, they suggested generating a series of potential RSLs. In the current study, a RSL of 1.0 was kept as a constant because we analyse a social network where associates are linked in various contexts. These associates, in theory, have no formal restrictions placed on their ability to communicate, or share with one other. However, the RSL may vary in differing networks, and should be adjusted to reflect this.

A link weight comprising the summated score of two centrality measures, normalized degree centrality and normalized betweenness centrality, make up *associate connectivity* (See Appendix A for the descriptive statistics). To calculate *associate connectivity*, the first measure considered was the “centrality” of the associate, that is, how connected the associate was within the network. These associates have access to many resources and are able to better utilize the network as a whole. The second measure was the “betweenness” of the associate, that is, the intermediary role of associates within each network. Associates with high betweenness measurements are strategically placed in that they connect associates that otherwise would not be connected. In some networks, high degree centrality may not be indicative of high betweenness centrality, or vice versa. Within the context of Target 1 and Target 2’s combined network, degree and betweenness scores were significantly correlated (r=0.91, p<0.01), thus favouring one measurement over another would not necessarily affect the target selection process.
Using the same method as attribute weights, link weights were summated. The average score of each associate was then standardized against the highest scoring node, ranging from 0.0 to 1.0. The formula for *associate connectivity* is:

\[
\text{Associate Connectivity} = \left[ \sum_{n=1}^{N_{\text{AW}_i}} \frac{A_{\text{W}_n}}{N_{\text{AW}_i}} \times R_{\text{SL}} \right] (L_{W_i})
\]

where

- \( i \) node
- \( \text{AW}_{1i}, \text{AW}_{2i}, \text{AW}_{3i} \) weighted number of crime-affiliated attributes: criminal record, gang links, firearm status, ranging from 0.0 to 1.0
- \( N_{\text{AW}_i} \) number of resources (3)
- \( R_{\text{SL}} \) the resource sharing level
- \( L_{W_i} \) weighted combined measures of normalized degree centrality and betweenness centrality ranging from 0.0 to 1.0

### 3.7. Community analysis

To detect community structure, the Girvan and Newman algorithm was applied to the combined network of Target 1 and Target 2. Community structure detection is a data analysis technique that is used to explore the structure of large-scale networks. It is based on the assumption that networks naturally divide themselves into subgroups or clusters. As such, divisions within a network are natural, as communities or subgroups may truly represent social groups, or homogenous cliques, where members are more likely to interact with one another.

The Girvan and Newman algorithm identifies cohesive sub communities by applying Freeman’s notion betweenness centrality to all edges in a network. Betweenness centrality is defined as the “shortest paths between a pair of other vertices that run through it” (Girvan & Newman, 2002, p. 7822). To find which paths in the network are most “between” other pairs, Girvan and Newman generalizes Freeman’s notion of betweenness
centrality to all edges, and defines the betweenness of an edge as the number of shortest paths between pairs of vertices that run along it. By removing these edges, networks are separated from one another, revealing the underlying structure of the graph. In sum, the algorithm for identifying communities by Girvan and Newman (2002) is (p. 7822-7823):

1. Calculate the betweenness for all edges in the network
2. Remove the edge with the highest betweenness
3. Recalculate betweenness for all edges affected by the removal
4. Repeat from step 2 until no edges remain

The community analysis is supplemented by a goodness-of-fit measure, known as the modularity score (\(Q\)). The modularity score was developed by the authors to help researchers systematically identify the best division of the network into communities. The community structure of the network corresponds to an arrangement of edges, where the modularity measure is a constant that quantifies the fraction of edges within a group, minus the expected number in an equivalent network with edges placed at random (Newman, 2006). By referencing the modularity score, the numbers of communities are systematically determined by the network itself. Modularity scores range from \(Q=0.0\) to \(Q=1.0\). Scores can be a negative or a positive number, where positive values indicate a community structure. The higher the modularity score, the stronger the division within that network. (Newman, 2006). A relatively high modularity score is around 0.40, but in application, scores practically range from 0.30 to 0.70 (Girvan & Newman, 2002; Athey & Bouchard, 2013).

3.8. Analytic strategy

Results describing the social relations of police targets fall into five sections. First, the social network in which police targets are embedded is described. Knowing the general structure of such networks provides law enforcement officials with a better understanding of the targets’ surroundings and social environment. Network-level measurements and
individual-level measurements are utilized to provide information on the network as a whole, whereas, attributes describe the characteristics of Target 1 and Target 2’s social circles. The second section considers key players. Using a revised version of Borgatti’s (2006) formula to identify key players, network capital derived from Schwartz and Rouselle (2009) and used in previous studies (see Westlake, Bouchard & Frank, 2011), which combines associate’s connectivity (how connected an associate is) and severity (contribution to the criminal network), is used to identify key players. In utilizing network capital, the third section provides the next round of police targets. That is, by attending to two goals of law enforcement: intelligence and disruption, in addition to the efficient use of limited police resources, key players in the network are prioritized within the network. Fourth, community analysis is used to partition the networks of the two targets into communities. In doing so, the broader criminal and non-criminal community in which offenders are embedded is assessed to see how social structure may influence potential co-offending opportunities and network disruption techniques. More specifically, community analysis situates key players within the larger social and criminal environment, assessing their relative placement in the network and the impact their removal would have on the general structure of the network.

Identifying key players and situating associates within the larger community, the general aim is to inform law enforcement through the optimization of resource allocation. Bringing the concept of key players, that is, associates whom naturally stand out in the network as opposed to others, and the underlying community structure of network of these two targets together, the final section looks at the potential impact of disruption on informed target selection as opposed to randomly selected targets. For instance, what would be the relative impact of removing a key player, or a combination of key players on network capital, and network structure? The aim is to examine whether the prioritization of targets using the network capital measures results in the greatest reduction in network capital, and fragmentation of the network, as opposed to randomly removing targets. Random target removal is a simulation technique to examine network vulnerability to the disruption of various sizes (Joffres & Bouchard, 2015) where the positional influence of targets and attributes are ignored. The ability to visualize the network pre and post
disruption provides law enforcement officials with a better understanding of what disruption could entail, as well as its overall effects on the network.

All visuals and measures were computed using UCINET version 6.527, Netdraw version 2.141 and Organizational Risk Analyzer (ORA).
Chapter 4.

Results

4.1. Network structure and associate attributes

Table 5 presents the features of the two networks. Target 1 and Target 2’s combined network comprises 101 associates within 199 queried events. Of 101 associates, 68 percent are males and 32 percent are females. This is indicative of a social network, where there will be a mix of males and females. There is a significant difference between the mean age of associates in Target 1’s network at 31 (SD=5.1), and Target 2’s network at 35 (SD=7.1). The relative proximity in age, between each target, and their mean network, suggests that targets associate with individuals who are generally within their age range.
Table 5. The properties of Target 1, Target 2, and their combined networks\(^1\)

<table>
<thead>
<tr>
<th></th>
<th>Target 1's network</th>
<th>Target 2's network</th>
<th>Combined networks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network size</td>
<td>56</td>
<td>54</td>
<td>101</td>
</tr>
<tr>
<td>Number of events</td>
<td>113</td>
<td>76</td>
<td>199</td>
</tr>
<tr>
<td>Density(^2)</td>
<td>0.05</td>
<td>0.10</td>
<td>0.062</td>
</tr>
<tr>
<td>Number of ties</td>
<td>142</td>
<td>280</td>
<td>630</td>
</tr>
<tr>
<td>% Network centralization (degree)</td>
<td>96</td>
<td>90</td>
<td>51</td>
</tr>
<tr>
<td>Age of target (range of network)</td>
<td>32(24 to 54)(^1)</td>
<td>38 (24 to 64)(^*)</td>
<td>33(^3) (24 to 64)</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Males</td>
<td>66 (37)</td>
<td>72 (39)</td>
<td>68 (69)</td>
</tr>
<tr>
<td>% Females</td>
<td>34 (19)</td>
<td>28 (15)</td>
<td>32 (32)</td>
</tr>
<tr>
<td>CPIC status</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Charged</td>
<td>32 (18)</td>
<td>30 (16)</td>
<td>29 (29)</td>
</tr>
<tr>
<td>% No charges</td>
<td>68 (38)</td>
<td>70 (38)</td>
<td>71 (72)</td>
</tr>
<tr>
<td>Firearm status</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Prohibited</td>
<td>20 (11)</td>
<td>15 (8)</td>
<td>17 (17)</td>
</tr>
<tr>
<td>% Firearm interest</td>
<td>18 (10)</td>
<td>28 (15)</td>
<td>23 (23)</td>
</tr>
<tr>
<td>% No restrictions</td>
<td>63 (35)</td>
<td>57 (31)</td>
<td>60 (61)</td>
</tr>
<tr>
<td>Gang status</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Gang associate/member</td>
<td>9 (5)</td>
<td>19 (10)</td>
<td>14 (14)</td>
</tr>
</tbody>
</table>

Note: \(^1\) Counts are presented in parenthesis
Note: \(^2\) Density for both Target 1 and Target 2’s networks, individually, are computed without the ego
Note: \(^3\) Indicates the mean age of the network
Note: \(^*\) A significant difference between the mean age of associates in Target 1 and Target 2’s network, p<0.01

Despite becoming police targets in 2013, the frequency and distribution of encounters between network participants and the police range. For instance, over a period of eight years, targets and their associates are checked by police 199 times with an average of 14 events per year for Target 1, and 10 events per year for Target 2. There exists a wide distribution as shown in Figure 4, 62 percent of associates encounter the police only once, whereas a few number of associates are checked in 9 to 13 incidents.
On average, however, targets and their associates had at least two interactions with the police.

![Graph showing frequency of police checks]

**Figure 4. Frequency of police checks between targets and their associates**

Measuring the interconnectedness of the combined network, the density is relatively low at 6 percent. Despite a similar sized network, Target 2’s network is twice as dense (10%), hence more connected, in comparison to Target 1’s network (9%). This is shown in Figure 2. Target 2’s network on the left has multiple pendants, with three large clusters on the periphery, whereas Target 1’s network on the right is generally sparse, with minimal connections, and the formation of a small clique on the bottom centre of the network. Network centralization, on the other hand, tells two stories. As both are ego networks, Target 1 and Target 2’s network, on their own, is highly centralized with coefficients ranging from 90-96 percent. High centralization indicates that both networks are concentrated around one central node (the ego). When networks are combined, centralization decreases to nearly half (51%) with Target 1 and Target 2 both acting as focal nodes.

Of the 101 associates in the network, 50 associates have some type of a criminal attribute. That is 50 percent of associates within the network are either gang-affiliated \((n=14)\), flagged by firearm officers \((n=40)\) or have, at a minimum, one criminal conviction \((n=29, \text{mean}=1.0)\). The 50 associates form the criminal backbone of the network. As such, if crime-affiliated associates (See Appendix B) are extracted from pure social associates
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(no crime-affiliated attributes) (See Appendix C) there are differences in both network density and number of ties. From the combined network of 101 associates, the network of pure social associates comprises 51 network participants. This network, on its own, has a density of 4 percent with 90 ties amongst network participants. The crime-affiliated network with 51 associates is more cohesive. While a similar sized network, there are 252 ties amongst network participants, with a network density of 10 percent. Particularly, amongst the 50 associates who have at least one crime-affiliated attribute, each associate, on average, is connected to five others who also share, a minimum of, one crime-affiliated attribute.

4.2. Network capital

Network capital proves to be a useful tool in finding key players who are both connected and have the most to contribute the criminal network. A form of strategic analysis involves the identification of vulnerabilities, or the key players within the network. Different from criminal organizations, or co-offending networks where network “vulnerabilities” would entail targets who may be “central, vital, key, or pivotal” and targeted for removal from the criminal network (Sparrow, 1991b, p. 261), this is the social milieu in which police targets are embedded. Ties indicate social ties, or ties based on suspicious encounters. Both of which may not necessarily result in formal criminal activity. Utilizing a measurement such as the network capital, the aim is to supplement police intelligence by maximizing knowledge of the network as a whole, and seeking key players with the potential to facilitate crime within these socially bounded networks.

Network capital comprises two components, connectivity and severity. On average, the network severity score is 0.27 (SD=0.33), whereas the connectivity score is 0.07 (SD=0.14). First, there are associates who naturally stand out in terms of their connectivity. Target 1 and Target 2 are at the center of the network with the highest connectivity scores (Target 1=1.0, Target 2=0.95). Outside of targets Target 1 and Target 2, an associate to both targets, A3, scores third highest on connectivity scores (0.35). A3, while only having a criminal record serves two roles in the network. A3 and Target 2 were business partners, co-owning a business in the early 2000s. A3 and A52 (present in the
network) were conspirators, charged in a drug conspiracy trial in the United States in 2007. Second, eight of the 101 network participants, not including Target 1, Target 2, or A3 who are top contributors to network connectivity, score 100 percent on severity, meaning that they are gang associated, have a criminal record, and a firearm status.

The distribution of network capital, amongst network participants, is presented in Figure 5. Node sizes indicate network capital scores, and labels identify all associates who score above average on the network capital measure. Each network capital score was multiplied by 1,000 for ease of interpretation. Network capital scores range from 0.0 to 0.16, with a network average of 0.034 (SD=0.36) (See Appendix D for all network capital scores). First, naturally, within the network, there emerges associates that stand out, possessing much higher network capital scores than others. For instance, Target 2 has the highest network capital score with 0.16, and Target 1 follows with 0.13. For the purpose of enforcement, if law enforcement is to choose between the two targets, Target 2 should be the target of interest, as he contributes most, albeit marginally, to the network resulting in the greatest reduction in network capital if removed.

Second, associates with higher network capital scores tend to form subgroups in the network. This can be explained in two ways. Associates in subgroups manage to associate with one another, increasing their connectivity scores. For instance, the cluster on the top left corner in Figure 5, all have ties to one another, with degree centrality scores ranging from 0.07 to 0.10 (with the exception of A73 who is deceased, degree centrality = 0.03). Alternatively, it could be due to associate homogeneity. Associates with similarities, for instance, those who know a similar number of people and share common attributes tend to gravitate towards one another. For instance, the cluster on the bottom left corner in Figure 5 comprises three associates of a biker gang (A112, A68, A69), all residing in the same city and tied to one another. Whereas, three of the four associates on the upper left corner are gang-affiliated. Generally, with the exception of a few, the majority of associates with high network capital scores are located either in the middle of the network as they are present in both networks, or are associated to Target 2 and located on the left side of the network.
Figure 5. Distribution of network capital for the combined egocentric networks of Target 1 and Target 2 (n=101)
4.3. Prioritizing targets: On to the next one?

As PTEP targets, Target 1 and Target 2 are on law enforcement radar. The question that naturally follows is who is next? If police are to systematically focus on one, or a selected few number off associates in Target 1 and Target 2’s network for investigative or enforcement purposes who should these targets be? Traditionally law enforcement agencies look for a lead, then work towards “exploit[ing] and develop[ing] that lead to its full potential” (Sparrow, 1991a, p.256). For the purpose of this study, key players for target selection are identified based on three criteria: 1) pure network capital scores; 2) structurally equivalent targets in the network indicated by their presence in both networks; and 3) a single target option reflecting limited law enforcement resources and time. Additionally, all key players have to score above the average network capital of 0.03 to be considered for prioritization.

First, if the goal of law enforcement is to target key players who contribute most to the network, relying on network capital scores is a suitable route. In Table 6, Option 1 lists potential key players ranked by their network capital scores. The inclination to stop at eight targets is due to a natural split in network capital scores. As seen in Option 1, network capital scores range from 0.100 to 0.107. Following A73, however, there is a significant drop in network capital scores by 0.03. This drop is notable, leading to a list of top eight targets. While there are eight targets listed in Option 1, A73 is deceased, thus seven targets are prioritized for consideration.

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1 https://www.youtube.com/watch?v=DBp_JhgaLsk
2 Of the nine targets who are structurally equivalent, three targets present in both Target 1 and Target 2’s networks are not included for prioritization in Option 2, as they have network capital scores below the network average of 0.034: (A10, NC=0.01), (A5, NC=0.003); (A11, NC=0.002)
Table 6. Key players and the next round of targets

<table>
<thead>
<tr>
<th>Rank</th>
<th>Associate</th>
<th>Option 1: NC scores</th>
<th>Option 2: Structurally equivalent targets</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A109 *</td>
<td>0.107</td>
<td>A9 *</td>
</tr>
<tr>
<td>1</td>
<td>A68 *</td>
<td>0.107</td>
<td>A4 *</td>
</tr>
<tr>
<td>1</td>
<td>A112 *</td>
<td>0.107</td>
<td>A7</td>
</tr>
<tr>
<td>4</td>
<td>A81 *</td>
<td>0.105</td>
<td>A3 *</td>
</tr>
<tr>
<td>4</td>
<td>A9 *</td>
<td>0.105</td>
<td>A6 *</td>
</tr>
<tr>
<td>6</td>
<td>A59 *</td>
<td>0.103</td>
<td>A8</td>
</tr>
<tr>
<td>7</td>
<td>A87 *</td>
<td>0.100</td>
<td></td>
</tr>
<tr>
<td>Dead</td>
<td>A73 *</td>
<td>0.100¹</td>
<td></td>
</tr>
</tbody>
</table>

Note: Key players in Option 2 all score above the average network capital score.

Note: Asterisks indicates criminal record.

Note: Bolded names indicate gang status.

Note: Italicized names indicate firearm status.

Note: ¹ Following A73 is A78 with a network capital score of 0.07

Topping the list in Table 6, Option 1 identifies sets of key players, A109, A68, and A112, who are tied with having the highest network capital score. They are followed closely by A81 and A9. All key players in Option 1 are present in Target 1 and/or Target 2’s network within the past four years, that is, they have been checked by the police from 2010 onwards (See Appendix D). In addition to connectivity scores reaching the network average of 0.07, all key players have a perfect severity index of 1.0. Criminal charges range from one to six offences, with a mean of 3.2 offences per key player in comparison to the network mean of one. A68, A73, and A109 lead in charges, with six charges for A68 and A73, and two charges for A109. These charges range from drug trafficking, drug production, weapon-related offences to assault. Moreover, from 2006 to 2013, key players were on average checked by the police in an event file 104 times, as opposed to the network average of 38 police encounters. They were also connected, with an average of 28 associates on PRIME-BC, as opposed to the network average of nine associates.
Second, if the goal of law enforcement is to investigate, or disrupt both networks with the fewest number of targets, targeting key players who are structurally equivalent, that is, are present in both networks, with ties to Target 1 and Target 2, is most efficient. The list of proposed targets is presented in Table 6, Option 2. Contacts present in both networks tend to have relatively high average connectivity scores at 0.11, both in comparison to the overall network (0.07), and in comparison to key players in Option 1 (0.07). They also have relatively high severity scores in comparison to the rest of the network associates (0.55 vs. 0.27), though not as crime-affiliated as targets in Option 1 (average severity score: 1.00). As shown in Figure 5, where node sizes indicate network capital scores, six of the nine structurally equivalent targets have network scores that reach above the network average. This may be due to skewed connectivity scores. First, contacts are associated to Target 1 and Target 2, hence associated with more contacts within each network. Or, second, it could be suggested that the attributes of these contacts, such as a criminal record, firearm status, or their gang ties places them in their intermediary roles as they provide resources, which in return contributes to their own network capital. Regardless of their attributes, these contacts are unique as they bridge the two networks. That is, they are positioned in strategic roles, controlling information. If the goal of law enforcement is to fragment the two networks, then in addition to Target 1 and Target 2 these targets should become the next set of priorities.

Finally, as Sparrow (1991a) noted, law enforcement agencies often have “far more leads to pursue than resources” (p. 256). Considering efficient target selection in addition to limited police resources and allocated time, Option 1 (network capital) and Option 2 (structural equivalence) are combined for a single target selection: A9. Present in both Target 1 and Target 2’s network, A9 ranks on top with a network score of 0.105. Charged with a drug production offence in 2011, A9 has had 99 encounters with the police and has 10 associates listed on PRIME-BC. In sum, A9’s network capital score, presence in both networks, and currency in police files makes him an efficient target, suitable for single target prioritization.
4.4. Community membership

The opportunity to study communities (or cohesive subgroups) in which network participants embed themselves helps identify how associates connect within the larger social and criminal milieu. In doing so, there is a need to: 1) compile information about the communities themselves; and 2) examine the type of individuals who comprise these communities (community members). Systemically locating cohesive subsets that may be referred to as “groups” or “communities” within the overall network creates a better understanding of how opportunities (criminal and non-criminal) and resources emerge, and may be shared with a selected few from the larger network.

Figure 6 presents the network of the two targets, partitioned by community membership. The shaded region in the figure represents each isolated community. Modularity scores shown in Table 7 range from 0.389 (23 communities) to 0.47 (26 communities). A review of the modularity scores shows that the optimal number of partitions is 26.³ This is indicated by a score of \( Q = 0.47 \), which is: 1) the highest modularity score amongst all possible partitions; and 2) the largest relative jump in modularity score between all possible partitions. For instance, the modularity score comprising 25 communities is 0.41, jumping by .06 with 26 communities.

³ To further validate the formation of communities as computed by the Girvan and Newman, a faction analysis to detect communities (smaller factions) from the larger network was conducted. The faction algorithm is an alternative partitioning tool that fits actors into groups and then measures how well it has been achieved through a badness of fit score. The faction analysis partitions the population into a pre-determined number of cohesive groups, where every actor must be placed into a unique group. Results based on the faction analysis indicate that the network be partitioned into 26 communities (factions) with a badness of fit score of 276.00. In comparison to the modularity score provided by the Girvan Newman, a lower badness of fit score indicates the best fit (see Hanneman & Riddle, 2005; Everton, 2012; Borgatti, Everett & Johnson, 2013). The number of community partitions computed by the Faction analysis supports the results computed by the Girvan and Newman algorithm.
Table 7. Range of community partitions indicated by the Girvan Newman

<table>
<thead>
<tr>
<th>Number of community partitions</th>
<th>Modularity score (Q)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.396</td>
</tr>
<tr>
<td>3</td>
<td>0.409</td>
</tr>
<tr>
<td>4</td>
<td>0.411</td>
</tr>
<tr>
<td>5</td>
<td>0.419</td>
</tr>
<tr>
<td>12</td>
<td>0.41</td>
</tr>
<tr>
<td>23</td>
<td>0.389</td>
</tr>
<tr>
<td>24</td>
<td>0.407</td>
</tr>
<tr>
<td>25</td>
<td>0.406</td>
</tr>
<tr>
<td>26</td>
<td>0.472</td>
</tr>
<tr>
<td>27</td>
<td>0.468</td>
</tr>
<tr>
<td>28</td>
<td>0.463</td>
</tr>
<tr>
<td>29</td>
<td>0.461</td>
</tr>
<tr>
<td>30</td>
<td>0.456</td>
</tr>
<tr>
<td>31</td>
<td>0.451</td>
</tr>
<tr>
<td>33</td>
<td>0.443</td>
</tr>
<tr>
<td>34</td>
<td>0.432</td>
</tr>
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<td>35</td>
<td>0.428</td>
</tr>
<tr>
<td>36</td>
<td>0.424</td>
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<tr>
<td>37</td>
<td>0.416</td>
</tr>
<tr>
<td>38</td>
<td>0.411</td>
</tr>
<tr>
<td>39</td>
<td>0.429</td>
</tr>
</tbody>
</table>

The Girvan-Newman analysis partitioned the network into 26 communities \((Q=.47)\), however, there are certain communities that stand out. In considering the number of communities, the Girvan-Newman considers all members in its partition totals, including pendants (associates with one link, usually to one of the targets), who may not be close to anyone else in the network. In social network terms, the smallest social structure that individuals can be a part of is two. These pairings are conventionally referred to as dyads, and not necessarily a group or community. Figure 6, shows the distribution of community
sizes. Of the 26 communities, 65 percent of the communities comprises one member (n=17), eight percent of communities have two members (n=2), with the remaining 27 percent of communities (n=7) comprising four to 25 members. The seven largest communities, on their own, comprise 79 percent of all members in the network (80 associates); hence, the focus remains on describing the overall make up of these communities.

**Figure 6. Number of communities based on community membership**

The breakdown of the seven largest communities comprising four or more members is shown in Table 8. Along with community size (members), the relative density, average degree centrality, number of ties present within each community is shown. Additionally, attributes such as average network capital score, average age, along with the percentage of crime-affiliated members within each community are presented. Across the seven communities, sizes range from four to 25 members. As expected, smaller communities are substantially more cohesive than larger communities.
Table 8. Community structure and membership

<table>
<thead>
<tr>
<th>Community properties</th>
<th>Alliance</th>
<th>Target 2</th>
<th>Target 1</th>
<th>Clique</th>
<th>Isolate</th>
<th>Social</th>
<th>Bridge</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nb. of members</td>
<td>10</td>
<td>22</td>
<td>25</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>11</td>
</tr>
<tr>
<td>Density</td>
<td>0.71</td>
<td>0.46</td>
<td>0.20</td>
<td>1.00</td>
<td>0.50</td>
<td>1.00</td>
<td>0.27</td>
</tr>
<tr>
<td>Nb. of ties</td>
<td>64</td>
<td>210</td>
<td>122</td>
<td>12</td>
<td>6</td>
<td>12</td>
<td>30</td>
</tr>
<tr>
<td>Avg. degree</td>
<td>6.40</td>
<td>9.56</td>
<td>4.88</td>
<td>3.00</td>
<td>1.5</td>
<td>3.00</td>
<td>2.73</td>
</tr>
<tr>
<td>Avg. NC</td>
<td>0.05</td>
<td>0.04</td>
<td>0.02</td>
<td>0.07</td>
<td>0.05</td>
<td>0.00</td>
<td>0.05</td>
</tr>
<tr>
<td>Avg. age</td>
<td>36</td>
<td>37</td>
<td>30</td>
<td>37</td>
<td>31</td>
<td>35</td>
<td>31</td>
</tr>
<tr>
<td>% Crime-affiliated members</td>
<td>70</td>
<td>50</td>
<td>32</td>
<td>100</td>
<td>75</td>
<td>0</td>
<td>73</td>
</tr>
<tr>
<td>% Criminal record</td>
<td>50</td>
<td>23</td>
<td>16</td>
<td>25</td>
<td>50</td>
<td>0</td>
<td>45</td>
</tr>
<tr>
<td>% Firearm status</td>
<td>10</td>
<td>14</td>
<td>16</td>
<td>25</td>
<td>0</td>
<td>0</td>
<td>46</td>
</tr>
<tr>
<td>% Gang status</td>
<td>40</td>
<td>18</td>
<td>4</td>
<td>50</td>
<td>25</td>
<td>0</td>
<td>9</td>
</tr>
</tbody>
</table>

Exploring community membership, Target 1 and 2 are members of two distinct communities. Target 1 is a member of the largest community, whereas, Target 2 is a member of the community with the highest number of ties. Within the networks, members who cluster, or form, communities often have some prominent characteristic. For instance, across the seven communities, the Clique, Isolate and Alliance, lead with the number of members who have some type of a crime-affiliated attribute, this can be seen with the relative node sizes in Figure 7. A further analysis of the communities and attributes of members who make up the communities are shown below:

**Clique:** Present within this community are four members, all connected to one another forming a perfect clique (Density = 100%). Additionally, all members have at least one criminal affiliated attribute (gang status, firearm status, criminal record). The clique is located in the middle, merging the two networks, with two key players (A8 and A7) that are an associate of Target 1 and Target 2, and A59. On average, the community as a whole has the highest network capital score (NC=0.07).
**Isolate:** The *Isolate*, similar to its neighboring community above, comprises four members, but encompasses half its density (50%). As a whole, the community is tied with the second highest average network capital score (NC=0.05). Of its four members, 75 percent comprise a crime-affiliated attribute; however, isolated within this community is one key player, A87. A87 ranks seventh in his contribution to network capital with a criminal record, firearm status, and gang link.

**Alliance:** Tied with the second highest average network capital (NC=0.05) score amongst its members, the *Alliance*, comprises 10 members. Members, on average, connect to six other members with the community, with an overall density of 71 percent. Present within this community are key players A73 (dead), A109 and A81. Relative to the overall network, A109 is ranked first with the highest network capital measure, followed by A81 who is ranked fourth in the network. All three members have a perfect severity score, with the presence of all three crime-affiliated attributes. Particularly, within this community, four members are connected to gangs. The *Alliance*, however, is divided with two members connected to one gang, and the remaining two members connected to a differing, yet, aligning gang.

**Target 2:** The second largest community is Target 2’s community. The 22 members within *Target 2’s* community are most connected to one another with, on average, 10 ties, and a network density of 50 percent. This can be seen with the partition of the community into two distinct subsets. A3, works as a broker, merging the two subsets, in addition to merging the networks of Target 1 and Target 2, more generally. Key players A112, and A68 (tied with the highest network capital score) and located in the upper pocket are affiliated with the same biker gang as two other community members (A69, A106) though they are less central to community. The community, as a whole, has an average network capital of 0.04.

**Target 1, Social, Bridge:** The following three communities comprise, for the most part, members from Target 1’s network, pure social associates with no crime-affiliated attributes (the *Social*), and key players who *bridge* (merge) the networks. Target 1 is embedded in the largest community, with the lowest density (20%). *Target 1’s* community
comprises 45 percent of his network, with 32 percent of its members linked to a gang, or having a firearm status, or criminal record. With the second lowest network capital score (NC=0.02), A6, who is an associate of both targets, and Target 1 are its only key members. The Social community is a perfectly knit community (Density=100%), with members connecting to, on average, three other community members. These ties, however, are purely “social” in nature, as none of its four members has a crime-affiliated attribute. The third largest community, outside the communities of Target 1 and Target 2, the Bridge, comprises 11 members. The community, relative to other communities, is not as cohesive (Density=27%), with members on average, connecting to three other members. Of the 11 members, 73 percent have some type of a crime-affiliated attribute. Members of the Bridge are key players A9 and A4, associates who “bridge” the networks of the two targets. A9 is also a main contributor to network capital, ranked fourth overall. In line with the Alliance, and the Isolate, the Bridge ranks second in overall network capital (0.05).
Figure 7. The formation of communities within the combined network (3 or more members, n=7)
4.5. Removal of key players

A reason to seek key players is to find targets that, if removed, would have the potential to create the most disruption to the network. To examine the importance of key players in the network, the network capital score for the network as a whole is calculated. From this, key players previously noted in Table 6, with the highest contribution to network capital, are cumulatively removed, one at a time, from the overall network. The choice to remove key targets, based on their relative contribution to the network, shows the impact their removal would have on the overall network, and the validity of the network capital measure in of itself. In return, this reflects how law enforcement officials may go about targeting their “key players” based on their placement in the network and crime-affiliated attributes, one at a time. By removing key players in several stages, the aim is to seek an optimal number in terms of target selection, then removal. A breakdown of the disruption process is presented below:

First: Using the network capital (NC) formula, the network capital score for the network, as a whole, is calculated.

| NC for reference model: | \[
\frac{27.64 + 6.92}{101 + [101 \times (101 - 1) - 1]} = 0.00339 \times 1000^2 \\
= 3.39
\] |

1 For the purpose of target selection, and network disruption, only the top scoring key players, based on their network capital measures, were chosen as opposed to all key players suggested in Table 6. The topped ranked key players had relatively similar network capital scores, ranging from 0.107 to 0.100, with a drop by 0.027 between associate A87 (seventh target in terms of his network capital score) and A4 (top ranking associate who is also present in both networks). This natural drop in network capital scores formed the threshold, leading to the selection of a “top seven” for all analyses within this section.

2 Network capital scores for all associates were multiplied by 1000 for ease of interpretation. To keep measures consistent and maintain a standard baseline, the network capital score for the overall network is also multiplied by 1000.
Second: Seven key players, based on their network capital scores are then removed from the network, one at a time. When recalculating network capital, Borgatti (2006) suggests changing the denominator of the network capital formula every time a node(s) is removed. Alternatively, Schwartz and Rouselle, (2009) keep the denominator in the equation the same. Because the network capital formula is a ratio, the authors stated that the current method makes greater sense as it considers “total actual network capital to the total potential network capital had everything remained intact” (p.197). Further, in keeping the denominator consistent, unintuitive results that are produced “whereby removing a network actor fails to decrease, or even increase, network capital” is avoided (Schwartz & Rouselle, 2009, p.197). Consistent with Schwartz and Rouselle (2009), the denominator is kept as a constant.

\[
\text{NC (reference model) – combined NC score of key player(s) = NC}
\]

Third: The difference in network capital is transferred into a change in percentage

\[
\frac{(\text{NC/NC for reference model})}{100} = \% \text{ NC reduction}
\]

Results in Table 9 show the relative impact of removing the top network capital contributors on network size, density, number of ties, community structure, and network capital. The reference model refers to the network in its original state, with no adaptations. To start the disruption process key players tied in network capital (A58, A109, and A112) are individually removed to see if their removal has any impact on the structure or composition of the network. Given that A68, A109, and A112 are tied in network capital, the selection of one target over another is not relevant.\(^3\) Thus, from a law enforcement perspective, the choice to focus on one target over another should be based on qualitative

\(^3\) Analyses were computed with A68, A109, and A112, each individually removed from the network. Results show that the removal of either of these nodes had the same overall impact on the network. In other words, whether A68, A109, or A112 were removed, the variables indicating changes in the network remained constant (density: 0.062; number of ties: 610; avg. degree: 6.10; communities: 7; NC: 3.28, and NC reduction: -3.15%)
differences such as criminal history (type, number of convictions), their movement across the province, and their potential risk to society (propensity to commit crime, and violence).

Table 9. Key target(s) removal, and relative impact on the network - Post removal

<table>
<thead>
<tr>
<th>Model</th>
<th>Ref.</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Removal</td>
<td>-</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Network size</td>
<td>101</td>
<td>100</td>
<td>99</td>
<td>98</td>
<td>97</td>
<td>96</td>
<td>95</td>
<td>94</td>
</tr>
<tr>
<td>Density</td>
<td>0.062</td>
<td>0.062</td>
<td>0.060</td>
<td>0.060</td>
<td>0.060</td>
<td>0.060</td>
<td>0.060</td>
<td>0.060</td>
</tr>
<tr>
<td>Number of ties</td>
<td>630</td>
<td>610</td>
<td>590</td>
<td>572</td>
<td>558</td>
<td>544</td>
<td>532</td>
<td>528</td>
</tr>
<tr>
<td>Degree (avg.)</td>
<td>6.24</td>
<td>6.10</td>
<td>5.96</td>
<td>5.84</td>
<td>5.75</td>
<td>5.68</td>
<td>5.60</td>
<td>5.62</td>
</tr>
<tr>
<td>Communities (3+ members); (Q)</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>NC</td>
<td>3.39</td>
<td>3.28</td>
<td>3.18</td>
<td>3.07</td>
<td>2.96</td>
<td>2.86</td>
<td>2.76</td>
<td>2.65</td>
</tr>
<tr>
<td>% Difference in NC</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Model 1: Removal of A68; A109 or A112
Model 2: Removal of 2 of the top three key players (A68; A109; A112)
Model 3: Removal of A68; A109; A112
Model 4: Removal of A68; A109; A112; A9
Model 5: Removal of A68; A109; A112; A9; A81
Model 6: Removal of A68; A109; A112; A9; A81; A59
Model 7: Removal of A68; A109; A112; A9; A81; A59; A87
Note: Reference model is the original combined network in its entirety
Note: NC scores are multiplied by 1000 for ease of interpretation
Note: 1 The number of optimal partitions, or communities, were based on: 1) the highest modularity score amongst all possible partitions, and 2) the largest relative jump in modularity score between all possible partitions
Note: 2 Signifies percentage differences in NC between the Model, and the Model prior to it

Table 9 shows that removing any two key players, together, as presented in Model 2 leads to the greatest change to the composition of the network. With the removal of two of the highest-ranking key players, the density of the network decreases to 6 percent (0.060). A density of 6 percent is maintained regardless of whether three, four, five, six, or all seven key players are removed in subsequent models. The removal of five targets, on the other hand, fragments the network into eight communities; this is shown in Figure 8.
Removing A9 who is an associate of both targets separates the *Bridge* community into two. The final model, Model 7, shows how the removal of all seven key players impacts the network. With the removal of all seven key players, network capital is reduced by 22 percent, with an average reduction of 3.1 percent, per key player. Overall, there is a consistent decrease in network capital, ranging from 3.39 to 2.65, every time a key player is removed.
Figure 8. The structure of the combined network and formation of communities at Model 5 – Post removal.
While it is expected that the removal of associates who contribute most to network capital would result in changes in network composition and a reduction in network capital, the question posed is whether this reduction is different to that which results from removing random nodes. With a random attack, each node in a network has an equal probability of being chosen. Random node selection ignores all attributes such as positional influences, and attributes of the node. To measure the effectiveness of random attacks, a random node generator was used to select seven associates from the network. These associates were removed, one at a time, following the same method as in the previous section. In doing so, the aim is to seek whether the impact on the network, based on network capital scores, and informed prioritization of key players are similar, or dissimilar to that of targeting random associates. In practical terms, selecting random associates for disruption is similar to investigations where law enforcement officials may be inclined to focus on any individual who associates with Target 1 and Target 2, notwithstanding their network importance or severity.

The results of random target removal are presented in Table 10. First, in comparison to the removal of selected key players, the removal of random nodes in the network leads to lower decreases in network capital. With every random node that is removed, network capital is reduced by 1.41 percent (as opposed to 3.1%). Second, the reduction in overall network capital is twice as high when all seven key players are removed (22%) (Table 9, Model 7), as opposed to a random selection of seven associates (10%) (Table 10, Model 7). Finally, whereas the removal of four key players results in the fragmentation of the network, that is, the addition of one more community (from 7 to 8), the removal of five random associates actually reduces the number of communities (from 7 to 6). Results in Table 9 and Table 10 show that informed target selection through the removal of key player’s results in a greater reduction of network capital, and change in network composition, as opposed to randomly selected nodes of associates.
Table 10. Random target removal and relative impact on the network - Post removal

<table>
<thead>
<tr>
<th>Ref. Model</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Removal</td>
<td>-</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Network size</td>
<td>101</td>
<td>100</td>
<td>99</td>
<td>98</td>
<td>97</td>
<td>96</td>
<td>95</td>
</tr>
<tr>
<td>Density</td>
<td>0.062</td>
<td>0.061</td>
<td>0.062</td>
<td>0.062</td>
<td>0.062</td>
<td>0.062</td>
<td>0.061</td>
</tr>
<tr>
<td>Number of ties</td>
<td>630</td>
<td>608</td>
<td>600</td>
<td>594</td>
<td>574</td>
<td>566</td>
<td>550</td>
</tr>
<tr>
<td>Degree (avg.)</td>
<td>6.24</td>
<td>6.08</td>
<td>6.06</td>
<td>6.06</td>
<td>5.92</td>
<td>5.90</td>
<td>5.79</td>
</tr>
<tr>
<td>Communities (3+ members); (Q)</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>NC</td>
<td>3.39</td>
<td>3.31</td>
<td>3.31</td>
<td>3.31</td>
<td>3.23</td>
<td>3.20</td>
<td>3.09</td>
</tr>
<tr>
<td>% Reduction in network capital</td>
<td>-</td>
<td>-2.23</td>
<td>-2.34</td>
<td>-2.43</td>
<td>-4.66</td>
<td>-5.73</td>
<td>-8.88</td>
</tr>
<tr>
<td>% Difference in NC</td>
<td>-</td>
<td>-0.12</td>
<td>0.09</td>
<td>2.23</td>
<td>1.07</td>
<td>3.15</td>
<td>1.01</td>
</tr>
</tbody>
</table>

Model 1: Removal of A69
Model 2: Removal of A69; A21
Model 3: Removal of A69; A21; A36
Model 4: Removal of A69; A21; A36; A79
Model 5: Removal of A69; A21; A36; A79; A26
Model 6: Removal of A69; A21; A36; A79; A26; A68
Model 7: Removal of A69; A21; A36; A79; A26; A68; A44

Note: NC for the whole network 3.4 (n=101)
Note: NC scores are multiplied by 1000 for ease of interpretation
Note: 1 The number of optimal partitions, or communities, were based on: 1) the highest modularity score amongst all possible partitions, and 2) the largest relative jump in modularity score between all possible partitions
Note: 2 Signifies percentage differences in NC between the Model, and the Model prior to it


Chapter 5.

Discussion

Networks play a foundational role in the understanding of crime and behaviour. One of the most consistent findings in criminological research is the notion that adolescents are likely to behave in a manner that is consistent with their peers (Gallupe & Bouchard, 2013; Haynie, 2002; Warr, 1993; Warr & Stafford, 1991; Weerman, 2003; Winfree et al., 1994b). The values, behaviours and attitudes required to commit crime, and engage in delinquent behaviours is learned through different processes of interactions within one’s network of friends and associates. Social network analysis provides a conceptual and methodological framework for understanding social structures and the formation of interrelations amongst individuals. The current study adopts a network perspective to investigate the social “worlds” of police targets. That is, their “world” as constructed through the variety of interactions they have with law enforcement officials. Particularly, the objectives were to 1) map the social environment of police targets using police data; 2) advance the understanding of the structure of networks containing both criminal and non-criminal elements; and 3) inform police target prioritization by creating a measure to identify key players (or set of players) who contribute most to the criminal network.

5.1. The formation of networks using police data

The principles guiding social network analysis naturally coincides with the goals of law enforcement officials (Morselli et al., 2007; Sparrow, 1991b). First, a methodological approach to extract network data from pure intelligence files was put forth. Network analysis organizes law enforcement data in a way that promotes more efficient and effective learning from these types of data. Law enforcement data and criminal intelligence is derived from criminal and non-criminal settings, and comprise countless types of interactions and complexities amongst police officers and the public (Ratcliffe, 2008). More importantly, the study demonstrates how police agencies’ own data are able to support an
analysis that can be used to identify who matters, and how, in a systematic and novel way. This is especially relevant for policing violent offenders within a particular jurisdiction.

The study uses event files produced by law enforcement officials to explore the social environment of PTEP targets. Law enforcement officials identify PTEP targets as posing a threat to the community. Targets are selected based on the potential risk they pose and the types of crimes they are allegedly involved in. Targets are embedded in a network where they are able to utilize their social ties and explore their social environment, while being heavily monitored, and routinely checked by law enforcement officials. Consequently, targets had the freedom to continue their daily activities but are equally constrained in doing so. This is indicated by the presence of pure social associates, in addition to multiplex relationships with associates playing a variety of roles (involved in suspicious events and social events), but at a lower frequency. Because networks are situated in a non-criminal environment, both targets are given an implicit opportunity to alter their relationships, and/or change their routines to avoid detection. For instance, targets and their associates use rental cars, or cars insured under other people’s names to conceal their whereabouts and avoid detection via traffic stops. Further, after a call has been made to the police by bar or restaurant owners indicting the presence of targets (violent individuals) or well-known associates at their establishment, targets and their associates have the opportunity to leave the bar before officers arrive to check them. In other words, the network is not subjected to the same internal or external controls that may come from pure criminal networks such as co-offending networks (Bouchard & Konarski, 2014; Sarnecki, 2001), gang networks (McCuish et al., 2014; Papachristos, 2009; McGloin, 2005), or drug trafficking networks (Morselli & Petit, 2007).

5.2. The structure of networks

Network analysis describes the properties of the network, testing the relationship between differing patterns of relations, and their influence on individual and group behaviour (McGloin & Kirk, 2010; Krohn, 1986). Further, it provides insight into the structural opportunities and constraints faced by network members (Morselli, 2010;
McGloin & Nguyen, 2012). Target 1 (n=56) and Target 2 (n=54) start with a relatively similar sized network. The two networks merge into a network of 101 associates with the presence of both targets in each other’s networks, and nine common associates, ranging in criminal attributes and network importance. Targets reside in the same city. They also reside in the same city as a majority of their network associates, with 55 percent of their associates residing within close geographical proximity. As such, the presence of interactions and mutual associates coincides with prior studies that note the importance of proximity in generating ties (Verbrugge, 1979; Feld, 1982).

A traditional measure of network cohesion, density, varies in both targets’ networks. Despite a similar sized network, Target 1’s network at 5 percent is half as dense as Target 2’s network at 10 percent. The combined network of 101 associates has a density of 6 percent. Previous studies that have measured density in criminal networks have suggested two things. First, participants who are part of non-redundant networks (networks with low density) are better positioned to use their network as a whole. As these individuals are not constrained to one population, they have greater access to various opportunities, skills, and expertise (McGloin & Piquero, 2010; McGloin & Nguyen, 2012; Burt, 1992; Granovetter, 1973). The weaker connections that come with non-redundant networks exposes network participants to greater avenues of social and human capital – one that goes beyond their immediate network (Granovetter, 1973; Burt, 1992). Alternatively, redundant ties in a network (highly dense networks) limit a participant’s exposure to new information and new opportunities (Granovetter, 1973; McGloin & Piquero, 2010; McGloin & Nguyen, 2012). This is because participants who are embedded in densely knit networks are exposed to the same types of opportunities.

Within the context of network density, results suggest that Target 2 has more constraints than Target 1 in his network. In practice, however, both density levels are relatively low and unlikely to provide an advantage to one or the other. The higher density of Target 2 emerges from the presence of three tightly knit communities associated to Target 1’s network. The fact that Target 1 still has access to a range of different subgroups within the network, as well as a number of associates more loosely affiliated to the rest of the network is unlikely to put him at a significant disadvantage compared to Target 2.
5.3. The role of associates

Just as network structures vary, so do the roles of network participants and their contribution to the network. Granovetter (1985) noted that “social influences construe […] the processes in which actors acquire customs, habits, or norms that are followed mechanically and automatically” (p. 485). Hence, a deeper understanding of social influences, and the process of interactions requires an examination into the characteristics of associates embedded in these networks. For instance, differential association theory postulates that crime and delinquency is learned through various forms of interactions, and exposure to delinquent friends (Reiss & Farrington, 1991, p. 363; Winfree et al., 1994a, 1994b). Social groups tend to be highly valued, where the effect of peers on behaviour is contingent on both the characteristics of the group, and the actions of members in that group (Gallupe & Bouchard, 2013; Haynie, 2001, 2002). Within these bounded social groups exists a complex set of interactions amongst criminal, and non-criminal associates. In fact, even amongst networks situated in non-criminal settings, certain associates will exert more “pull” and “influence” within the context of crime.

Within the networks of Target 1 and Target 2, associates, on average, link to six other social or crime-affiliated associates. Honing in on the criminal backbone of associates, which comprises 50 percent of all network participants, crime-affiliated associates interconnect exclusively with each other as well. Associates who have a crime-affiliated attribute link to, on average, five others who also share a crime-affiliated attribute (criminal record, gang status, firearm status). This is in comparison to the 51 pure social associates who share, on average, only two ties to one another. Even though police targets surround themselves with an equal number of non-criminal and crime-affiliated associates, associates within the network are more likely to interact with a selected number of others who share similar characteristics.
5.4. Using network importance and individual attributes to see who matters

A goal of this study was to provide a framework for detecting key players within the social environment of the two PTEP targets. Within such networks, there are going to be associates who naturally stand out, and those who do not. As such, the questioned posed is, who matters? The environments in which these targets surround themselves with vary, along with the nature of ties and relations. Network capital guides the target selection process, and provides insight into the effectiveness of disruption and investigative strategies overall. Particularly, network capital amalgamates several attributes relevant to the current context, and weights these attributes equally.

A combination of these attributes helps identify the most important individuals in a network, providing insight into their role, and their position relative to all others (Morselli & Petit, 2007; Morselli, 2010; Bouchard & Nguyen, 2010). For instance, with link and attribute weights, network importance and individual level attributes are combined to seek whom targets choose to socialize with, and the cliques that they form. This provides the opportunity to differentiate between highly connected nodes who do not contribute to the criminal network (ineffective police targets), associates who are crime affiliated, but remain on the periphery (minimal network importance, hence minimal influence) from those who contribute to both the criminal and non-criminal network, and are likely to facilitate crime like behaviours.

To guide police target prioritization, and seek the “next round of targets” within the networks of Target 1 and Target 2, three systematic strategies are put forth: 1) pure network capital scores; 2) structural equivalence; and 3) sole target selection. To be considered, it was required that targets score above the mean network capital of 0.03. Additionally, to incorporate the sensitive nature of time in pursuing investigations, and key players, all targets are recent targets. Key players needed to be present within the networks of Target 1 and Target 2 within the past four years.
The first suggestion put forth is to focus on pure network capital scores. Pure network capital scores show that A109, A112, and A68 equally contribute most to network capital. All three targets are important to the network with ties throughout, and have a perfect severity score (gang-affiliated, firearm status, and criminal record). These targets are well-known to law enforcement officials with 86 encounters (in comparison to the network average of 38) with the police from 2006 to 2013.

Alternatively, if the goal is to investigate both networks, with the fewest number of targets, then the six associates who merge the two networks should be considered. Theoretically, these targets are structurally equivalent. The six “brokers” are positioned to direct the flow of information between the two networks. They have access to both Target 1 and Target 2, and may thus exert greater control over criminal and non-criminal activities (Morselli, 2010). The final strategy hones in on a sole target. Here the emphasis is placed on limited law enforcement time and resources. Honing in on a single target such as A9, who is present in both networks, and has a relatively high network capital score is a good starting point for both investigative and economical purposes.

5.5. Detecting communities

To supplement network capital, the study hones in on communities. Communities provide insight into the social structure of the networks of Target 1 and Target 2. In doing so, the network of 101 associates is reduced to seven of the largest communities computed by the Girvan and Newman algorithm. These communities on their own comprise 79 percent of all network associates, ranging from four to 25 members. The seven largest communities vary in structural composition (size, density) and attributes (network capital, characteristics of members). For instance, five of the seven communities house at least one key player (Alliance, Target 2, Clique, Isolate, and Bridge). Two communities, the Social and Target 1’s community do not. Both of these communities house the fewest number of members with a crime-affiliated attribute and have, on average, the lowest network capital score. The Clique leads with the highest average network capital score with all four of its members having some type of crime-affiliated
attribute. The *Alliance* and *Target 2*’s community are concentrated around three well-known gangs. They are also home to four of the seven key players.

The mere presence of key players within communities may facilitate the exchange of delinquent behaviours. For instance, Engel et al. (2008) noted that violence often stems from loosely knit social networks of individuals embedded in larger networks. These groups do not necessarily reach the status of a “gang”; rather, their pure affiliation or membership in a group is likely to draw a potential pool of co-offenders (Gould, 2003; Engel et al., 2008). Similarly, Reiss noted that “one’s co-offenders […] are likely to be drawn from cliques or constellations of cliques from which one is affiliated” (p. 129). In other words, criminal opportunities typically emerge via the pool of potential co-offenders these networks represent (Tremblay, 1993; Reiss, 1986). As cliques are part of the larger network, they create an immediate pool of contacts from which co-offenders are selected as opposed to the large community (Tremblay, 1993; Reiss, 1986; Weerman, 2003). Selection is most likely to occur amongst individuals who are present in each other’s immediate community, and those who they directly partake in joint events with, as opposed to the larger community of 101 associates.

From a law enforcement perspective, identifying cohesive subgroups may be a useful tool for exploiting the group nature of crime, and channelling resources to identify members of these groups. Particularly, interventions on groups, or types of crimes that are concentrated around cohesive subgroups (gangs, co-offending networks, group crime) may be an effective means for disrupting the network, and informing crime control policy (Kennedy, 1997). For instance, focused deterrence interventions that coordinate and voice predictable consequences for groups who engage in violence have been successfully implemented in Boston (Braga et al., 2001), Chicago (Papachristos et al., 2007), and Cincinnati (Engel et al., 2011). When attempting to disrupt the group nature of crime, these interventions exploit the ties between individuals to communicate the risk of sanctions (Engel et al., 2011, p. 5; Tillyer & Kennedy, 2008). Groups were encouraged to police themselves without becoming a police priority. Violent groups were notified that if someone in their network committed a crime, the group would become the target as law enforcement officials would proactively aim to disrupt their whole network (Braga, 2001;
Tillyer et al., 2010, p. 975). Consequently, before any type of target selection or removal occurs, community analysis provides a visual breakdown of the network, identifying how key players are connecting within the larger social and criminal structure. More specifically, with the placement of key players, it helps better assess how partnerships, specifically criminal, may emerge from the larger network.

Findings support the need to vary, and adjust approaches based on the goals of law enforcement strategies. A systematic framework that combines network importance (number and quality of contacts) with individual level attributes leads to informed policing practices, as well as effective strategies for target prioritization, selection, and removal. Within the context of this study, simulations that examined network vulnerability and the effect of disruption of various sizes supplemented the utility of using a measure like network capital for informed target selection. Simulations examined network adaptability, and the differential impact of targeting key players (or set of key players), as opposed to random associates. Results suggested that removing key players, that is, associates who contribute most to network capital results in greater reductions in network capital, and overall change in network composition, as opposed to randomly selected nodes of associates. The consistent reduction in network capital, and change in the structure (density, number of ties, communities) of the network indicates that the use of network capital is an effective measure for differentiating between associates who matter most to the criminal network, and those who are simply part of the larger social environment. It also shows that not all key players need to be removed from the network for changes to occur. Instead, it takes the removal of the top two key players to alter the cohesion (density) of the network, and five key players to alter community structure. In practice, systemically targeting key players using an intersection of multiple factors, as opposed to randomly pursuing every lead, will generate greater success for police investigations, whether the goal is to obtain intelligence information or to dismantle the network.
5.6. Limitations

Results should be interpreted within the limitations of this study. In particular, five limitations are noted. First, there exist limitations in the validity of police-reported data. The social networks of police targets are extracted solely from police reported incidents. That is, events where the target and their associates encounter the police or the police encounter persons of interest from 2006 onwards. While the nature of interactions range, they are all social or suspicious in context, hence we miss co-offending ties. More specifically, we miss what these targets do (on their own, or as a group), that may often go undetected by law enforcement. This is demonstrated by the fact that Target 1 does not even have a criminal record. Police reported data comprises incidents that have been detected by law enforcement officials, hence leading to an underestimation of the total volume of incidents. For instance, there may be incidents where associates interact with one another but are not detected by the police. There may be times where police interact with these targets, but do not report such interactions on file. Dependency on incidents reported by the police leads to a conservative estimate of Target 1 and Target 2’s social networks. Despite missed interactions, however, we capture the social environment of targets, and their network of contacts, which are not typically captured in pure co-offending networks. Data extracted from PRIME-BC is a valid source of law enforcement data with detailed incident reports, police officer synopsis, and consistent data entry. Since Target 1 and Target 2 are priority targets, police were encouraged to report any sort of interaction they had with the targets. They were also encouraged to proactively investigate their whereabouts, and provide a detailed synopsis if interactions were made.

Second, there exist limitations with using PRIME-BC. PRIME-BC is implemented within certain jurisdictions and agencies in the province of British Columbia (Lower Mainland, Vancouver Island Region, North Southeast Districts, and Combined Forces Specialized Enforcement Unit). Police incidents outside of these areas or outside of BC are not considered for analysis. Nevertheless, both targets, and their associates reside, and socialize in areas that are under PRIME-BC’s mandate. Limiting data collection to the PRIME-BC data system provides a fair depiction of these targets’ social environments. Additionally, as part of a systematic purge – files that police consider as minor incidents -
are routinely purged from the system within a period of two to three years. Purges are rare for investigative data, or for files involving PTEP targets, but could have affected the data available when data were collected.

A third limitation of this study lies with the selection of the next round of targets. When prioritizing targets, the focus is on target selection within the context of Target 1 and Target 2’s network. Any key player(s) not connected directly to one of the targets are missed. Since the study is restricted to the ego networks of the targets, network capital measures are contingent on the positioning (centrality measures) of associates within this network. Measurements are not indicative of the associates’ full social capital; rather, measures are constrained to the network boundaries at hand. As such, “better targets” may be overlooked. Target 1 and Target 2 are selected as targets by the department because they pose the greatest risk to the community. They are involved in drug-related offences and are connected to other well-known individuals. Hence, the aim was to proactively seek which associates, within their networks, were most likely to replace the targets if they were removed. It was not an exhaustive enquiry of all the possible candidates within the jurisdiction. The movement of individuals outside the presence of these two targets and their associates does not influence the methodology of the selection process; rather it paves a framework for detecting key players who are structurally equivalent in similar types of ego networks.

It is important to comment on the generalizability of the data. Target selection (Target 1 and Target 2), and hence, key player formation is limited to the objectives of one agency, during a specific period of time. Agencies across the country, province and within each jurisdiction will differ. Particularly, as Kennedy (2015) noted, agencies vary in how they approach problems, what their concerns are, or what their departmental objectives and mandates are. These variations influence the formation of operational and tactical strategies. For instance, when, what (events, crimes) or who is a big problem in one city may not necessarily be the same in a neighbouring city. Other cities in the Lower Mainland may focus more specifically on other types of targets, certain gangs involved in violence, or instead on chronic offenders involved in large numbers of property crimes. In reality,
Target 1 and Target 2 may not even have been on the radar of law enforcement officials in another city should their priorities lie elsewhere.

The final limitation lies with the sensitive nature of time, especially in the context of policing, and the changes which inevitably occur in one’s network over time. From a policing perspective, it is possible that targets who are considered problematic at one point become less problematic, or disappear from the radar of police officers at another time. This also applies to the networks of such targets. For instance, over time new associates enter, leave, and ties sever for various reasons. Networks evolve to reflect such variations. In other words, network structure, target selection, and prioritization are not constant. As a result, there is a need to tailor networks as they evolve. Target 1 and Target 2 are followed for a period of eight years – enquiry into their networks began when they were in their mid-20s. Adult networks are more cohesive and may be less susceptible to significant changes overtime, especially with enduring attachments to one’s family and the work place (Marsden, 1987; Sampson & Laub, 1993). Target 1 and Target 2 show some level of stability. For instance, both were raised in the city under study. Their network comprises many associates whom they went to high school with and who reside in the same city, or are within close proximity. Thus, target selections based on the last four years is appropriate for the networks at hand, but may be too short or too long in other contexts (See Appendix E and Appendix F for a comparison).
Chapter 6.

Implications and conclusion

This study goes beyond the networks of police targets, and seeks to uncover how participants, criminal and non-criminal, overlap within social networks. The aim of this research is to provide insight into the practical application of network analysis with law enforcement data. A concern of law enforcement is devising policing methods that are strategic, reducing time and resources allocated to managing investigative data. Often police have resources and investigative data to target individuals in isolation, but limited resources thereafter to seek the networks of targets, and their roles in criminal, and non-criminal environments.

The current study demonstrates how networks could be formed from law enforcement data. In doing so, networks are constructed using a department’s own investigative data. Event files extracted from PRIME-BC are accessible to officers at all levels, and can be used to feed network analysis. Network analysis supplements this type of data by providing a methodological framework for honing in on law enforcement objectives and investigative goals. It can supplement investigations, and provide an efficient means for directing the allocation of police officer time and resources. Before any sort of framework is suggested, however, there is a need for dialogue between researchers conducting research and law enforcement agencies (Engel & Whalen, 2010; Kennedy, 2015).

This study began with a series of meetings between criminal analysts, investigators, senior level officers, and researchers. These meetings were beneficial for all parties involved. Why? First, meetings build rapport between the police and researchers. Here, we were able to show law enforcement personnel the utility of using network analysis and how it could be applied to law enforcement data. This initiated discussions on best practices, while considering general objectives and goals of the department. Second, dialogue helped direct the study. We constructed a systematic
framework that was both objective, and useful for enforcement officials in the department. Particularly, as a group, we were able to converge on PTEP targets, and decide why Target 1 and Target 2 were important to the community. Discussions at these meetings considered the limitations of the department, the limitations of social network analysis, as well as limitations with conducting research using law enforcement data. As such, strategies were formed in a way that provided meaningful value to all parties, and promoted practices that could be transferred to officers at all levels (investigators to general duty).

To further validate our methodology and results, findings were presented to various members of the RCMP within the department, and across the Lower Mainland of British Columbia, integrated agencies such as the Combined Forces Special Investigative Unit, and other personnel with vested interest in PTEP targets. Given the nature of the PTEP program, departments have to provide updates on their targets (Target 1 and Target 2), and a report on any actionable tasks they have conducted since targets were chosen. These presentations validated the methodology and confirmed our results (with a few surprises) on target selection, and community structure.

First, two key players who scored high on network capital, A109, and A9, received special attention by law enforcement officers, as they were considered individuals of interest in the city understudy and were, more generally, active throughout the Lower Mainland of British Columbia. Second, was the presence of interlinks between associates who shared a crime-affiliated attribute. The criminal backbone of our network of associates was relatively cohesive, and it demonstrated that associates who have crime-affiliated attributes are indeed connected to one another, as opposed to ones that did not. Thus, we were able to reduce the network of 101 associates to a list of 50 associates. This reflected a primary objective of the department, as they wanted insight (and a list), of who, at the most basic level, showed a greater propensity to commit crime, and cause problems in the community.

Third, the identification of communities provided insight into community structure, and community membership. The seven largest communities indicated which associates
were close to one other, and further from other associates in the combined network. Particularly, Target 2’s and A68’s common membership in Target 2’s community validated Target 2’s informal ties to gangs, particularly the biker gang in which A68 and his immediate network were members of. It also showed Target 2’s ties to other gangs within the community, specifically to members of two different gangs forming the Alliance. Communities illustrated cohesive subgroups, or “gangs” that were operating within the neighborhood. Generally, however, communities reduced the network to loosely formed social groups - identifying who exactly belonged to each community, and their attributes.

Fourth, we were able to hone in on structurally equivalent targets, and their relative location within the network. While officers knew that Target 1 and Target 2 were associates, they had not yet explored the level of overlap, or identified common associates. The nine structurally equivalent targets generated additional Intel information for the department. For instance, their placement in the network demonstrated how the two networks merged, and what role these structurally equivalent targets played in linking associates who were a part of either network. Finally, what the current methodology did was provide a template for crime analysts. That is, the opportunity to expand and work with our data, adding to the network when new associates enter, and establishing new ties between associates as officers detect them. This saves crime analysts time, and provides a realistic means for following networks as they evolve overtime. In other words, as long as Target 1 and Target 2 are relevant to the department, their networks can be tracked in real time.

This study demonstrates how the “police-academic” partnership is beneficial as researchers and law enforcement agencies both have much to gain (Engel & Whalen, 2010). To maintain the relationship between researchers and police, we reiterate the need for applied research, one that involves collaboration amongst law enforcement officials, researchers, and partnerships with multiple agencies such as community based organizations, and members from the criminal justice system (Engel et al., 2011; Papachristos et al., 2007; Braga et al., 2001; Tillyer & Kennedy, 2008). An expansion of our work is to replicate previous focused deterrence-based initiatives, focusing purely on the network of violent offenders. In practice strategies such as this have been
implemented in Boston (Braga et al., 2001), Chicago (Papachristos et al., 2007), and Cincinnati (Engel et al., 2011). However, these strategies have focused primarily on reducing gang related homicides, homicides in hot spot neighborhoods, and/or firearm offences. Within the context of PTEP targets in general, the goal is to communicate sanction risks to targets, that is, individuals on the PTEP list, who have the potential to generate the crime problem, and to the groups that they are embedded in. Here, a clear and consistent message would be continuously delivered by law enforcement officials informing targets of the fact that they are formally being watched (through the PTEP program), across the Lower Mainland of British Columbia, as opposed to one jurisdiction, and advising them of the risk of sanctions. Starting from targets, the goal is to utilize their ties to one another, relying on targets to spread this message to their immediate network (community) of associates. This would require effort from multiple agencies, and would be the first step towards using deterrence based policing strategies for preventing crime and violence before they occur in the Lower Mainland of British Columbia.

Alternatively, studies that use an ego as a focal point are useful as they comprise a meaningful starting point for network construction and follow the logic of the criminal justice system that prosecutes single individuals (for the most part). However, they are constrained, as they are limited to the network boundaries of the ego, and their associates. Within the context of this study, networks are limited to Target 1 and Target 2’s social environment. As noted in limitations, network capital scores reflect active targets within the networks of Target 1 and Target 2, hence “better targets” that are present, and active in the city but not within the current context are overlooked. To address this limitation, future studies should build upon egocentric networks, expanding network boundaries to reach a greater population. Particularly, within the context of this study, the analysis will expand to include the ego networks of associates who score high on network capital (key players) and are structurally equivalent. Expanding data collection to include the ego networks of the next “wave” of key players provides a thorough depiction of the social environment outside of the Target 1 and Target 2. It also provides greater insight into the target selection process.
Finally, it is beneficial that studies, which focus on police reported data, use the intersection of multiple methods such as qualitative interviews to supplement findings. Over the course of two months, we went on ride-alongs with general duty officers. These ride-alongs, while outside the scope of this study, provided insight into how officers conducted their police checks. Because we rely on police officer synopsis and police checks, it was useful to see the nature of interactions, and how first respondents use the centralized data system. For instance, how checks occurred, the variables officers completed as events were entered, and the level of interaction between the public and officers. Methodologically, these ride-alongs provided an opportunity to see how PRIME-BC operates, and how events are transferred into the data management system in real time. More generally, qualitative interviews with law enforcement officials supplement the quality and comprehensiveness of police reported data. Police officers, especially general duty officers, have the highest frequency of encounters with the public. These officers patrol the city, and a requirement of their job is to maintain some level of contact with the public. Interviews or some level of dialogue with officers provide insight on the prevalence of crime-affiliated behaviours outside of databases such as CPIC, and account for movements that may not always be noted on PRIME-BC. In return, these added layers of interactions enhance the quality of data, contextualizing the role of associates beyond what is detected. Interviews are also useful for “filling in the blanks” that come after data collection - that is, accounting for missing ties, and addressing the limitations that come from using police reported data. In all aspects, the triangulation of data, and the use of multiple methods overtime is useful for directing and informing law enforcement practices.
References


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Appendix A.

Descriptive statistics for normalized degree centrality and normalized betweenness centrality

<table>
<thead>
<tr>
<th>Statistic</th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Skewness Statistic</th>
<th>Skewness Std. Error</th>
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</thead>
<tbody>
<tr>
<td>Degree centrality</td>
<td>101</td>
<td>.010</td>
<td>.560</td>
<td>.062</td>
<td>.081</td>
<td>4.81</td>
<td>.24</td>
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<tr>
<td>Betweenness centrality</td>
<td>101</td>
<td>0.0</td>
<td>.574</td>
<td>.013</td>
<td>.077</td>
<td>6.80</td>
<td>.24</td>
</tr>
</tbody>
</table>

Note: Centrality measures are normalized
Appendix B.

Criminal backbone of the network of associates: Presence of interlinks between associates that have a criminal record, gang status, and/or firearm status (50 associates, 252 ties, density = 0.10)
Appendix C.

Pure social associates: Presence of interlinks between associates that have no crime-affiliated attribute (51 associates, 90 ties, density = 0.04)
Appendix D.

Distribution of network capital scores: Target 1, Target 2 and their associates (n=101)

<table>
<thead>
<tr>
<th>Associate ID</th>
<th>Network capital score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target 1</td>
<td>0.130</td>
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<tr>
<td>Target 2</td>
<td>0.159</td>
</tr>
<tr>
<td>A3</td>
<td>0.067</td>
</tr>
<tr>
<td>A4</td>
<td>0.073</td>
</tr>
<tr>
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<td>0.003</td>
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<td>A7</td>
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<td>A8</td>
<td>0.036</td>
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</tr>
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Appendix E.

Combined egocentric networks of Target 1 and Target 2, and the presence of key players from 2010 to 2013 (74 associates, 400 ties, network density = 0.07)
Appendix F.

Combined egocentric networks of Target 1 and Target 2, and the presence of key players from 2006 to 2009 (64 associates, 282 ties, network density =0.07)

Legend
- Key players:
  Table 6: Option 1 and Option 2 (n=10)