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Multilevel determinants of collaboration between organised criminal groups

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Abstract:

Collaboration between members of different criminal groups is an important feature of crime that is considered organised, as it allows criminals to access resources and skills in order to exploit illicit economic opportunities. Collaboration across criminal groups is also difficult and risky due to the lack of institutions supporting peaceful cooperation in illicit markets. Thus cross-group collaboration has been thought to take place mostly among small and transient groups. This paper determines whether and under what conditions members of different, larger organised crime groups collaborate with one another. To do so we use intelligence data from the Canadian province of Alberta, centering on criminals and criminal groups engaged in multiple crime types in multiple geographic locations. We apply a multilevel network analytical framework and exponential random graph models using Bayesian techniques to uncover the determinants of cross-group criminal collaboration. We find cross-group collaboration depends not only on co-location, but also on the types of groups to which the criminals are affiliated, and on illicit market overlap between groups. When groups are operating in the same geographically-situated illicit markets their members tend not to collaborate with one another, providing evidence for the difficulty or undesirability of cross-group collaboration in illicit markets. Conversely, members of Outlaw Motorcycle Gangs are more likely to collaborate across groups when markets overlap, suggesting the superior capacity and motivation of biker gangs to coordinate criminal activity. Our paper contributes to the understanding of criminal networks as complex, emergent, and spatially embedded market phenomena.

1. Introduction

Criminal collaboration within groups is a key feature of crime that is considered 'organised' (Calderoni, 2014; Gottschalk, 2010). Organised crime groups (OCGs) act as sites of social interaction and identification that lead to criminal tie formation (Papachristos et al., 2013); as criminal opportunity structures which match criminals with suitable co-offenders and facilitate the sharing of skills and resources (Blokland et al., 2019); and as entities through which illicit economic activity is coordinated (Levitt and Venkatesh, 2000). While there is a burgeoning research literature on collaboration within such groups (Bichler et al., 2017; Faust and Tita, 2019), there is less research on collaboration between members of *different* criminal groups. There are reasons to expect that collaboration across groups is difficult due to problems with trust, communication, and bargaining (Gambetta, 2009; Levitt and Venkatesh, 2000; von Lampe and Ole Johansen, 2004), and the lack of overarching institutions enabling the peaceful coexistence of competing organisations (Schneider, 2013). Nonetheless, intergroup collaboration *does* occur (Malm et al., 2011; Ouellet et al., 2019), and it may be important to the resilience of illicit markets (Bouchard, 2007). However, such collaboration is thought to take place mainly among small and transient groups (Bouchard and Morselli, 2014). This paper aims to determine whether and under what conditions members of different, larger organised criminal groups collaborate with one another.

To this end, we exploit a large dataset on organised crime groups collected by a central intelligence agency in the Canadian province of Alberta. The anonymised data draws on intelligence collected over a two-year period and includes information on individuals known or suspected to be involved in organised criminal activities, the criminal collaborative ties between them, their memberships of organised crime groups, the locations in which they were active, and the illegal activities in which they were involved. We conceptualise this data as a multilevel network (Lazega et al., 2008), and apply Exponential Random Graph Models (ERGM) (e.g. Lusher et al., 2013) using Bayesian techniques (Caimo and Friel, 2011; Koskinen, 2008) to uncover the multilevel determinants of collaboration between members of different groups. We focus on criminal groups with more than 18 members, which can be considered relatively large (Ouellet et al., 2019). We demonstrate that the tendency for criminals to form interpersonal collaborative ties across these larger groups depends not only on spatial co-location, but also on the types of groups to which the criminals are affiliated, and on the embeddedness of those groups in a macro-level context of spatially-situated illicit markets. More specifically, we define illicit market overlap between groups in terms of their members engaging in drug trafficking activities in the same geographic locations. We argue that market overlap at the organisation level creates potential for criminals to take one another into account and collaborate at the interpersonal level. We find that, in general, members of different OCGs tend not to collaborate with one another when their respective organisations' illicit markets overlap. Conversely, members of different Outlaw Motorcycle Gangs (OMCGs) display a tendency to collaborate with one another both when they are operating in the same locations, and when their organisations' markets overlap. The findings provide evidence for the generally competitive nature of illicit markets, where cross-group collaboration is difficult or undesirable; but also suggest that OMCGs have the capacity and motivation to overcome coordination problems and collaborate for economic gain. Thus we lend support to claims that OMCGs are engaged in particularly well-organised forms of crime (Lauchs, 2019; Morselli, 2009a).

Our paper contributes to the understanding of organised crime as a complex, emergent, socially and spatially embedded market phenomenon (Dwyer and Moore, 2010; Magliocca et al., 2019). Our anonymised intelligence data set is unique not only in terms of its ecological validity but also its size and multilevel scope, involving individuals, groups, locations and multiple crime types. Our analytical framework allows us to address how network interdependence (market overlap) at the group level in a criminal network shapes collaborative tie formation at the individual level *in the context* of the overall criminal ecology. This advances previous research on illicit economic networks which often draws exclusively on archival data, focuses narrowly on one type of economic activity (e.g. drug supply), and neglects how such activity is embedded in broader illicit and licit networks (Bichler et al., 2017; Bright et al., 2019). We also add to a growing stream of literature which accounts for the multilevel determinants of criminal activity (Deryol et al., 2016; Ward et al., 2019). Finally, we heed calls for studies that adopt a more theory-driven approach to the role of geographic space in crime (Tita and Radil, 2011); and for studies which combine groups, social networks, criminal activity and geographic space in the same analysis (Piquette et al., 2014).

The remainder of the paper proceeds as follows. In Section Two we review evidence on determinants of collaborative tie formation at different levels of analysis. In doing so we derive hypotheses about the circumstances under which members of different criminal organisations will form collaborative ties with one another. In Section Three we describe the data we use to test our hypotheses and its multilevel structure, and explain how ERGM can be used to understand complex criminal networks. In Section Four we demonstrate the utility of the analytic framework by testing our hypotheses about the circumstances under which members of different large OCGs collaborate with one another. Section Five concludes by discussing the implications of our analysis for the understanding of organised crime and for the study of criminal networks.

2. Theoretical background and hypotheses

Crime that can be considered organised takes place in a multilevel social system. Each level in the system consists of actors that have both agency and interdependencies that constrain or enable their actions; and lower-level actors are nested within higher-level actors (Lazega, 2016). Thus individual criminals and their relational dependencies (such as collaborative relationships or antagonisms) are nested within criminal groups which themselves have relational dependencies (such as rivalries or alliances) (e.g. Descormiers and Morselli, 2011). In addition, groups and their constituent individuals are situated in a geographic context which constrains or enables actions through factors such as spatial composition and configuration (Small and Adler, 2019).

Multilevel social systems can be conceptualised as a multilevel network (Lazega, 2016). A multilevel network consists of several sets of nodes where each set defines a level, with ties defined within or between levels (Lazega et al., 2008; Wang et al., 2016, 2013). Tie formation at one level may be influenced by dependencies across levels and at other levels. The social processes behind these dependencies are known as cross-level mechanisms in tie formation. The multilevel network perspective has brought useful insights to the study of social systems such as legitimate markets and organisations (Brass and Greve, 2004; Brennecke and Rank, 2017, 2016; Glückler and Doreian, 2016; Hollway and Koskinen, 2016; Meredith et al., 2017; Paruchuri et al., 2019; Zappa and Robins, 2016). It can also contribute to the study of illicit markets, but has only recently been applied for covert networks (Stys et al., 2019). Criminal network ties are determined not only by individual attributes and interpersonal factors, but also by group membership; interdependencies among groups; the geographic distribution of criminal activity; and interactions among these factors (Descormiers and Morselli, 2011; Malm et al., 2011; Papachristos et al., 2013, 2012). These factors can be represented as multilevel network dependencies, and ERGM can be used to model collaboration networks as emergent phenomena that arise from multilevel dependencies, providing evidence on the mechanisms that give rise to criminal collaboration ties.

Thus, for the purposes of investigating our main research question we treat our data conceptually as a multilevel network of interpersonal ties and two distinct types of affiliation nodes – organisations and locations (as illustrated in Figure 1). The one-mode collaboration network in combination with the two bipartite networks allow us to specify a range of interactions reflecting the dependencies between locations, organisations and collaboration ties. We then treat these dependencies as fixed in our statistical analysis and model the interpersonal collaborative ties.

We focus on collaboration ties in a population that is engaged in multiple kinds of organised criminal activities, rather than on a sub-network associated with a specific crime-type such as drug trafficking (e.g. Bright and Delaney, 2013). While there is evidence for systematic differences in the structural features of different kinds of criminal network (Bichler et al., 2017); there is also evidence that the differences between networks such as drug trafficking, terrorism and legitimate economic activity are not as large as previously thought (Ünal, 2019; Wood, 2017). Further, different kinds of criminal networks, different criminal activities and different illicit exchanges are frequently interconnected (Asal et al., 2015; Bright et al., 2015; Calderoni, 2012; Malm and Bichler, 2011); as well as being embedded within broader social settings (Dwyer and Moore, 2010; van de Bunt et al., 2014). Given the interconnectedness of criminal activity and the nascent nature of the literature on criminal network structure (Bichler et al., 2017), we seek to understand the structure of collaboration networks within a large ecosystem that includes multiple, often interrelated, types of crime. Our study therefore presents evidence of the structure of criminal networks within their broader context. Existing research provides clues to the particular multilevel dependences that are important in collaborative tie formation. These include dependencies at the dyadic level; dependencies across levels in the form of group and location affiliations; cross-level interactions between membership of different groups and shared locations; and multilevel dependencies in the form of higher-level relationships among groups, specifically overlap in their geographically-located illicit market activity.

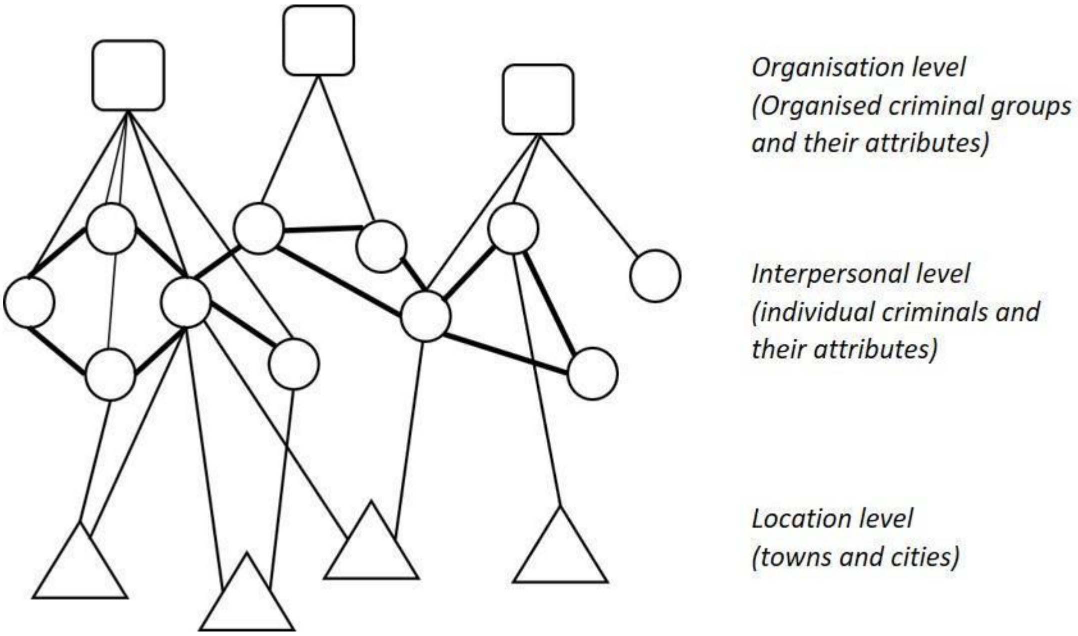


Figure 1: the multilevel structure of the data, illustrating interpersonal ties between criminals, criminals' affiliations to OCGs, and criminals' affiliations to locations

2.1. Dyadic, group and location-level determinants of collaboration among organised criminals

Research on criminal networks has revealed determinants of collaboration between individual criminal actors (Bright et al., 2019; Diviák et al., 2019a; Grund and Densley, 2012; Ouellet et al., 2017). Mechanisms that stimulate collaborative tie formation among actors may either be endogenous network mechanisms, mechanisms related to individual attributes, or mechanisms related to dyadic variables. Endogenous mechanisms express tendencies of actors to form ties based on the existence or absence of other ties. In criminal networks, two frequently studied endogenous mechanisms are tie accumulation and triadic closure. Criminal actors are expected to have tendencies against tie accumulation, not only because accumulation is costly in terms of time and other resources (Snijders, 2013), but also because it increases the visibility of actors and thus the likelihood that they will be detected and subsequently arrested. Empirical findings provide support for this explanation (Bright et al., 2019; Diviák et al., 2019b). Triadic closure is considered important in criminal networks as collaborating within closed triads may provide control and support and thus facilitate trust (Coleman, 1988), which may otherwise be scarce in illicit contexts. Again, this is supported by previous research (Bright et al., 2019; Diviák et al., 2019b; Grund and Densley, 2012; Ouellet et al., 2017). Mechanisms related to individual attributes reflect the fact that actors with different predispositions and characteristics may have different propensities towards tie formation. This may be manifested through generalised social selection or homophily (Robins, 2009). Generalised social selection denotes tendencies of actors with certain attributes form ties differently than other actors (such as having more ties) whereas homophily denotes the tendency of actors with given attribute to interact with similar others (Mcpherson et al., 2001). Dyadic variable ties in the form of other types of ties (such as pre-existing ties or different types of exchanges) also influence the formation of collaboration ties (Bright et al., 2015; Diviák et al., 2019b).

Importantly, the determinants of criminal collaboration go beyond the individual and dyadic levels. They include shared group affiliation, and shared locational affiliation. Criminal collaboration is considered more likely between members of the same group for several reasons. First, individuals are attracted to OCGs as sources of non-criminal resources including protection, belonging, social support, and the meeting of needs in deprived communities (Papachristos et al., 2013; Piquette et al., 2014). Repeated social interaction over time leads to the creation of group-based resources, such as a shared identity, a shared culture, common behavioural norms, and a sense of togetherness, which can facilitate criminal collaboration and amplify individual criminal behaviour (Nese et al., 2018; Papachristos et al., 2013). Second, groups represent criminal opportunity structures. Social selection processes attract individuals with pre-existing criminal tendencies to criminal groups (Baron and Tindall, 1993). Group membership provides opportunities for those with criminal tendencies to collaborate by matching individuals with suitable co-offenders and allowing the sharing of information and other resources (Bouchard and Morselli, 2014). Ongoing involvement in OCGs allows individuals to accumulate skills and social capital, facilitating long-term offending (Blokland et al., 2019). Third, criminal groups facilitate the coordination of illicit economic activities through organisational practices such as formal hierarchies and a division of labour (Levitt and Venkatesh, 2000).

Collaboration is also more likely between criminals who are co-located. In general, it has been shown at all levels of analysis that nodes that are physically near to one another are more likely to be connected, other conditions being equal (Festinger et al., 1950; Kadushin, 2012). In the case of organised criminals, collaborative ties may form as a consequence of geographic proximity increasing the chances and ease of interaction (Papachristos et al., 2013). Beyond such ‘propinquity’ effects, it has been argued that particular geographic locations are key to the coordination of complex criminal activities such as drug trafficking (Felson, 2006). Offenders are likely to converge in particular settings, such as bars or other locations associated with criminality. These convergence settings are the site of illicit transactions, or act as the starting point for criminal activity conducted elsewhere. They therefore 'set the stage for crime by assembling accomplices and getting an illicit process started' (Felson, 2006, p. 9). In our analysis, we go beyond the conceptualisation of space as spatial proximity by considering space as a location and therefore as an additional level in our network. This allows us to investigate the effects of specific locations on cooperation among criminal actors.

While we have good reasons to believe that collaboration is more likely between members of the same criminal group and co-located criminals, we know relatively little about how organisational membership and geographic space interact to determine criminal collaboration. In general, knowledge of group context is necessary to understand the cross-level effects of group membership on individual outcomes (Klein et al., 1994). There are qualitative differences between different kinds of OCG which are reflected in the criminal behaviour of their members (Blokland et al., 2019; Bruinsma and Bernasco, 2004; Nese et al., 2018; Ruddell and Gottschall, 2011; Schneider, 2013). Evidence suggests that when members of different criminal organisations are co-located, the type of group to which they belong will influence their tendency to collaborate with one another.

2.2. Group identity, geographic space and collaboration across organised criminal groups

Certain criminal groups have collective identities that are closely tied to the occupation of geographic space, and which lead to rivalry with other co-located groups. For example, street gangs are de-facto social institutions which meet the needs of individuals (especially youth) in disadvantaged communities (Piquette et al., 2014; Skaperdas, 2001). Gang members identify strongly with their neighbourhood (Papachristos et al., 2013). For such groups, inter-gang rivalry over territory is source of shared identity and group bonding (Piquette et al., 2014). Violent acts and aggressive posturing against members of other gangs are means to both individual status attainment within gangs, and to signal the reputation of a gang to outsiders (Blokland et al., 2019; Papachristos et al., 2013). Rivals are easily identified as street gangs use signals such as clothing to differentiate themselves from non-gang members and from members of rival gangs (Blokland et al., 2019). Similarly, ethnic OCGs bring co-offenders together based on their or their parents birth-place and location (Malm et al., 2011). Members have a strong shared ethnic identity and are less likely to collaborate with members of other ethnic groups (Bruinsma and Bernasco, 2004; Grund and Densley, 2012; Malm et al., 2011; von Lampe and Ole Johansen, 2004). The ethnic- and neighbourhood-based identities of gangs often overlap, as economic inequalities mean that members of particular ethnic groups are co-located in deprived areas (Papachristos et al., 2013; Skaperdas, 2001). In sum we expect that membership of OCGs which are associated with neighborhood-based or ethnic identities will inhibit individuals from collaborating with members of other OCGs with whom they are co-located. Proximate members of other groups are more likely to be seen as rivals or outsiders than potential accomplices. We propose:

> *Hypothesis 1*: Operating in the same locations is negatively related to the likelihood of collaboration between members of different OCGs.

In contrast, we might expect members of different OMCGs to collaborate with one another when they are co-located. Although OMCGs have engaged one another in violent conflicts over territory for both economic and non-economic reasons, territorial conflict among OMCGs does not appear to be the norm (Schneider, 2013). Where violence does occur it is often sporadic and incidental to a 'barbarian' biker culture of drinking and fighting (Lauchs, 2019). In fact, an overarching biker identity that is associated with common organisational practices may transcend individual club identities and aid cooperation across groups (Ritter et al., 2012; Robins, 2009). Clubs have a culture of strict secrecy and loyalty, and members must serve a probationary period where they prove their criminal capabilities (Lauchs, 2019). Thus OMCG membership may act a signal to potential accomplices of an individual's criminal capabilities and discretion (cf. Gambetta, 2009). The use of clothing and insignia that designate membership helps identify bikers to other bikers as members of the brotherhood and potential criminal collaborators (Lauchs, 2019; Morselli, 2009a). Additionally, OMCGs are known to use particular convergence settings, especially drinking establishments, to coordinate and conduct criminal activity (Quinn, 2001; Schneider, 2013). Thus bikers from different gangs operating in the same locations may be more likely to form collaborative ties. We posit:

> *Hypotheses 2:* Operating in the same locations is positively related to the likelihood of collaboration between members of different OMCGs.

We propose that collaboration between criminals is determined by more than the cross-level interaction of the kind of group to which they belong with their individual space-based activity. It likely also results from higher-level intergroup dependencies that shape the behaviour of individual group members. A relevant form of intergroup dependency is overlap in space-based illicit market activity.

2.3. Illicit market overlap and collaboration across organised criminal groups

Legal markets are localised institutions, where organisations overlap in their geographically-located production and consumption activities (Baum and Korn, 1999; Lomi and Pallotti, 2012; Markman et al., 2009). We refer to this as market overlap (Kilduff, 2019; Markman et al., 2009). Organisations with overlapping markets rely on the same spatially-situated resources or marketplaces. This creates potential for competition between the organisations, but it also creates the conditions required for collaboration that leads to mutual gain. Market overlap creates social spaces in which organisational actors meet. These actors may build relationships with one another to manage their common resource dependencies. Communication across these relationships leads to greater awareness of each other's activities and mutual understanding of interests. This in turn may facilitate the coordination of economic activities across markets to alleviate competitive pressures and exploit mutual economic opportunities. Indeed, research in legal markets has demonstrated that market overlap between two organisations can lead to collaboration in order to relieve competitive pressures rather than competition for market share (Baum and Korn, 1999; Kilduff, 2019; Yu and Cannella, 2013), and that the more two organisations' markets overlap the more likely we are to observe social ties between them (Lomi and Pallotti, 2012).

Definitions of market overlap in the literature on legitimate organisations are highly nuanced (e.g. Baum and Korn, 1999). Illicit markets such as drug markets consist of various illicit commodities (e.g. methamphetamine, crack cocaine); market niches (e.g. production, importation, and various levels of distribution); particular individual economic roles (e.g. meth cook, street dealer); and geographic territories such as open-air marketplaces (Bichler et al., 2017; Bright and Delaney, 2013; Dwyer and Moore, 2010; Hofmann and Gallupe, 2015; Johnson et al., 2000). Illicit market overlap could be defined with reference to these elements. However, unlike legal markets, there is no precedent for a more nuanced definition of market overlap in the illicit market context. The commodities exchanged, individual roles, market niches, and the structure and composition of collaboration networks in illicit markets are often flexible due to an uncertain and dynamic economic environment in combination with law enforcement pressure (Bichler et al., 2017; Bright and Delaney, 2013; Johnson et al., 2000; Morselli and Petit, 2007). Unlike legitimate organisations, which may find it difficult or unnecessary to switch rapidly between different commodity markets or market niches, this diversity and adaptability in economic activity may be a necessary adaptation of criminal groups. Further, organised crime often deals with commodities and resources that are spatially located (e.g. open air drug markets, extortion of businesses). We should therefore account for spatial embeddedness, which has been shown to shape similar geographically-focused economic activities (cf. Small and Adler, 2019). Given the importance of both space and adaptability in market behaviour, it may be that broad overlap in activity is enough to stimulate collaboration or competition in illicit markets. We therefore define market overlap at a high level in terms of criminal groups, their members and those members' geographically-located criminal activities. Two groups have overlapping markets if their members are doing the same criminal activities in the same places. Illicit market overlap creates opportunities for members of different groups to take one another into account and to engage in competitive or collaborative behaviour.

While criminal networks are flexible, there are limits to this flexibility as economic coordination must be somewhat predictable (Johnson et al., 2000). It is therefore worth asking under what conditions groups engaged in the same broad economic activity in the same spaces form ties to one another. Are we likely to observe a relationship between the overlap of criminal groups' illicit markets defined in this way and collaborative ties between members of those groups? Collaboration is economically beneficial to criminal groups. Coordinating illicit economic activity requires bringing to bear diverse skills, resources and activities across various steps in the criminal supply chain (Bruinsma and Bernasco, 2004; Morselli, 2009b; Skaperdas, 2001). Exploiting opportunities or reacting to changes in the supply and demand of illicit commodities may therefore necessitate the incorporation of new or greater skills, resources and activities into a group's repertoire (Bright and Delaney, 2013). Collaboration across OCGs is one means to taking advantage of economic opportunities. In cases where a group does not possess or have access to all the resources required to exploit an economic opportunity, access can be sought in the form of cooperation with owners of resources (Gottschalk, 2010). Cooperation may take multiple forms ranging from the more ambitious, such strategic alliances and joint ventures, down to individual transactions (Williams and Godson, 2002). Further, cross-group collaboration could support adaptation in the face of law enforcement disruption of supply chains (Morselli and Petit, 2007), and so may be a key element of illicit market resilience (Bouchard, 2007).

However, collaboration across groups is challenging due to a lack of governance institutions to undergird peaceful cooperation in illicit markets. In legal markets peaceful competition is managed through legal instruments and overarching institutional arrangements, the presence of which also make possible cooperation between competing firms (Grandori and Soda, 1995). Criminal groups lack recourse to legitimate institutions to manage their relationships with other actors (Bouchard and Morselli, 2014; Skaperdas, 2001). Instead, competition between groups is managed through coercion, violence, and the use of financial resources for corruption (Gottschalk, 2010). OCGs use violence to consolidate their markets, enforce contracts, settle disputes, and as a means to market expansion (Levitt and Venkatesh, 2000; Skaperdas, 2001). Illicit markets have therefore been thought to display a 'sort of monopolistic competition' in which each group maintains a monopoly in a certain bounded geographic area (Skaperdas, 2001). Groups may need to threaten or engage in violence to maintain their monopoly and deter competitors from encroaching on their market share (their 'turf') (Morselli, 2010). Consequently, economic coordination across criminal groups is characterised by problems with trust, communication, and bargaining (Bright and Delaney, 2013; Gambetta, 2009; Levitt and Venkatesh, 2000; von Lampe and Ole Johansen, 2004). It is often volatile, ad hoc, inconsistent, or short-lived (Bruinsma and Bernasco, 2004; Descormiers and Morselli, 2011; Gambetta, 2009; Malm et al., 2011; Skaperdas, 2001).It may be less risky to address resource needs by switching roles and learning new skills within an existing group (Bright and Delaney, 2013). Cross-group collaboration may take place primarily among small and transient groups (Bouchard and Morselli, 2014). We therefore expect:

> *Hypotheses 3:* Illicit market overlap is negatively related to the likelihood of collaboration between members of different OCGs.

We know that different criminal groups have different motivations (e.g. hedonism vs economic gain) (Quinn, 2001), different collective norms of behaviour (e.g. opportunism vs loyalty) (Nese et al., 2018), and varying levels and forms of group organisation (Bichler et al., 2017; Kleemans, 2014). There are reasons to think biker gangs in some geographies have greater organisational capabilities and motivation to collaborate to exploit market opportunities than other groups. First, some OMCGs use organisational practices which include cooperation across clubs and which have allowed them to solve market governance and economic coordination problems. As shown by Morselli (2009a) and Lauchs and Staines (2019), biker gangs display status hierarchies both *within* and *between* clubs. Within clubs, individuals higher up the hierarchy direct the action of those lower down the hierarchy. Between clubs, members of high status gangs direct the actions of members of low status ‘puppet’ or ‘support’ clubs. OMCG members can ascend the ranks within a club, or move to a higher-status club, by acting at the behest of their superiors to prove their criminal abilities. These practices solve market governance problems and aid economic coordination by providing individual incentives for cooperation across groups, and by allowing senior gang members to effectively direct activities across groups without a large degree of direct involvement that would compromise their own security (Morselli, 2009a). They have also allowed older, more experienced members with organisational and entrepreneurial skills to rise to the top of clubs (Morselli, 2009a; Skaperdas, 2001), which could facilitate the exploitation of economic opportunities that require cross-group collaboration. Further, OMCGs have created specialist roles that have allowed coordination across geographically-dispersed markets, including roaming gangs of elite bikers who are unaffiliated to a particular territory, and elite subgroups of violent members who handle enforcement (Lauchs, 2019; Morselli, 2009a). Thus OMCGs may have achieved dominance in particular geographic markets by solving contractual enforcement and coordination problems across the criminal supply chain (Morselli, 2009a; Schneider, 2013; Skaperdas, 2001).

Second, there is some evidence that OMCGs in some jurisdictions have developed a ‘radical’ culture, with less emphasis on violence; greater emphasis on illegal enterprise; and a more stratified organisational structure allowing for the coordination of social, paramilitary and economic operations (Lauchs et al., 2015; Quinn, 2001). On this view, law enforcement crackdowns have led clubs to renounce violence in order to protect illicit profits and ensure the survival of the biker subculture. Thus a shared opposition to law enforcement may have increased incentives towards collaboration across biker gangs. Alignment of interests could result in economic expansion via the relatively peaceful alliances with rival clubs instead of wars (Donkin, 2017). Indeed, Malm et al. (2011) observed that OMCGs operating in Canada are more similar to one another in their co-offending patterns than other types of group, providing evidence for unified purpose and shared norms. Thus we posit:

> *Hypothesis 4:* Illicit market overlap is positively related to the likelihood of collaboration between members of different OMCGs.

In sum, we expect that group type, locational affiliations, and market overlap will interact to determine the presence or absence of observed collaborative ties among organised criminals who are members of different groups. In particular, we expect members of different OMCGs to be more likely to display collaborative behaviour when they are operating in the same locations or when their organisations have overlapping markets compared to other OCGs. We test our hypotheses by applying exponential random graph models to intelligence data on organised criminals operating in Canada.

3. Data and analytic approach

3.1. Overview of the data

The anonymised data consist of 3137 individuals suspected or known to be involved in organised crime in and around the Canadian province of Alberta over a two-year period up to 2016. Organised crime is defined according to the Criminal Code of Canada as a group of three or more people whose main purpose or activity is the facilitation or commission of serious criminal offences that, if committed, would likely result in material benefits (including financial benefit) for at least one member of the group. There are 17 interpersonal tie types in the data, representing relational states such as friendship and familial ties, and relational events such as co-arrest and being seen together by police surveillance. There are individuals' affiliations to 188 criminal organisations, and attributes of the organisations, including type of OCG. There are also individuals' affiliations to 293 geographical locations. Residential and activity locations are recorded at the city or town level, and do not represent uniform geospatial units. The locational affiliations of individuals in the dataset span a wide geography, including sites across Canada as well as in the United States and Mexico. Finally, there are data on types of crime individuals are known to be involved in. Individuals represented in the data are involved in a number of illegal activities, including drug trafficking, property crimes, vehicle-related crimes, financial crimes, human trafficking, extortion/intimidation, weapons offences, and violent crime. It is possible for an individual to be affiliated to multiple crime types, multiple organisations and multiple locations.

Drug trafficking is the most common type of criminal activity in the dataset. Drug trafficking centres around the transport and distribution of synthetic drugs, which represents a serious problem in Alberta and other Canadian provinces (*Canadian Drug Summary: Methamphetamine*, 2018). Drug-related criminality is here known or suspected by intelligence analysts to be embedded in networks that include other criminal offences, some of which are used to support drug trafficking (such as violence and property crime), and some which may be financed through drug trafficking (such as weapons trafficking).

3.2. Data collection and limitations

Data were collected by multiple local police forces using a standardised form which prompts intelligence analysts for information regarding individuals under investigation, and were then collated by analysts at a central police intelligence agency. The data come from multiple sources, including human intelligence (such as source reports, police surveillance), signals intelligence (such as the interception of communications), and open source intelligence (such as information freely available online). Common limitations of such data include missingness (Koskinen et al., 2013; Morselli, 2009a), measurement error (Butts, 2003), intentional errors (e.g. use of aliases), unintentional errors (e.g., incorrect input of names), sample selection bias, and group boundary misspecification (Burcher and Whelan, 2015; Malm and Bichler, 2011). These limitations aside, it is worthwhile reflecting on the benefit of these types of data relative to other common data sources used in the illicit networks literature (see Bright et al., 2012, for a discussion of different archival sources and their drawbacks). Our data has an ecological validity that is often lacking in data based on archival sources. Contrary to, for example, offender databases and court transcripts, the individuals are at large and as such the data do not suffer from the biases associated with data on apprehended criminals. Unlike these sources and, in addition, news media, our data are not archival, but, in a sense, a real-time impression of the criminal ecosystem. Nor do they suffer to the same extent from being biased towards the pursuit of an investigation of a particular crime or criminal (although some of the records emanate from persons of interest). Data are mostly properly dyadic and not, like co-offending, derived from co-affiliation with events, something that might reflect other processes (Broccatelli et al., 2016).

3.3. Data subset selection

Certain kinds of interpersonal ties recorded by law enforcement can be seen as indicative of co-operation between criminals in the process of criminal enterprise and can be modelled as an interpersonal network (Bouchard and Konarski, 2014). A subset of interpersonal tie-types was selected, including ties which both analysts at the intelligence agency and existing research suggest are likely to indicate active collaboration in criminal enterprise (Diviák, 2019). These included ties derived from police case-files, ties observed as a result of police street checks, ties identified by police informants, and ties between individuals designated by intelligence analysts as known associates or suspected associates. Selecting ties in this way excluded from the subset less specific tie-types such as familial, friendship or romantic relations. These ties were sometimes recorded by police as relevant to investigations into criminal suspects, even though police may not believe that the related parties are collaborating with the suspect.

Hypotheses 3 and 4 are contingent upon the opportunity for a group to compete for spatially-situated markets or to cooperate when its market overlaps with another group. Larger OCGs may be more likely to take one another into account and respond in a coordinated manner when their markets overlap. Indeed, it has been shown that larger OCGs are more likely to engage in intergroup violence, and that group size correlates positively with the presence of more developed organisational structures (Eck and Gersh, 2000; Papachristos et al., 2013). Further, smaller OCGs are more likely to be transient (Bouchard and Morselli, 2014). In the legal context it has been shown that firms are more likely to compare themselves to, and develop rivalries with, firms that are similar to them in terms of size (Kilduff, 2019). Therefore we chose to focus only on the larger organisations in the data set when testing our hypotheses. Specifically, we selected a subset of the data consisting of OCGs with more than 18 members, which can be considered relatively large – Ouellet et al. (2019) found that on average Montreal criminal groups had 18.32 members.

Choosing a subset based on larger groups also allowed us to deal with specific limitations of our data. Intelligence analysts indicated that the larger criminal groups are in fact established organisations with a group identity, in contrast to smaller groups which may have been recorded as a result of a single police observation of suspects in the same location. This is supported by existing literature, which suggests that larger groups are less likely to be ephemeral (Bouchard and Morselli, 2014). Further, focusing on members of larger groups excluded petty criminals from our analysis. Local police analysts tended to only record individuals as group members if they were relatively confident that they were serious criminal members of a group. Thus our subset does not include drug users who commit property crime to fund their drug habit and who may have been recorded as members of smaller, transient groups, or as affiliated to no group at all.

The selection criteria gives a subset of 1263 individuals, 44 organisations and 52 locations. Table 1 shows the types of organisations in the subset. 15 (34%) are ethnic OCGs or street gangs, and 15 are OMCGs. Different chapters of the same OMCG and puppet/support clubs are recorded as separate groups. The names of clubs and chapters are not identified in the data. There are nine groups defined by analysts as Independent or Other/Unknown.[1]

Summary statistics for the subset are shown in Tables 2-4. The sociogram of the interpersonal network plus person-organisation affiliation ties for the subset is shown in Figure 2. The sociogram of the interpersonal network plus person-location affiliation ties for the subset is shown in Figure 3.

Table 1: Types of organised crime group in the subset

Organisation type	Number in subset
Aboriginal OC	4
African OC	4
Asian OC	2
Southwest Asian OC	2
Eastern European OC	1
Independent OC	5
Outlaw Motorcycle Gang	15
Street Gang	2
Other/Unknown	9

[1] There is no clearly defined and consistent definition of the categories 'Other/Unknown' used by the analysts responsible for data collection. Analysts in local police forces choose OCG categorisation from a list of group types. They must choose one categorisation only, or can leave the category field blank. Analysts at the central intelligence agency who collated the data observed that local police analysts sometimes choose 'Other/Unknown' when they are of the opinion that no other category is applicable, or when multiple are applicable. The forced-choice nature of group categorisation ought to be acknowledged as a limitation of the data collection method. It may be that group categorisation is not a reflection of the sum-total of evidence regarding the group's characteristics, and different analysts may choose categories based on different decision criteria. However, given that Outlaw Motorcycle club members tend to be clearly identifiable by their insignia, it is unlikely that any OMCGs are included in the category 'Other/Unknown', and so the data subset is sufficient for testing our hypotheses about the differences between OMCGs and other types of criminal group.

Table 2: Summary statistics for interpersonal collaboration network

Network	N	No. of ties	Isolates	Components (excluding isolates)	Max. component size	Mean degree	Density
Collaboration	1263	893	726	30	351	0.70705	0.00112

Table 2 (*cont.*): Summary statistics for interpersonal collaboration network

Network	Clustering coefficient	Median path length for nodes that are reachable	Median path length for largest component
Collaboration	0.00817	7	8

Table 3: Summary statistics for two-mode person to organisation network

Network	N (organisations)	Total affiliation ties	Average no. of organisations per individual	Average members per organisation	Bipartite clustering coefficient
Two-mode person to organisation	44	1342	1.06255	30.5	0.06046

Table 4: Summary statistics for two-mode person to location network

Network	N (locations)	Total affiliation ties	Average no. of locations per individual	Average no. of individuals per location	Bipartite clustering coefficient
Two-mode person to location	52	768	0.60801	14.76923	0.07954

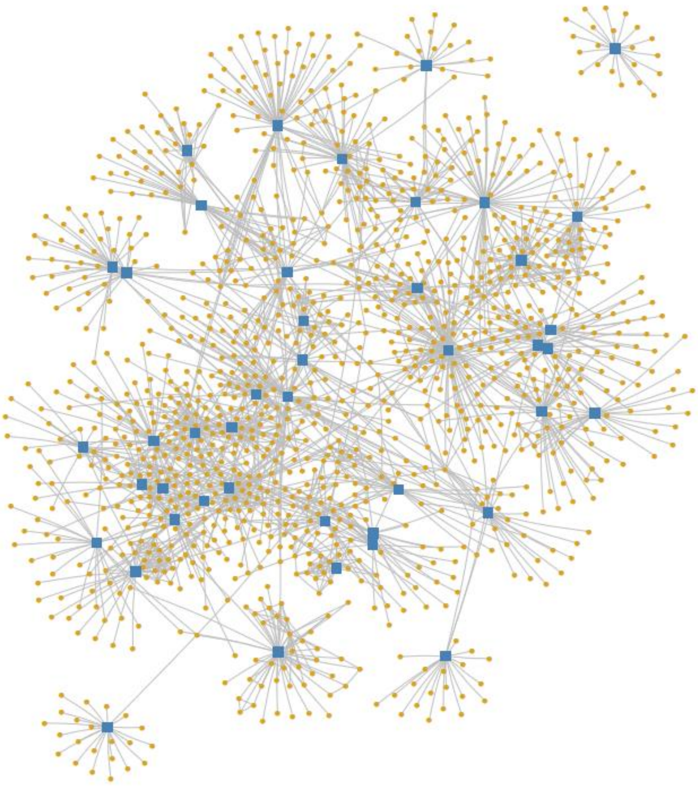


Figure 2: The interpersonal network plus organisational affilation ties. Individuals are represented as yellow circles and OCGs are represented as blue squares

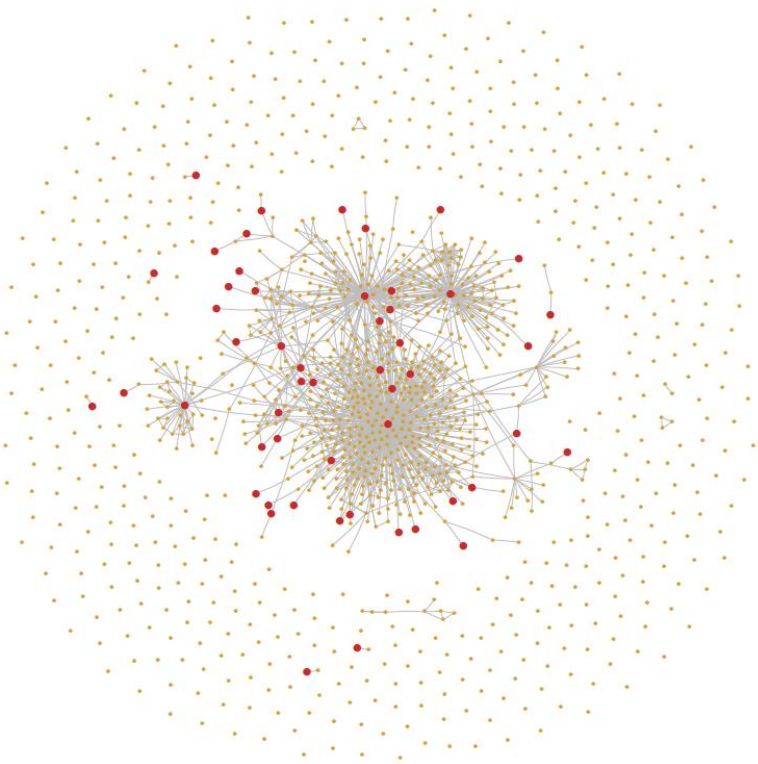


Figure 3: The interpersonal network plus locational affiliation ties. Individuals are represented as yellow circles and locations are represented as red circles

3.4.Modelling multilevel organised criminal networks using ERGM

Exponential random graph models (ERGM) (see Lusher et al., 2013, for an introduction) allow the modelling of complex networks by treating tie formation as an endogenous process, and modelling global network structure as a result of local tie-formation processes. Ties are assumed to be conditionally dependent, where the presence of a tie depends on the presence of other network ties conditioning on the rest of the network (Wang et al., 2016). Regularities in underlying social processes are hypothesised to be responsible for observed local-structural regularities in the network, and the global network is assumed to arise from these structural regularities plus a degree of randomness. By incorporating a number of micro-level network configurations simultaneously into an ERGM, we can uncover evidence as to the kinds of social processes that lead to the overall network structure, for example, homophily, reciprocity or triadic closure (Lusher et al., 2013). Thus ERGM can be used to model complex criminal networks and provide evidence on the social processes that give rise to observed network structure (Grund and Densley, 2012; Papachristos et al., 2013).

Multilevel ERGM (MERGM) (Wang et al., 2016, 2013) allows the modelling of networks with multiple levels; that is, networks with two or more types of node, and distinct types of tie within and between the node sets (Wang et al., 2016). In MERGM network ties are interdependent both within and across levels. Since our hypotheses concern interpersonal collaboration ties contingent on affiliations and the ties between organisations, we keep the latter types of ties fixed in the estimation process. We thus follow the procedure of Stys et al. (2019), where change-statistics associated with cross-level effects are coded as dyadic-covariates. Similar to the case in that study, affiliations (there to armed groups) can be said to be antecedents to individuals ties due to the different time-scales on which these operate. We also apply a Bayesian inference scheme implemented as in Koskinen, Broccatelli, Wang, and Robins (2019) and Stys et al. (2019). This relies on the approximate exchange algorithm also used in Caimo and Friel (2011). We assume constant priors, use multivariate normal proposals with optimal variance-covariance matrix (see Koskinen et al., 2013), and the adequacy of the auxiliary variable draws is monitored through post-hoc simulations of predictive networks (due to the size of the network, the burn-in for simulating one network was set to 2.56 million iterations throughout). The posterior distributions for the model parameters fully describes the uncertainty about parameters given the observed network. These distributions are summarized using the expected values as point estimates, and the posterior standard deviation as a measure of the uncertainty about these point estimates. We also provide approximate 95% credibility intervals, noting that the resolution of credibility intervals based on Markov chain Monte Carlo can be limited.

3.5. Model specification

In order to test Hypotheses 3 and 4 we must define market overlap between OCGs. Market overlap between organisations has been defined by economic sociologists as the intersection between the organisations' geographically-situated production and/or consumption activity (Lomi and Pallotti, 2012). Building on this definition, we define the presence of market overlap between two OCGs in terms of their members doing the same criminal activities in the same places. We focus on drug trafficking, because this is an important part of organised criminal activity in Canada; is the most common activity undertaken by individuals in the dataset; constitutes serious organised crime (Lauchs, 2019); and is thought to take place in a context that can be described as market-like (Boivin, 2014; Malm and Bichler, 2011; Morselli et al., 2017; Sanderson et al., 2014; Schneider, 2013). We operationalise market overlap as an organisation-level network. For each pair of OCGs the presence or absence of overlap tie is derived from counting the number of members of the two OCGs who are engaged in drug trafficking in the same places. We then normalise by location size in terms of the absolute number of criminals operating in a location, on the assumption that groups are more likely to develop awareness of one another when there is only a small number of criminals operating in a location than when there are many criminals operating in a location. This gives a dyadic valued relation which is dichotomised above a certain level to form an undirected, binary tie. More specifically, for each OCG i, the organisation location-activity matrix is defined as $w_i = (w_{iuv})$, where w_{iuv} counts the number members of i that are active in location v doing crime of type u. A valued measure of the overlap between i and j is given by the trace $a_{ij}^* = tr(w_i \Lambda w_j^T)$ or sum of the entries of $a_{ij}^* = l^T w_i \Lambda w_j^T l$, where Λ is a weight matrix. Here we chose to scale by the sizes of the locations $\Lambda = diag(1/n_u)$. We define the overlap ties as the 95% strongest ties in the row-normalised a_{ij}^*. The sociogram of the organisation-level market overlap network for the all the organisations in the subset is shown in Figure 4. Table 5 reports summary statistics for the market overlap network.

We acknowledge that market overlap may be alternatively defined as some intersection of activity involving specific commodities, roles, market niches and geographic space. However, the data does not include fine-grained information on the commodities, roles and market niches of individuals and groups, and so it is not possible to define market overlap in this more nuanced way. Nonetheless, based on information from intelligence analysts we know that the majority of drug-related information in the data involves the transport and supply of drugs. Locations captured in our data are predominantly 'end markets' for the distribution of drugs, with larger geographic locations representing 'distribution hubs'. More established groups in the context (such as the larger groups that are the focus of our analysis) tend to have well-established supply lines and will try to supply whatever drug is in demand. Such groups are less subject to the vagaries of supply than lower-level dealers. This suggest that ours is a context in which a competitive, territorial logic does indeed apply, as larger groups will compete for territory and customers in order to distribute their drugs. As argued above, high-level overlap may catalyse cooperation or competition among adaptable criminal groups. Ours is therefore a suitable context to test our hypotheses.

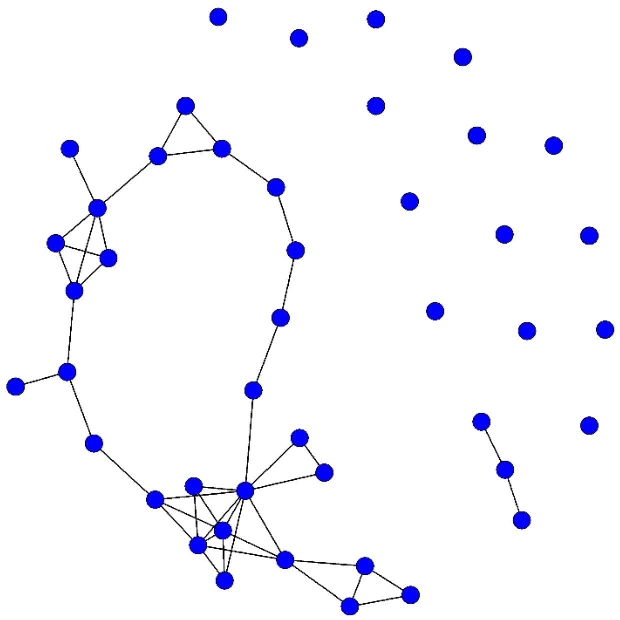


Figure 4: Market overlap network among organisations. The nodes represent OCGs, and there is a tie between two nodes if two groups' drug trafficking markets overlap with one another

Table 5: Summary statistics for interorganisational market overlap network

Network	N	No. of ties	Isolates	Components (excluding isolates)	Max. component size	Mean degree	Density
Market overlap	44	45	14	2	27	0.97777	0.04757

Table 5 (*cont.*): Summary statistics for interorganisational market overlap network

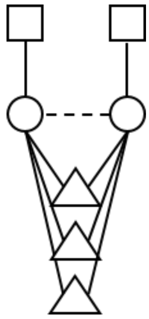
Network	Clustering coefficient	Median path length for nodes that are reachable	Median path length for largest component
Market overlap	0.11374	4	4

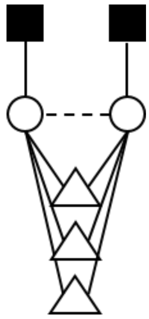
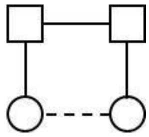
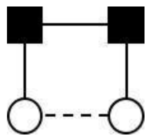
The dependent variable in our models is the presence of a collaboration tie between a pair of individuals. Our hypotheses are derived with reference to the effects of multilevel dependencies on the interpersonal ties. Consequently, as indicated above, multilevel dependencies are treated using dyadic covariates and are fixed in the model estimation (Robins and Daraganova, 2013; Stys et al., 2019). Table 6 shows the local structural effects that are relevant to testing our hypotheses, represented as configurations (Moreno and Jennings, 1938).

Control variables are treated as dyadic or node covariates and are fixed in the model estimation. We control for a number of factors likely to relate to formation of collaboration ties among criminals. These include individuals' shared affiliations to organisations and geographic locations. A node covariate effect for organisational activity was fitted, to test whether being affiliated to more criminal groups is associated with having more interpersonal collaborative ties; and an edge covariate effect was fitted for organisational assortativity, to test whether individuals who are members of many organisations tend to be tied to one another. These two effects control for multilevel brokerage (Stys et al., 2019) across groups via multiple memberships. Doing so allows us to account for the possibility that connections across groups result from certain individuals who belong to many groups (Bruinsma and Bernasco, 2004; Fijnaut et al., 1998; Morselli and Tremblay, 2004). When testing Hypotheses 3 and 4 we control for 3-path effects, which represent the correlation between market overlap ties at the organisation level and collaboration ties at the individual level. We include attribute activity and attribute homophily effects for a number of attributes to control for whether individuals with those attributes are more likely to have collaborative ties, or are more likely to have collaborative ties with one another. Attributes included are whether an individual is involved in violent offences, as there is evidence that violent offenders tend to collaborate with other violent offenders (Lauchs, 2019); individual sex and age, as both attributes shape co-offending networks (von Mastrigt and Carrington, 2014); and known or suspected group leadership role, as leaders may display different networking behaviour from non-leaders for efficiency or security reasons (Grassi et al., 2019; Morselli, 2009a). Finally, alternating triangle and alternating star effects (Snijders et al., 2006) were included to control for triadic closure (clustering) and preferential attachment processes - endogenous, self-organising tendencies that are commonly observed in social networks (Lusher et al., 2013).

Three separate models were estimated. Model 1 includes only effects used as controls. Model 2 includes controls plus effects which test Hypotheses 1 and 2. Model 2 therefore examines whether members of different organisations who are active in the same locations are more or less likely to form collaborative ties with one another, given the controls. Model 3 includes controls, effects which test Hypotheses 3 and 4, and 3-path effects as additional controls. Model 3 represents a refinement of Model 2, in that it assumes that the likelihood that members of different organisations form collaborative ties with one another depends not only on those individuals' being active in the same locations, but also on whether other members of their respective organisations are doing the same criminal activities in the same places (market overlap).

Table 6: ERGM configurations used to test hypotheses

Effect	Configuration	Description
Shared location(s), different organisations		Being members of different organised criminal groups and operating or being resident in the same location(s) affects the tendency to form interpersonal collaborative ties. Hypothesis 1 suggests a negative effect.

Shared location(s), different OMCGs		Being members of different Outlaw Motorcycle Gangs and operating or being resident in the same location(s) affects the tendency to form interpersonal collaborative ties. Hypothesis 2 suggests a positive effect.
4-cycle		Being members of different organised criminal groups with overlapping drug trafficking markets affects the tendency to form interpersonal collaborative ties. Hypothesis 3 suggests a negative effect.
OMCG 4-cycle		Being members of different Outlaw Motorcycle Gangs with overlapping drug trafficking markets affects the tendency to form collaborative interpersonal ties. Hypothesis 4 suggests a positive effect

4. Modelling results

Modelling results are shown in Table 7.[2] For a given parameter estimate, if zero lies within the credible intervals for that estimate then there is insufficient evidence for concluding that the parameter is different from zero, in other words, the associated mechanisms has no effect. If the 95% interval does not include zero, data tells us that the parameter is different from zero. In general the interval is such that the parameter lies in that interval with 0.95 posterior probability.

Model 2 includes control effects plus cross-level interaction effects that test the effect on collaborative tie formation of being active or resident in the same locations but being members of different OCGs. The credible interval for shared location(s), different organisations includes zero, indicating that this there is no effect associated with the parameter. Hypothesis 1 is not supported. The posterior for shared location(s), different OMCGs indicates that the parameter is positive, suggesting that members of different motorcycle gangs who are active or resident in the same locations are more likely to share a tie. This provides support for Hypothesis 2.

[2] The parameters are estimated in R drawing on functionality from the *ergm* package (Handcock et al., 2003).

Model 3 includes controls plus 4-cycle effects which test the relationship between market overlap ties at the organisation level and collaborative tie-formation at the interpersonal level. The parameter for the 4-cycle effect is negative, ranging from -0.51 to -0.02, indicating that members of different organised criminal groups that have overlapping markets are less likely to collaborate with one another. Hypothesis 3 is supported. A positive credible interval was also obtained for OMCG 4-cycles. Members of different outlaw motorcycle gangs that have overlapping markets are more likely to collaborate with one another. Thus Hypothesis 4 is supported.

Overall the modelling results confirm our expectations that interdependencies at the organisation level affect the likelihood of criminal collaboration at the individual level, and that the direction of this effect depends on group type. In general, when criminal groups have overlapping markets cross-group collaboration among their members is less likely. But for outlaw motorcycle gangs the relationship between market overlap and cross-group collaboration is exactly the opposite. These findings suggest the generally rivalrous nature of drug trafficking markets, in which collaboration between groups is difficult or undesirable; but also that OMCGs in Canada have found ways to overcome rivalry and collaborate for mutual gain. Interestingly, we also find that members of different biker gangs who are active in the same locations are more likely to collaborate with one another; while for members of other types of criminal group there is no significant effect of being active in the same locations on interpersonal collaboration. This provides evidence for the existence of mechanisms that operate at the dyadic level and that aid biker collaboration, such as signaling or the use of convergence settings (Felson, 2006; Gambetta, 2009; Lauchs and Staines, 2019).

Goodness-of-fit procedures were used to test how well the models capture features of the observed network that were not modelled explicitly (Hunter et al., 2008). The goodness-of-fit distributions are draws of networks from the posterior predictive distributions, that is, networks are simulated for different parameter values in the posterior distribution (Koskinen and Snijders, 2007). All three models capture acceptably the degree distribution, geodesic distances and the edgewise-shared-partner distances of the observed network. Model 3 gives a marginally improved fit compared to Models 1 and 2 in terms of capturing the geodesic distances of the observed network. Figure 5 shows the results of the goodness-of-fit procedure for Model 3.

Table 7: ERGM parameter means and credible intervals

	Model 1				Model 2				Model 3			
Parameter (effect)	Mean	sd	2.5% quantile	97.5% quantile	Mean	sd	2.5% quantile	97.5% quantile	Mean	sd	2.5% quantile	97.5% quantile
Edges	-11.72	0.67	-13.04	-10.46	-12.07	0.65	-13.35	-10.77	-12.00	0.67	-13.39	-10.72
Shared organisation	4.61	0.14	4.36	4.88	4.85	0.17	4.51	5.19	4.60	0.14	4.32	4.86
Shared location (operating at)	0.72	0.07	0.60	0.85	0.69	0.06	0.57	0.83	0.79	0.07	0.66	0.92
Shared location (address)	0.82	0.10	0.63	1.00	0.79	0.10	0.58	0.98	0.85	0.10	0.64	1.04
Organisation activity	1.44	0.30	0.86	2.04	1.59	0.30	1.01	2.16	1.65	0.30	1.08	2.28
Organisation assortativity	-1.57	0.25	-2.08	-1.06	-1.71	0.26	-2.22	-1.22	-1.72	0.27	-2.28	-1.22
Violent activity	1.89	0.35	1.16	2.54	1.85	0.31	1.16	2.40	1.77	0.35	1.01	2.41
Violent homophily	2.06	0.41	1.22	2.78	2.03	0.37	1.18	2.72	2.07	0.42	1.14	2.80
Sex activity	-0.01	0.18	-0.40	0.30	0.01	0.17	-0.39	0.31	0.02	0.18	-0.40	0.33
Sex homophily	-0.02	0.21	-0.46	0.36	-0.01	0.20	-0.43	0.36	-0.04	0.21	-0.50	0.35
Leader activity	0.55	0.23	0.05	0.98	0.56	0.21	0.15	0.94	0.66	0.22	0.20	1.03
Leader homophily	0.04	0.26	-0.51	0.52	0.06	0.23	-0.42	0.48	0.05	0.25	-0.47	0.48
Age activity	0.09	0.02	0.06	0.13	0.09	0.02	0.05	0.12	0.07	0.02	0.03	0.10
Age homophily	-0.39	0.05	-0.50	-0.29	-0.39	0.06	-0.50	-0.29	-0.40	0.05	-0.50	-0.29
Shared location, different organisations	-	-	-	-	0.47	0.25	-0.05	0.95	-	-	-	-
Shared location, different OMCGs	-	-	-	-	1.47	0.40	0.64	2.19	-	-	-	-
3-path	-	-	-	-	-	-	-	-	-0.01	0.01	-0.03	0.01
4-cycle	-	-	-	-	-	-	-	-	-0.26	0.12	-0.51	-0.02
OMCG 3-path	-	-	-	-	-	-	-	-	0.04	0.02	0.00	0.08
OMCG 4-cycle	-	-	-	-	-	-	-	-	0.40	0.16	0.08	0.71
Alternating star	-0.84	0.10	-1.01	-0.65	-0.83	0.09	-1.02	-0.65	-0.86	0.10	-1.06	-0.67
Alternating triangle with lamda=2	1.19	0.08	1.04	1.36	1.19	0.08	1.03	1.35	1.18	0.09	1.01	1.35

As noted above, drug trafficking constitutes a large proportion of the observed criminal activity in our data. To ascertain whether the observed effects could be explained by the behavior of only those actors involved in drug trafficking, we estimated a model that included an activity and a homophily effect for a monadic covariate indicating whether an actor had been recorded for any drug-related offence. This extended model did not provide conclusive results as there is not enough information in the data to investigate these additional effects in addition to those of our final model. However, in the data there is not a complete overlap between ties among people that are involved in drug trafficking and ties that close the OMCG market overlap 4-cycle. This indicates that structure of the criminal collaboration networks captured in our data cannot be accounted for by focusing on the network of known drug-related crime alone.

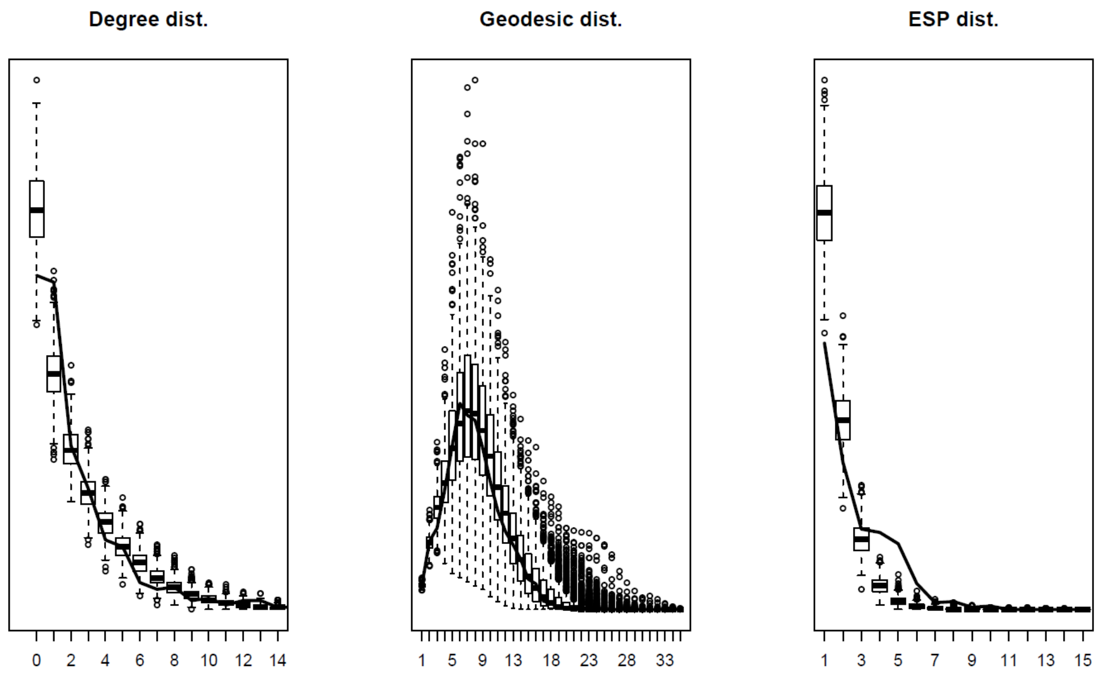


Figure 5: Goodness-of-fit (Model 3)

5. Discussion and conclusions

Collaboration in both legal and illegal economic settings is subject to contingencies at multiple levels of analysis, including interpersonal, organisational, spatial and economic contingencies. Collaboration may be stimulated by opportunities to interact if actors operate in close proximity to each other, or if they are members of groups that enhance collaboration (Nese et al., 2018; Rand and Nowak, 2011). Collaboration may be hindered where groups compete over resources or profits, such as between competitors in certain industries (Kilduff, 2019). Yet even in competitive arenas, we can see the emergence of collaboration between supposedly competing actors (Lazega et al., 2016; Lomi and Pallotti, 2012; Yu and Cannella, 2013). Our research sheds light on the circumstances under which criminal collaboration occurs between actors involved in different OCGs that operate in the same locations.

Collaboration between actors in criminal settings is even more difficult than in legitimate settings, because actors have to avoid detection by law enforcement and cannot appeal to legal institutions to settle their disputes. Such collaboration relies on interpersonal and intergroup trust which is in short supply, and difficult to ascertain, in illicit contexts (Aziani et al., 2019; Gambetta, 2009; von Lampe and Ole Johansen, 2004). Our results indicate that criminal actors are less likely to collaborate when they belong to different OCGs that operate in overlapping markets. This accords with research which suggests that cross-group collaboration may be detrimental to criminal groups above a certain size (Ouellet et al., 2019). However, we also find that OMCG members are *more* likely to collaborate across groups when markets overlap. It is presumably profitable to invest resources into collaboration and production instead of depleting resources on attrition. What enables members of different OMCGs to make this investment, even though criminal markets are permeated with mistrust, risk, and deception (von Lampe and Ole Johansen, 2004)? There are three possible explanations. Firstly, members of different OMCGs may be more willing to trust one another compared to other types of OCGs. OMCG members share subcultural attitudes, practices and norms (Lauchs, 2019; Lauchs and Staines, 2019). In addition, the practices of riding motorcycles and wearing distinctive clothing including group-signifying patches may make members of OMCGs more easily identifiable compared with members of other OCGs. OMCGs also tend to be easily identifiable in groups, particularly given the tendency of such groups to 'hang out' at club houses that are well established and easily recognized (at least by members of the criminal fraternity). The combination of these factors may mean that trust can be more easily established between members of different OMCGs compared to other OCGs. In particular, the problem of false positives (i.e., attempting to make contact with someone you think is criminal when they are not; see Gambetta, 2009) is significantly reduced. Further, in legitimate settings the visibility of defection from collaborative agreements is a key contingency that ensures ongoing inter-organisational collaboration (Yu and Cannella, 2013), and it may be hard for OMCGs members to operate without being noticed by other groups.

The second explanation, which complements the first one, also builds upon previous research showing that OMCGs display high levels of organisation and strong internal culture containing norms, symbols, and rituals (Bjørgo, 2019; Lauchs and Staines, 2019; Morselli, 2009a; Quinn, 2001). These organisational and cultural aspects may provide compensation for the lack of contract-reinforcing institutions by establishing norms of cooperation and settling disputes. Internal hierarchies also act as aggregating mechanisms, or enablers of information flows across different levels of relationships in a collectivity (Shipilov, 2012). The hierarchical structure within OMCGs might allow information obtained due to groups encountering one another in overlapping markets to be diffused across the organisation and responded to by organisational members in a coordinated way. Internal coordination is another contingency influencing whether legitimate organisations respond to market overlap (Yu and Cannella, 2013).

The third explanation is that since OMCGs are seen as a major threat in numerous jurisdictions, law enforcement agencies try to combat and control OMCGs via interventions against them (Bjørgo, 2019). Actors in criminal networks respond and react to both the situation within and outside the network (Bright and Delaney, 2016; Dwyer and Moore, 2010; Kenny, 2007). These interventions may trigger unintended consequences by prompting the OMCGs to devote attention and resources to resisting law enforcement pressure. Recognising law enforcement as the primary enemy, OMCGs might set aside their mutual disputes. Such unintended consequences in strengthening cohesion of criminal networks have been previously documented (Duijn et al., 2014). Explanations two and three are not mutually exclusive. Collaboration in response to law enforcement pressure might have stimulated the development of OMCG organisation and culture or the cultural and organisational elements might have helped to form collaboration among OMCGs vis-á-vis law enforcement interventions (cf. Quinn, 2001). The role and relationship between these two explanations could be answered with longitudinal data coupled with qualitative or ethnographic evidence, which would be a fruitful extension for our current research.

In network research, geographic space is usually conceptualised as a measure of spatial proximity between nodes (Sohn et al., 2019). We conceptualised space in our analysis as a type of spatial composition: location (Small and Adler, 2019). This allowed us to formulate hypotheses about the role of co-location in the network. Locations form a structure of opportunities in which actors and groups interact. It is not only that locations make interaction possible, they may also encourage it by focusing it in a specific place (Small & Adler, 2019). In criminology, the concept of convergence settings (Felson, 2006; 2009) has been used to denote spatial settings in which actors meet, recruit members, find motivated co-offenders, and share information and resources for conducting criminal activity. Viewing locations as a separate mode in a multilevel network offers an opportunity to operationalise locations. Future research could extend our approach and investigate attributes of locations such as prevalence of different types of crime, economic inequality, neighbourhood segregation, population density or size; and ties among them such as distances, similarities or traffic routes. Attributes of locations and ties among them may help explain how spatial composition encourages criminal activity, and further contribute to theory-driven analyses of the role of space in crime (Tita and Radil, 2011).

Our analysis relies on the spatial overlap of drug market activities at the organisation level as an indicator of the potential for competition or collaboration between group members at the individual level. Future research should refine our conceptualisation of illicit market overlap. Refined conceptualisations of market overlap might draw on what we know about the effects of market overlap in legitimate markets, but should also account for the unique features of illicit markets which mean that market overlap has different contours and implications for criminal behaviour. They might take into account the intersection of illicit activities involving specific commodities, roles, and market niches, as well geographic space. They should not neglect the interconnectedness between different types of criminal (and non-criminal) networks and activities.

Another organisation-level factor that may strengthen or prevent collaboration is the presence of explicit competitive relationships between groups, manifested as violent conflict (Papachristos et al., 2013), or rivalry (Descormiers and Morselli, 2011). If two OCGs are competitors in these ways, collaboration between the groups may be thought unlikely. However, research in legal settings shows that the relationship between rivalry and competitive interactions is complex (Kilduff, 2019; Lazega et al., 2016). Conflict or rivalry between groups may actually foster collaboration between two OCGs when they share a common foe or colloquially, when enemy of an enemy becomes a friend (Cartwright and Harary, 1956; Lerner, 2016). Analysing directly how intergroup relationships such as violence and rivalry emerge, and how these ties in turn affect the emergence of intergroup collaboration, may help us to further explain the structure of criminal networks at both levels of actors and groups.

Finally, our analysis uses intelligence data, which is one of the best available means for understanding covert networks (Cunningham et al., 2016), but is subject to limitations such as missingness, measurement error and biases. Our decisions when selecting a data subset for analysis were intended to help address these limitations, but there remains the possibility that findings are artefacts of data collection, recording and collation methods. Future research should address these limitations at the point of data collection and recording (Diviák, 2019).

References

Asal, V., Milward, H.B., Schoon, E.W., 2015. When Terrorists Go Bad: Analyzing Terrorist Organizations' Involvement in Drug Smuggling. Int. Stud. Q. doi:10.1111/isqu.12162

Aziani, A., Berlusconi, G., Giommoni, L., 2019. A Quantitative Application of Enterprise and Social Embeddedness Theories to the Transnational Trafficking of Cocaine in Europe. Deviant Behav. doi:10.1080/01639625.2019.1666606

Baron, S.W., Tindall, D.B., 1993. Network structure and delinquent attitudes within a juvenile gang. Soc. Networks. doi:10.1016/0378-8733(93)90008-9

Baum, J.A.C., Korn, H.J., 1999. Dynamics of Dyadic Competitive Interaction. Strateg. Manag. J. 20, 251–278. doi:10.2307/3094105

Bichler, G., Malm, A., Cooper, T., 2017. Drug supply networks: A systematic review of the organizational structure of illicit drug trade. Crime Sci. doi:10.1186/s40163-017-0063-3

Bjørgo, T., 2019. Preventing organised crime originating from outlaw motorcycle clubs. Trends Organ. Crime. doi:10.1007/s12117-017-9322-7

Blokland, A., van Hout, L., van der Leest, W., Soudijn, M., 2019. Not your average biker; criminal careers of members of Dutch outlaw motorcycle gangs. Trends Organ. Crime. doi:10.1007/s12117-017-9303-x

Boivin, R., 2014. Drug Trafficking Networks in the World Economy, in: Morselli, C. (Ed.), Crime and Networks. Routledge, New York, pp. 182–191.

Bouchard, M., 2007. On the resilience of illegal drug markets. Glob. Crime. doi:10.1080/17440570701739702

Bouchard, M., Konarski, R., 2014. Assessing the core membership of a youth gang from its co-offending network, in: Morselli, C. (Ed.), Crime and Networks. Routledge, New York, pp. 81–93.

Bouchard, M., Morselli, C., 2014. Opportunistic structures of organized crime', in: Paoli, L. (Ed.), The Oxford Handbook of Organized Crime. Oxford University Press, Oxford, pp. 288–302.

Brass, D.J., Greve, H.R., 2004. Taking stock of networks and organizations: a multilevel perspective. Acad. Manag. J. 47, 795–817. doi:10.2307/20159624

Brennecke, J., Rank, O., 2017. The firm's knowledge network and the transfer of advice among corporate inventors—A multilevel network study. Res. Policy. doi:10.1016/j.respol.2017.02.002

Brennecke, J., Rank, O.N., 2016. The interplay between formal project memberships and informal advice seeking in knowledge-intensive firms: A multilevel network approach. Soc. Networks 44, 307–318. doi:10.1016/j.socnet.2015.02.004

Bright, D., Koskinen, J., Malm, A., 2019. Illicit Network Dynamics: The Formation and Evolution of a Drug Trafficking Network. J. Quant. Criminol. doi:10.1007/s10940-018-9379-8

Bright, D.A., Delaney, J.J., 2016. Evolution of a drug trafficking network: Mapping changes in network structure and function across time, in: Advances in Research on Illicit Networks. doi:10.1080/17440572.2013.787927

Bright, D.A., Delaney, J.J., 2013. Evolution of a drug trafficking network: Mapping changes in network structure and function across time. Glob. Crime. doi:10.1080/17440572.2013.787927

Bright, D.A., Greenhill, C., Ritter, A., Morselli, C., 2015. Networks within networks: using multiple link types to examine network structure and identify key actors in a drug trafficking operation. Glob. Crime. doi:10.1080/17440572.2015.1039164

Bright, D.A., Hughes, C.E., Chalmers, J., 2012. Illuminating dark networks: a social network analysis of an Australian drug trafficking syndicate. Crime, Law Soc. Chang. 57, 151–176. doi:10.1007/s10611-011-9336-z

Broccatelli, C., Koskinen, J., Everett, M., 2016. Temporal Dynamics in Covert Networks. Methodol. Innov. 9, 1–14.

Bruinsma, G., Bernasco, W., 2004. Criminal groups and transnational illegal markets: A more detailed examination on the basis of Social Network Theory. Crime, Law Soc. Chang. 41, 79–94. doi:10.1023/B:CRIS.0000015283.13923.aa

Burcher, M., Whelan, C., 2015. Social network analysis and small group 'dark' networks: an analysis of the London bombers and the problem of 'fuzzy' boundaries. Glob. Crime 16, 104–122. doi:10.1080/17440572.2015.1005363

Butts, C.T., 2003. Network inference, error, and informant (in)accuracy: A Bayesian approach. Soc. Networks. doi:10.1016/S0378-8733(02)00038-2

Caimo, A., Friel, N., 2011. Bayesian inference for exponential random graph models. Soc. Networks 33, 41–55. doi:10.1016/j.socnet.2010.09.004

Calderoni, F., 2014. Social Network Analysis of Organized Criminal Groups, in: Encyclopedia of Criminology and Criminal Justice. doi:10.1007/978-1-4614-5690-2_239

Calderoni, F., 2012. The structure of drug trafficking mafias: The 'Ndrangheta and cocaine. Crime, Law Soc. Chang. doi:10.1007/s10611-012-9387-9

Canadian Drug Summary: Methamphetamine, 2018.

Cartwright, D., Harary, F., 1956. Structural balance: a generalization of Heider's theory. Psychol. Rev. doi:10.1037/h0046049

Coleman, J.S., 1988. Social Capital in the Creation of Human-Capital. Am. J. Sociol. 94, S95–S120. doi:10.1086/228943

Cunningham, D., Everton, S., Murphy, P., 2016. Understanding Dark Networks: A Strategic Framework for the Use of Social Network Analysis. Rowman & Littlefield Publishers, Lanham.

Deryol, R., Wilcox, P., Logan, M., Wooldredge, J., 2016. Crime Places in Context: An

Illustration of the Multilevel Nature of Hot Spot Development. J. Quant. Criminol. doi:10.1007/s10940-015-9278-1

Descormiers, K., Morselli, C., 2011. Alliances, conflicts, and contradictions in montreal's street gang landscape. Int. Crim. Justice Rev. doi:10.1177/1057567711418501

Diviák, T., 2019. Key aspects of covert networks data collection: Problems, challenges, and opportunities. Soc. Networks. doi:10.1016/j.socnet.2019.10.002

Diviák, T., Dijkstra, J.K., Snijders, T.A.B., 2019a. Poisonous connections: a case study on a Czech counterfeit alcohol distribution network. Glob. Crime. doi:10.1080/17440572.2019.1645653

Diviák, T., Dijkstra, J.K., Snijders, T.A.B., 2019b. Structure, multiplexity, and centrality in a corruption network: the Czech Rath affair. Trends Organ. Crime. doi:10.1007/s12117-018-9334-y

Donkin, K., 2017. Police watching for expansion of motorcycle gangs in New Brunswick. CBC.

Duijn, P.A.C., Kashirin, V., Sloot, P.M.A., 2014. The relative ineffectiveness of criminal network disruption. Sci. Rep. doi:10.1038/srep04238

Dwyer, R., Moore, D., 2010. Understanding illicit drug markets in Australia notes towards a critical reconceptualization. Br. J. Criminol. doi:10.1093/bjc/azp065

Eck, J.E., Gersh, J.S., 2000. Drug trafficking as a cottage industry. Crime Prev. Stud.

Faust, K., Tita, G.E., 2019. Social Networks and Crime: Pitfalls and Promises for Advancing the Field. Annu. Rev. Criminol. doi:10.1146/annurev-criminol-011518-024701

Felson, M., 2006. The Ecosystem for Organized Crime (No. 26). Helsinki.

Festinger, L., Schachter, S., Back, K., 1950. The spatial ecology of group formation. Soc. Press. informal groups 141–161.

Fijnaut, C., Bovenkerk, F., Bruinsma, G., van de Bunt, H., 1998. Organized Crime in the Netherlands, Security Studies. Kluwer Law International, The Hague.

Gambetta, D., 2009. Codes of the underworld: How criminals communicate. Princeton University Press, Princeton.

Glückler, J., Doreian, P., 2016. Editorial: Social network analysis and economic geography-positional, evolutionary and multi-level approaches. J. Econ. Geogr. doi:10.1093/jeg/lbw041

Gottschalk, P., 2010. Entrepreneurship in organised crime. Int. J. Entrep. Small Bus. 9, 295. doi:10.1504/IJESB.2010.031923

Grandori, A., Soda, G., 1995. Inter-firm Networks: Antecedents, Mechanisms and Forms. Organ. Stud. 16, 183–214. doi:10.1177/017084069501600201

Grassi, R., Calderoni, F., Bianchi, M., Torriero, A., 2019. Betweenness to assess leaders in criminal networks: New evidence using the dual projection approach. Soc. Networks. doi:10.1016/j.socnet.2018.08.001

Grund, T.U., Densley, J.A., 2012. Ethnic heterogeneity in the activity and structure of a Black street gang. Eur. J. Criminol. 9, 388–406. doi:10.1177/1477370812447738

Handcock, M.S., Hunter, D.R., Butts, C.T., Goodreau, S.M., Kravitsky, P., Morris, M., 2003. ergm: Fit, Simulate and Diagnose Exponential-Family Models for Networks. The Statnet Project. R package version 3.7.1.

Hofmann, D.C., Gallupe, O., 2015. Leadership protection in drug-trafficking networks. Glob. Crime. doi:10.1080/17440572.2015.1008627

Hollway, J., Koskinen, J., 2016. Multilevel embeddedness: The case of the global fisheries governance complex. Soc. Networks 44, 281–294. doi:10.1016/j.socnet.2015.03.001

Hunter, D.R., Goodreau, S.M., Handcock, M.S., 2008. Goodness of fit of social network models. J. Am. Stat. Assoc. doi:10.1198/016214507000000446

Johnson, B.D., Dunlap, E., Tourigny, S.C., 2000. CRACK DISTRIBUTION AND ABUSE IN NEW YORK. Crime Prev. Stud.

Kadushin, C., 2012. Understanding Social Networks: Theories, Concepts, and Findings [WWW Document]. Oxford Univ. Press. URL https://www.amazon.com/Understanding-Social-Networks-Theories-Concepts/dp/0195379470/ref=sr_1_1?s=books&ie=UTF8&qid=1396465285&sr=1-1&keywords=kadushin+understanding+social+networks

Kenny, M., 2007. From Pablo to Osama: Trafficking and Terrorist Networks, Government

Bureaucracies, and Competitive Adaptation. Pennsylvania State University Press, University Park.

Kilduff, G.J., 2019. Interfirm Relational Rivalry: Implications for Competitive Strategy. Acad. Manag. Rev. doi:10.5465/amr.2017.0257

Kleemans, E.R., 2014. Theoretical perspectives on organized crime, in: Oxford Handbook of Organized Crime. Oxford University Press, Oxford, pp. 32–52.

Klein, K.J., Dansereau, F., Hall, R.J., 1994. Level issues in theory development, data collection, and analysis. Acad. Manag. Rev. 19, 195–229.

Koskinen, J., Broccatelli, C., Wang, P., Robins, G., 2019. Bayesian Analysis of ERG Models for Multilevel, Multiplex, and Multilayered Networks with Sampled or Missing Data. doi:10.1007/978-3-030-21158-5_9

Koskinen, J.H., 2008. The Linked Importance Sampler Auxiliary Variable Metropolis Hastings Algorithm for Distributions with Intractable Normalising Constants. Melbourne.

Koskinen, J.H., Robins, G.L., Wang, P., Pattison, P.E., 2013. Bayesian analysis for partially observed network data, missing ties, attributes and actors. Soc. Networks 35, 514–527. doi:10.1016/j.socnet.2013.07.003

Koskinen, J.H., Snijders, T.A.B., 2007. Bayesian inference for dynamic social network data. J. Stat. Plan. Inference. doi:10.1016/j.jspi.2007.04.011

Lauchs, M., 2019. Are Outlaw Motorcycle Gangs Organized Crime Groups? An Analysis of the Finks MC. Deviant Behav. doi:10.1080/01639625.2017.1421128

Lauchs, M., Bain, A., Bell, P., 2015. Outlaw Motorcycle Gangs: A Theoretical Perspective, Outlaw Motorcycle Gangs: A Theoretical Perspective. doi:10.1057/9781137456298

Lauchs, M., Staines, Z., 2019. An analysis of outlaw motorcycle gang crime: are bikers organised criminals? Glob. Crime. doi:10.1080/17440572.2019.1583107

Lazega, E., 2016. Synchronization Costs in the Organizational Society: Intermediary Relational Infrastructures in the Dynamics of Multilevel Networks, in: Multilevel Network Analysis for the Social Sciences. doi:10.1007/978-3-319-24520-1_3

Lazega, E., Bar-Hen, A., Barbillon, P., Donnet, S., 2016. Effects of competition on collective learning in advice networks. Soc. Networks. doi:10.1016/j.socnet.2016.04.001

Lazega, E., Jourda, M.T., Mounier, L., Stofer, R., 2008. Catching up with big fish in the big pond? Multi-level network analysis through linked design. Soc. Networks 30, 159–176. doi:10.1016/j.socnet.2008.02.001

Lerner, J., 2016. Structural balance in signed networks: Separating the probability to interact from the tendency to fight. Soc. Networks. doi:10.1016/j.socnet.2015.12.002

Levitt, S.D., Venkatesh, S.A., 2000. An Economic Analysis of a Drug-Selling Gang's Finances*. Q. J. Econ. 115, 755–789. doi:10.1162/003355300554908

Lomi, A., Pallotti, F., 2012. Relational collaboration among spatial multipoint competitors. Soc. Networks 34, 101–111. doi:10.1016/j.socnet.2010.10.005

Lusher, D., Koskinen, J., Robins, G., 2013. Exponential random graph models for social networks : theory, methods, and applications. Cambridge University Press, New York.

Magliocca, N.R., McSweeney, K., Sesnie, S.E., Tellman, E., Devine, J.A., Nielsen, E.A., Pearson, Z., Wrathall, D.J., 2019. Modeling cocaine traffickers and counterdrug interdiction forces as a complex adaptive system. Proc. Natl. Acad. Sci. U. S. A. 201812459. doi:10.1073/pnas.1812459116

Malm, A., Bichler, G., 2011. Networks of Collaborating Criminals: Assessing the Structural Vulnerability of Drug Markets. J. Res. Crime Delinq. 48, 271–297. doi:10.1177/0022427810391535

Malm, A., Bichler, G., Nash, R., 2011. Co-offending between criminal enterprise groups. Glob. Crime. doi:10.1080/17440572.2011.567832

Markman, G.D., Gianiodis, P.T., Buchholtz, A.K., 2009. Factor-market rivalry. Acad. Manag. Rev. doi:10.5465/AMR.2009.40632072

Mcpherson, M., Smith-lovin, L., Cook, J.M., 2001. Birds of a feather: homophily in Social Networks. Annu. Rev. Sociol. 27, 415–444. doi:10.1146/annurev.soc.27.1.415

Meredith, C., Van den Noortgate, W., Struyve, C., Gielen, S., Kyndt, E., 2017. Information seeking in secondary schools: A multilevel network approach. Soc. Networks 50, 35–45. doi:10.1016/j.socnet.2017.03.006

Moreno, J.L., Jennings, H.H., 1938. Statistics of Social Configurations. Sociometry 1, 342. doi:10.2307/2785588

Morselli, C., 2010. Assessing Vulnerable and Strategic Positions in a Criminal Network. J. Contemp. Crim. Justice 26, 382–392. doi:10.1177/1043986210377105

Morselli, C., 2009a. Hells Angels in springtime. Trends Organ. Crime 12, 145–158. doi:10.1007/s12117-009-9065-1

Morselli, C., 2009b. Inside criminal networks. Springer International Publishing, New York.

Morselli, C., Paquet-Clouston, M., Provost, C., 2017. The independent's edge in an illegal drug distribution setting: Levitt and Venkatesh revisited. Soc. Networks. doi:10.1016/j.socnet.2017.04.003

Morselli, C., Petit, K., 2007. Law-enforcement disruption of a drug importation network. Glob. Crime. doi:10.1080/17440570701362208

Morselli, C., Tremblay, P., 2004. Criminal achievement, offender networks and the benefits of low self-control. Criminology. doi:10.1111/j.1745-9125.2004.tb00536.x

Nese, A., O'Higgins, N., Sbriglia, P., Scudiero, M., 2018. Cooperation, punishment and organized crime: a lab-in-the-field experiment in southern Italy. Eur. Econ. Rev. doi:10.1016/j.euroecorev.2018.05.004

Ouellet, M., Bouchard, M., Charette, Y., 2019. One gang dies, another gains? The network dynamics of criminal group persistence*. Criminology. doi:10.1111/1745-9125.12194

Ouellet, M., Bouchard, M., Hart, M., 2017. Criminal collaboration and risk: The drivers of Al Qaeda's network structure before and after 9/11. Soc. Networks. doi:10.1016/j.socnet.2017.01.005

Papachristos, A. V., Hureau, D.M., Braga, A.A., 2013. The Corner and the Crew: The Influence of Geography and Social Networks on Gang Violence. Am. Sociol. Rev. doi:10.1177/0003122413486800

Papachristos, A. V., Meares, T.L., Fagan, J., 2012. Why do criminals obey the law? The influence of legitimacy and social networks on active gun offenders. J. Crim. Law Criminol.

Paruchuri, S., Goossen, M.C., Phelps, C., 2019. Conceptual Foundations of Multilevel Social Networks, in: The Handbook of Multilevel Theory, Measurement, and Analysis. SE Humphrey and JM LeBreton. doi:10.1037/0000115-010

Piquette, J.C., Smith, C.M., Papachristos, A. V, 2014. Social Network Analysis of Urban Street Gangs, in: Bruinsma, G., Weisburd, D. (Eds.), Encyclopedia of Criminology and Criminal Justice. Springer New York, New York, NY, pp. 4981–4991. doi:10.1007/978-1-4614-5690-2_240

Quinn, J.F., 2001. Angels, bandidos, outlaws, and pagans: The evolution of organized crime among the big four 1% motorcycle clubs. Deviant Behav. 22, 379–399. doi:10.1080/016396201750267870

Rand, D.G., Nowak, M.A., 2011. The evolution of antisocial punishment in optional public goods games. Nat. Commun. doi:10.1038/ncomms1442

Ritter, A., Bright, D., Gong, W., 2012. Evaluating drug law enforcement interventions directed towards methamphetamine in Australia.

Robins, G., 2009. Understanding individual behaviors within covert networks: The interplay of individual qualities, psychological predispositions, and network effects. Trends Organ. Crime 12, 166–187. doi:10.1007/s12117-008-9059-4

Robins, G., Daraganova, G., 2013. Social Selection, Dyadic Covariates and Geospatial Effects, in: Lusher, D., Koskinen, J., Robins, G. (Eds.), Exponential Random Graph Models for Social Networks: Theory, Methods and Applications. Cambridge University Press, Cambridge.

Ruddell, R., Gottschall, S., 2011. Are All Gangs Equal Security Risks? An Investigation of Gang Types and Prison Misconduct. Am. J. Crim. Justice. doi:10.1007/s12103-011-9108-4

Sanderson, K., Bell, P., Merrington, S., 2014. A case study analysis of the Montreal (Canada) Chapter of the Hells Angels Motorcycle Club (HAMC) (1995-2010): Applying the Crime Business Analysis Matrix (CBAM). Mustang J. Law Leg. Stud.

Schneider, S., 2013. Violence, organized crime, and illicit drug markets: A Canadian case study. Sociol. Probl. e Prat. 71, 125–143. doi:10.7458/SPP2013712334

Shipilov, A., 2012. Strategic multiplexity. Strateg. Organ. doi:10.1177/1476127012452825

Skaperdas, S., 2001. The political economy of organized crime: providing protection when the state does not. Econ. Gov. 2, 173–202. doi:10.1007/PL00011026

Small, M.L., Adler, L., 2019. The Role of Space in the Formation of Social Ties. Annu. Rev. Sociol. doi:10.1146/annurev-soc-073018-022707

Snijders, T.A.B., 2013. Network Dynamics, in: Handbook of Rational Choice Social Research. Stanford University Press, Stanford, pp. 252–280.

Snijders, T.A.B., Pattison, P.E., Robins, G.L., Handcock, M.S., 2006. New specifications for exponential random graph models. Sociol. Methodol. doi:10.1111/j.1467-9531.2006.00176.x

Sohn, C., Christopoulos, D., Koskinen, J., 2019. Borders Moderating Distance: A Social Network Analysis of Spatial Effects on Policy Interaction. Geogr. Anal. doi:10.1111/gean.12218

Stys, P., Verweijen, J., Muzuri, P., Muhindo, S., Vogel, C., Koskinen, J.H., 2019. Brokering between (not so) overt and (not so) covert networks in conflict zones. Glob. Crime. doi:10.1080/17440572.2019.1596806

Tita, G.E., Radil, S.M., 2011. Spatializing the Social Networks of Gangs to Explore Patterns of Violence. J. Quant. Criminol. doi:10.1007/s10940-011-9136-8

Ünal, M.C., 2019. Do terrorists make a difference in criminal networks? An empirical analysis on illicit drug and narco-terror networks in their prioritization between security and efficiency. Soc. Networks. doi:10.1016/j.socnet.2018.11.001

van de Bunt, H., Siegel, D., Zaitch, D., 2014. The Social Embeddedness of Organized Crime, in: Paoli, L. (Ed.), The Oxford Handbook of Organized Crime. Oxford University Press, Oxford, pp. 321–339.

von Lampe, K., Ole Johansen, P., 2004. Organized Crime and Trust: On the conceptualization and empirical relevance of trust in the context of criminal networks. Glob. Crime 6, 159–184. doi:10.1080/17440570500096734

von Mastrigt, S.B., Carrington, P.J., 2014. Sex and Age Homophily in Co-Offending Networks: Opportunity or Preference?, in: Morselli, C. (Ed.), Crime and Networks.

Routledge, New York, pp. 28–51.

Wang, P., Robins, G., Matous, P., 2016. Multilevel Network Analysis Using ERGM and Its Extension, in: Multilevel Network Analysis for the Social Sciences. Springer International Publishing, pp. 125–143.

Wang, P., Robins, G., Pattison, P., Lazega, E., 2013. Exponential random graph models for multilevel networks. Soc. Networks 35, 96–115. doi:10.1016/j.socnet.2013.01.004

Ward, T., Durrant, R., Sullivan, J., 2019. Understanding crime: a multilevel approach. Psychol. Crime Law. doi:10.1080/1068316x.2019.1572754

Williams, P., Godson, R., 2002. Anticipating organized and transnational crime. Crime, Law Soc. Chang. 37, 311–355. doi:10.1023/A:1016095317864

Wood, G., 2017. The structure and vulnerability of a drug trafficking collaboration network. Soc. Networks 48, 1–9. doi:10.1016/j.socnet.2016.07.001

Yu, T., Cannella, A.A., 2013. A Comprehensive Review of Multimarket Competition Research. J. Manage. doi:10.1177/0149206312462456

Zappa, P., Robins, G., 2016. Organizational learning across multi-level networks. Soc. Networks 44, 295–306. doi:10.1016/j.socnet.2015.03.003