Criminal networks: actors, mechanisms, and structures

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by

Tomáš Diviák

born on 29 March 1991

in Litoměřice, the Czech Republic

I hereby declare that I have wrote and worked on this PhD dissertation on my own using adequately cited and referenced materials. I also declare that this thesis was not used to obtain any other the degree at any other university than the double degree between University of Groningen and Charles University.

On 29th October 2019 in Prague.

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1. Introduction

The term organized crime comprises a considerably broad category of criminal activities from trafficking and smuggling of illegal commodities such as drugs or weapons, corruption, mafias to all conceivable ideological and religious varieties of terrorism (cf. Abadinsky, 2010; Paoli, 2014; van Dijk & Spapens, 2013; von Lampe, 2016). Each of these criminal activities is considered to be a serious security threat for society. That is the reason why governments all over the world devote substantial effort and resources towards combatting organized crime. It is not surprising that such phenomena also raised scholarly attention, be it as a way to help fight organized crime, to critically evaluate law enforcement approaches, or to analytically deepen scientific knowledge about organized crime. In fact, the interest in organized crime from policy makers, law enforcement agents, and academic researchers led to a growth of the research yielding a multitude of conceptualizations and definitions[1] of organized crime (von Lampe, 2016). Here, I define organized crime in accordance with the United Nations as a crime that involves three or more people who come together in committing criminal offenses over a sustained period of time (cf. Fielding, 2016). The choice of this definition is pragmatic – it is broad and allows to study various activities and groups[2]. Also, this definition makes no a priori assumption about the structure and organization of organized crime, allowing its empirical investigation instead.

One of the key questions in research concerning organized crime and related phenomena is quite emblematic – since the term is organized crime, how is it *actually* organized (von Lampe, 2009)? Criminologists have theorized numerous models of organized crime in attempts to answer this question (Kleemans, 2014; Le, 2012). A bureaucratic model of organized crime (Cressey, 1969) assumes that organized criminal groups are organized much like their legal counterpart, such as armies or corporations, in rigid hierarchical structures overseen by powerful actors at their top. Although the bureaucratic model gained noticeable attention especially in popular culture, its scientific shortcomings in explaining structures of organized crime led criminologists to formulate alternative theoretical models (von Lampe,

[1] The website of Klaus von Lampe (2019) lists over two hundreds of available definitions of organized crime based on different jurisdictions or scientific approaches.

[2] This definition allows to include terrorist groups as well, which I in accordance with some other researchers conceive of as criminal groups different, but principally comparable to other criminal groups (cf. Morselli, Giguère, & Petit, 2007; van Dijk & Spapens, 2013; Wikström & Bouhana, 2017).

2009). Some of these alternatives were based on accentuating ethnicity-based relations among criminals, or viewing organized crime through an economic lens as a market governed by illicit supply and demand (Kleemans, 2014). What all such approaches have in common is that they assume some sort of structure (hierarchy, market etc.) rather than empirically describing it (Morselli, 2009).

In response to some of the limitations of earlier theoretical models, one of the more recent propositions is that organized crime can best be described as a network. The term network has been used with two rather different meanings. On the one hand, organized crime has been thought to have adapted to the new social and economic circumstances related to globalization by adopting network structure as a new mode of organization. In this view, networks are supposed to be a new mode of organization which is flexible, adaptable, resilient, and polycentric, giving criminals an advantage over law enforcement (Campana, 2016; Le, 2012; van Dijk & Spapens, 2013). On the other hand, the concept of network has been used as an instrument for studying organized crime from the perspective of social network analysis (SNA; Campana, 2016; Carrington, 2011). This instrumentalist approach makes no assumption about the properties of networks other than that they are built from human relations and interactions (Carrington, 2011; McIlwain, 1999; von Lampe, 2009). Additionally, mapping relations and interactions among criminals allows empirical analysis of these networks given suitable data.

SNA has been employed in recent years in research of a vast range of types of organized crime ranging from gangs, smuggling and trafficking of illegal commodities to terrorism (Cunningham, Everton, & Murphy, 2016; Gerdes, 2015; Morselli, 2009, 2014a). However, further development of criminal network analysis faces three challenges (Morselli, 2014b) – formulating adequate theoretical explanations, application of appropriate methods, and collection of valid data. By analysing particular cases and answering particular research questions, I aim to address these three challenges in this dissertation. In doing so, I aim to contribute to answering the principal overarching question - how is organized crime in fact organized.

1.1. Overview

In chapter 2, I follow this brief introductory chapter by introducing the most important concepts and methods from SNA and reviewing their application in the study of criminal networks. First, basic terms such as network, nodes, and ties are defined. What sets SNA apart from more metaphorical approaches to the study of organized crime is a clear definition of the concepts it uses. Second, in chapter 2 I define basic descriptive measures such as centrality indices, whole network measures, and subgroup detection methods. Third, the introduction of basic methods and measures is followed by an introduction of more complex statistical models for social network and their use in criminal networks research. At the end of the second chapter, three challenges in criminal networks research are discussed, namely building theory, collecting data, and applying appropriate methods.

Chapter 3 is a case study of a Czech political corruption scandal known as the Rath affair. Because corruption networks have been relatively understudied, this chapter first argues how political corruption can be seen as organized crime and analysed from a network perspective. The aim of the analysis is to answer three interrelated research question. The first question is whether the network is structured as a core-periphery network, as there are theoretical reasons to expect core-periphery structures in corruption networks. Second, a framework for considering multiple different types of ties (i.e., pre-existing ties, collaboration, and resource transfer) is introduced and subsequently the role these ties play in the structure of the networks is investigated. Third, the most central individuals are identified with respect to their positions within the network structure.

Chapter 4 is another case study from the Czech Republic. This particular case is known as the methanol affair and it is a case of manufacturing and distribution of illegal and poisonous alcoholic beverages. The study aims at explaining the structure of the distribution network by combining a theoretical framework of analytical sociology with statistical models for network data. First, the structure of the network is described in terms of the efficiency of the flows of the beverages in the network. Second, hypotheses about how actors may tend to pattern their ties are derived from a theory of action and, subsequently, tested with an exponential random graph model.

The goal of chapter 5 is to test a well-established theory about the structure of criminal networks called the efficiency/security trade-off. This theory postulates differences between structures of profit-driven and ideology-driven criminal networks. Whereas profit-driven networks are supposed to have efficient structures, ideology-driven network are supposed to have secure structures. The main argument of the chapter is that whereas the theory is formulated at the analytical level of networks, it should also account for actor-level mechanisms, as actors are the locus of intentionality, but results of their actions may not always line up with their intentions. In order to test the theory, eleven profit-driven networks are compared to nine ideology-driven networks in terms of their structures. Furthermore, implications of the theory for tendencies of actors are explored using exponential random graph models.

In chapter 6, I investigate the dynamics of criminal networks under disruption in two cases of Dutch jihadi terrorist networks. The aim of this study is to bridge the gap between studies that assess disruption strategies by law enforcement agencies for criminal networks on the one hand and studies mapping the evolution of criminal networks over time on the other hand. The effect of disruption can be traced at the level of networks, where structural properties of a given network change after disruption, and at the actor level, where actors change their tendencies to form ties in response to network disruption. This change may be explained by forming ties to either enhance trust among actors or reduce risk of detection from outside. In order to analyse the change at network level, various whole network measures are used together with measures for change, whereas the effect of different mechanisms is tested with stochastic actor-oriented models.

The last chapter is a methodological elaboration on one of the biggest challenges in the research on criminal networks – data collection. In this chapter, I advocate a more systematic and transparent approach to collecting data on criminal networks. Six aspects of covert network data are identified – nodes, ties, attributes, levels, dynamics, and context – and challenges as well as opportunities related to each of the six aspects are discussed together with the problems of secondary and missing data. Checklists and graph databases are proposed as potential solutions to enhance clarity and a systematic approach towards data collection.

2. How to analyse organised crime with social network analysis?[3]

In recent years, there has been a huge influx of interest in networks in basically every scientific field and also in our everyday language. Networks are now studied in such various fields as computer science, physics, biology, and social sciences such as economics and sociology (Newman, 2010). Some researchers even speak of a brand new field of study[4] – network science (Robins, 2015). In the social sciences, the term network has been connected to globalisation, social media, and more generally to a fundamentally new form of social organization. Networks are supposed to be fluid, flexible, dynamic, global, and omnipresent, yet it is often not clear, what exactly these networks are, how they are defined or how should we think about them. Amidst the "network revolution" the term *network* has been used so widely, that it could be considered a buzzword. Even though there have been earlier attempts to marry network perspective with criminology and criminal intelligence (Krebs, 2002; Sparrow, 1991), some researchers argue that criminology might have been left a little bit behind this network trend (Papachristos, 2014). However, the network perspective has much to offer for criminology and especially for the study of organized crime. This paper introduces the network thinking in criminological research and points out potential benefits of this synthesis.

It is important to clarify what is meant by networks here. The concept of network may be rather broad. The network is defined here as a set of actors and a relation among them, indicated by a collection of dyadic ties (see Figure 1). This is a definition commonly used in social network analysis (SNA). And since all forms of organisation are based on human interactions and relations, they can be subsumed under networks (Carrington, 2011; von Lampe, 2009). Within this conceptualization, networks capture "the least common denominator" of organized crime – human relations (McIlwain, 1999). Networks in this sense are thus an instrument which can capture any hypothetical form that can be taken by organized crime – be it hierarchy, market or ethnic communities (Le, 2012). Social network analysis methods can then empirically describe and test to which extent they are hierarchical

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[3] This chapter is based on Diviák, T. (2018). Sinister connections: How to analyse organised crime with social network analysis? AUC PHILOSOPHICA ET HISTORICA, 2018(2), 115–135. https://doi.org/10.14712/24647055.2018.7 .

[4] While network science is a new development, social network analysis has considerably deeper roots than that, as its origins can be traced to 1930's and its take-off can be seen already in 1970's (cf. Freeman, 2004).

or decentralized, stable of fluid, or in general - how they are structured and *how* they are organized. After all, this is a major question in the whole field of organized crime studies (von Lampe, 2009).

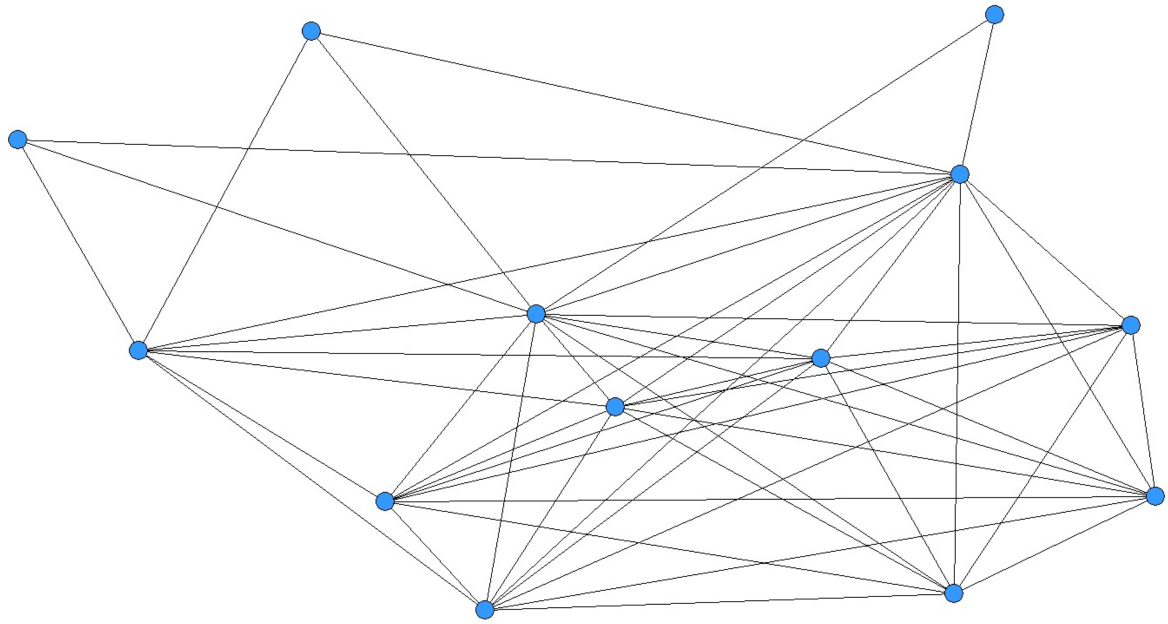


Figure 1: A graph of a network with nodes (points) and edges (lines)

Criminal networks are special cases of so-called covert networks[5]. The underlying assumption is that covert networks are defined by the need of actors involved in them to remain concealed (Oliver, Crossley, Everett, Edwards, & Koskinen, 2014). Such an environment and context, where a principal motive is to hide, modifies interactions and relations (Morselli, 2009: 8). When studying criminal networks, we first construct a network from interactions and relations among a group of offenders, and subsequently analyse this network representation with the use of SNA. In this chapter, we introduce the most important concepts in SNA, from the basic terminology, through descriptive measures to advanced models. We will also illustrate criminological applications of these concepts.

[5] For a deeper discussion on the relation of covertness and legality of various networks, see Milward & Raab (2006).

2.1. Basic terminology

We define a network as a set of nodes and ties[6] between them (Borgatti, Everett, & Johnson, 2013; Hanneman & Riddle, 2005; Wasserman & Faust, 1994)[7]. *Nodes* can represent any entity, but in social sciences, they usually represent social actors. Specifically, in the study of organized crime, nodes represent offenders such as traffickers, terrorists, gang members etc. Nodes can carry various *attributes*, for example they may have different genders (binary attribute), possess different skills (categorical attribute), have different attitudes towards various things (ordinal attribute) or be of different wealth (continuous attribute). *Ties* are what connect them; the collection of all ties between the nodes in the node set defines the *relation*. This definition encompasses a broad range of phenomena. Relations may be either undirected or directed. Undirected relations are by definition mutual such as being at the same place at the same time (co-attendance), being members of the same organization (co-membership) or sharing a background (e.g. being university classmates or relatives). Directed relations allow for specifying from which node to which other the tie goes. These often represent flows of resources (e.g., money or drugs) or communication (e.g., who calls whom). Generally, in cases of one actor sending a tie to another and the other potentially sending or not sending it back (so-called reciprocity), the ties are defined as directed, whereas in cases the reciprocity is "automatic", ties should be defined as undirected. In addition to directionality, ties may also vary in their strength or value. The simplest case is a network of binary ties, where a tie between any pair of nodes is either present or absent. Like other variables, tie variables can be dichotomous (the simplest case just mentioned), ordinal, discrete, or continuous. Another important distinction is between positive (friendship) and negative (enmity) relations. All these distinctions have implications for which methods to use and how. Most methods have been developed for relations with dichotomous tie variables. All these aspects of network can be visually represented in network graphs. These visualizations are also known as sociograms and they were invented by Jacob L. Moreno (1934), the father of sociometry – a precursor to SNA.

[6] The term "node" is interchangeable with the term "vertex" and in social sciences with the term "actor" (in the cases where nodes represent actors). Similarly, the term "tie" is sometimes interchanged with the term "edge" or "arc" (arc refers to a directed tie).

[7] There are many more network concepts and measures than those described here. For further reference, see the introductory text by Borgatti, Everett, & Johnson (2013) or an intermediary book by (Robins, 2015).

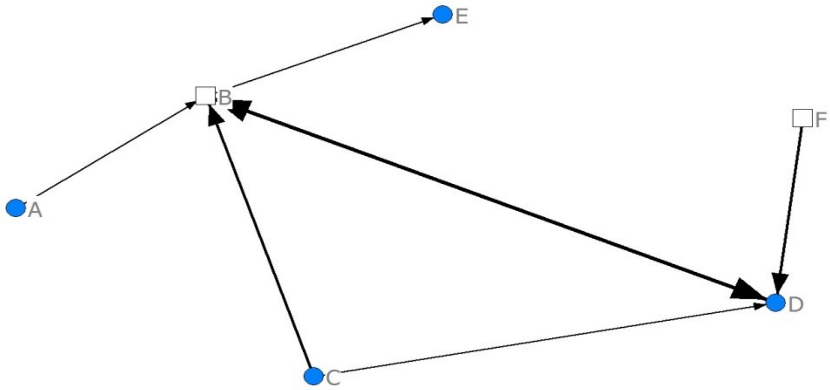


Figure 2: An example network with 6 nodes with a binary attribute displayed with different colors and shapes (white squares = female, grey circles = male) and 7 directed weighted ties among them (the B to D tie is reciprocated, i.e., goes in both directions)

The construction of a network is based on the available data. Collecting the data can be a daunting task as observing a group of people who by definition try to avoid any detection excludes usual ways of collecting data in social sciences. Therefore, we usually analyse secondary data on criminal networks. This data may come, for example, from police investigation and surveillance, trial testimonies, court documents, archives, other research or from media reports. All these sources have different liabilities and advantages – police data may not be accessible, testimonies may be purposefully distorted by defendants, archival data may be incomplete and media reports may have questionable validity. What is important is to be wary of the shortcomings of the data we use and be as careful as possible with their processing and analysis. I will come back to the issue of data in this field in the last part of this chapter and in greater detail in chapter 7.

2.2. Centrality measures[8]

Centrality measures are probably the most well-known and the most widely used concept within the SNA (Morselli, 2009: 38). Centrality measures are a set of methods which are used to identify the most prominent nodes in the network (L. C. Freeman, 1979). This is obviously very important in the context of criminal network analysis, as the most central actors are typically crucial for the functioning of the network and thus also suitable targets for monitoring and subsequent disruption of the network, which is of great interest for law enforcement (Sparrow, 1991). Furthermore, organizing activities of central actors often

[8] Overview of centrality measures can be found in a paper by (Borgatti, 2005).

explain the organization of the whole group, its ability to adapt to a changing environment, profit or survive in the face of disruption (Bright et al., 2012; Morselli, 2009; Oliver et al., 2014). There are tens of different centrality measures and while it is by far not necessary to compute all of them, it is also never redundant to compute more than one. Even though they relate to the same concept (that is the relative importance of a node within a network), each of them approaches this concept from a different angle and thus they are complementary to each other. Here, we will take a look at just two of these measures, which are arguably the most important and also the most frequently used; degree and betweenness.

Degree captures the simplest intuitive notion of an important actor – it is a node that has the most ties to other nodes. The high number of direct contacts allows such an actor to access a lot of information and potentially exercise direct control over adjacent actors in the network. Formally, the degree of a node is the sum of its ties. In directed networks, we can distinguish two kinds of degree – indegree and outdegree. Whereas indegree refers to the number of incoming ties (directed towards the node), outdegree refers to the number of outgoing ties (directed from the node). In valued networks, not only the plain number of ties can be computed, but also the sum of their values, so that degree tells us for example how many times a particular node met with others or how much money he or she received. In Figure 2, B is the node with the highest degree.

The centrality measure called *betweenness* defines important nodes from a different point of view. Central actors in terms of betweenness are those who stand between many other nodes in the network. Between each pair of nodes within the network, if there is a sequence of connected nodes between them, we can find the shortest sequence known as the *geodesic path*. For example, between nodes A and F in the Figure 3, there are numerous paths leading from one to the other. However, only the path through nodes I and H is the shortest (of length 3) making it the geodesic path between A and F. The betweenness of a node then is the proportion of geodesic paths between all pairs of nodes in the network that pass through this node. Betweenness is very important for relations that have to do with communication or other processes where indirect connectedness is important while long path lenghts are costly, because then high betweenness means having an important position through which much of the flows will pass. Actors with high betweenness scores are sometimes coined as brokers or gatekeepers – they bridge connection to others in the network and control flows of, for instance, information, or goods, in the network. In the network in Figure 3, the node with the highest betweenness is I, whereas A has the highest degree. Brokers may also be crucial for keeping the network connected (Morselli & Roy, 2008).

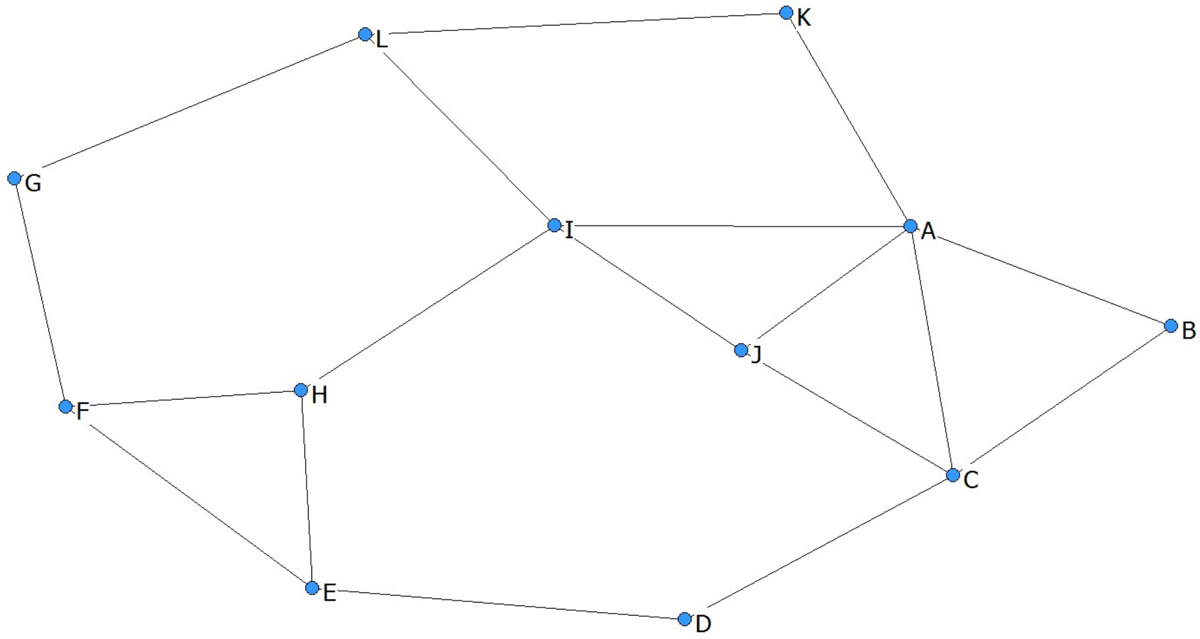


Figure 3: An example network

In some networks degree and betweenness are highly correlated, that is, nodes which have high score in one measure tend to have high score in the other as well. However, this is not necessary - criminal networks in particular are often exceptions to this pattern. Having a high degree may have a significant drawback in such networks, because a high number of ties means a high number of interactions and therefore high visibility, which in turn leads to a higher chance of being detected – which the actors in criminal networks obviously try to avoid. Some actors may act in such a way that they try to minimize redundant connections by assuming key brokerage positions, which allows them to retain control of the most important information, resources, and co-offenders in the network, while being less visible and thus susceptible to detection. This is called strategic positioning (Morselli, 2010). For actors who have high scores in both degree and betweenness, the vulnerability connected with high degree may outweigh the advantages of betweenness (Morselli, 2009). Strategically positioned actors have been observed for example in networks of drug trafficking operations of the Hells Angels gang (ibid.), an Australian drug trafficking network (Bright, Greenhill, Ritter, & Morselli, 2015), or Calabrian N'dranghetta's cocaine dealing activities (Calderoni, 2012). However, in some other cases where it was studied, this phenomenon has not been present, such as in the case of political corruption (Diviák, Dijkstra, & Snijders, 2018) or in another case of drug trafficking network (Hofmann & Gallupe, 2015). These results suggest that while strategic positioning is not universal, it is worth paying attention to it.

A topic closely related to the centrality of actors is the problem of criminal network disruption. Since law enforcement usually has only limited resources for disrupting criminal networks, it needs to allocate them as efficiently as possible. Disruption is a state of a network in which it can no longer serve the purpose it was designed to serve (Carley, Lee, & Krackhardt, 2002; Bright, 2015). In a disrupted network, resources and information cannot flow properly and actors involved in them cannot communicate smoothly and reach a consensus (Carley, Lee, & Krackhardt, 2002). Central nodes within the network, and brokers in particular, have been proven to be suitable targets for such an efficient disruption, as in both simulation and longitudinal studies, it was found that removal of a central node caused the most damage to the network in comparison to random node removal or removal based on attributes of nodes (such as possession of skills and resources; Bright, 2015). This fact has been demonstrated in number of empirical studies – in the case of a hacker network (Décary-Hétu & Dupont, 2012), terrorist, drug trafficking, and gang networks (Xu & Chen, 2008), and ringing operations network (Morselli & Roy, 2008). This area of research is very vivid and more research is being done, particularly in relation to network dynamics and their ability to recover from disruption (Bright, 2015; Duijn, Kashirin, & Sloot, 2014).

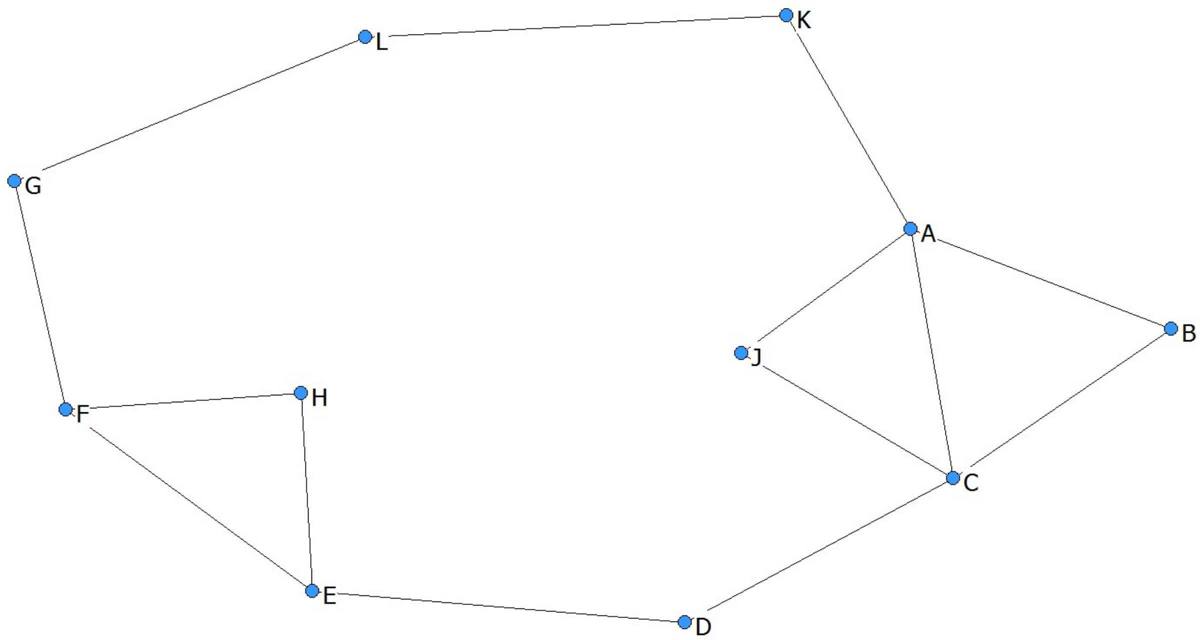


Figure 4: A graph showing the effect of a central node (I) removal

2.3. Cohesion measures

Whereas centrality measures focus on individual nodes within the network, cohesion measures focus on the network as a whole. Specifically, cohesion measures indicate how well connected or cohesive (hence the name) the whole network is. In more cohesive networks, information and resources flow easily, goals can be reached effectively, infiltration and disruption may be more difficult, and norms and identity among the nodes tend to be similar (Borgatti, Everett, & Johnson, 2013: 181; McGloin & Kirk, 2010). Much like in the case of centrality, there are different ways of expressing cohesiveness of a network which are mutually complementary. Here, we will introduce measures which are based on the number of ties within the network, on the spread of the ties within the network, and on the distance among the nodes.

The intuitive image of a cohesive network is a network in which nodes are well connected to each other. *Density* is a measure which captures this. It is the proportion of ties present in the network relative to the maximum number of possible ties in the network (that is the number of all pairs of nodes). The result ranges from 0 to 1, where 0 means that the network is just composed of all isolated nodes, while 1 means that each node has a tie to all other nodes in the network. This implies that density can also be expressed as a percentage. The average of the degrees is an alternative measure of cohesion. This contains the same information as the density, because the average degree is the density multiplied by the number of nodes minus 1. For most social networks the average degree is a more directly interpretable measure than the density, because it is more directly experienced by the actors. Density is mostly inversely related to the network size – with an increase of the number of nodes, the density tends to decrease (Everton, 2012).

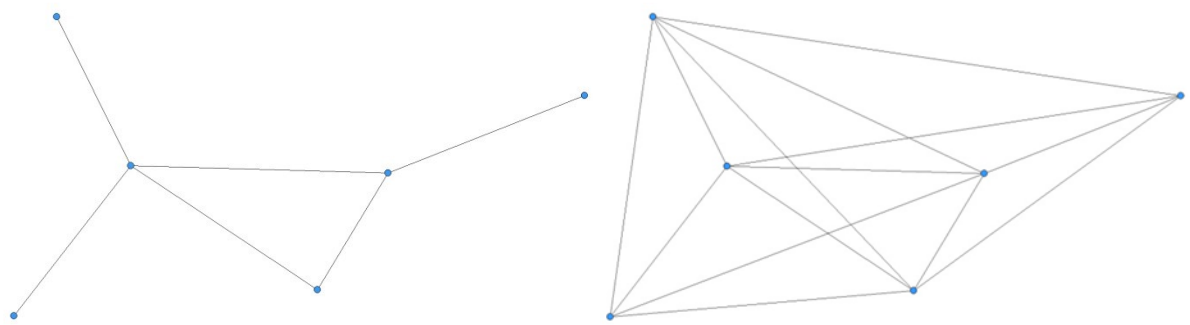


Figure 5: A sparse (density=0.4) and a dense (density=0.8) network with 6 nodes

It is not only the sheer number of ties that matters for cohesiveness of the network, but also their spread. In other words, in some cases, ties can be concentrated around a few very central nodes and in other cases, ties may be evenly spread among all the nodes. This is captured by measures called *centralization*. Essentially, centralization tells us to which extent a particular network resembles a star network, which is a maximally centralized network around one node with ties to all others and no other ties among them. If centralization equals 1, it is a star network, while if it equals 0, then each node in the network has the same number of ties. Similarly to average degree, we can also use the standard deviation of degrees to indicate the spread of ties in the network as an alternative to centralization (Snijders, 1981).

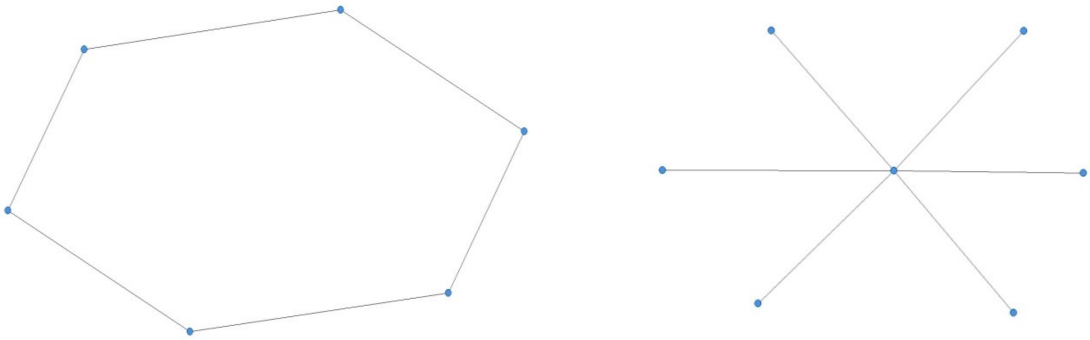


Figure 6: A circle network and a star network

When above we defined the betweenness, we used the concept of geodesic distance. *Geodesic distance* is the shortest path (the smallest number of ties) between a given pair of nodes. In this vein, we can think of a cohesive network as a network with short geodesic distances among the nodes. We can then simply characterize a network with an average geodesic path length. The smaller this average is, the more cohesive the network is in these terms. A measure of variability of geodesic path length is the *diameter* of the network. The diameter is the longest geodesic distance in the network, and indicates how many steps a piece of information or a resource needs for traveling between the two most remote nodes in the network.

Greater cohesion of the network initially increases its flexibility and the potential for interaction of its actors. However, beyond a certain point, increased cohesion may stifle these advantages (Everton, 2012). Both extreme sparsity and extreme density can be disadvantageous. On the one hand, very low density leads to insufficient cooperation, coordination, social control among the actors and thus the inability to reach goals. On the other hand, overtly dense network structure leads to too much social control and too much similarity among the actors, which hampers their ability to perform complex tasks and to adapt to varying conditions. This relates closely to what Morselli, Giguére, and Petit (2007) called the efficiency/security trade-off. They argue that “criminal network participants face a consistent trade-off between organizing for efficiency or security” (ibid.: 143). Efficiency indicates that participants in criminal networks interact and communicate with each other frequently by having a lot of ties. But as we have already shown on the strategic positioning, having a lot of ties comes at the price of being easily detectible and thus vulnerable, undermining the security of the network. If criminals opt for more secure communication design with a lower number ties instead, their ability to efficiently coordinate the whole network decreases. According to Morselli and colleagues (2007), the goal determines whether a network will be structured efficiently or securely. Ideologically driven networks (terrorists) are supposed to be particular at assuring security, as they operate within long time frames preparing to carry out one carefully planned action (typically an attack). To achieve this, they have to remain as secure as possible. Efficiency is supposed to be a feature of networks driven by financial profit, such as smugglers, traffickers or drug dealers, who operate within short time frames in order to generate profit and thus need numerous ties. This idea challenges the very basic assumption of the field of criminal networks – the primary emphasis on security and covertness of actors within these networks. Testing this hypothesis empirically is currently one of the focal points in the field (Ünal, 2019; Wood, 2017).

2.4. Subgroups detection[9]

One common feature of networks created by human actors is the tendency of actors to create smaller groups which are more cohesive (i.e., dense) than the overall network (Newman & Park, 2003). This tendency is called clustering. Within such subgroups actors are more likely to share norms, values, resources, and thus actors involved in them are strongly influenced by other members of their subgroup (Borgatti et al., 2013: 181). In criminal networks, subgroups might represent closely cooperating task groups. As with the centrality measures, there are numerous ways to define subgroups and even more ways how to detect them[10]. For simplicity, we can distinguish between bottom-up and top-down approaches to subgroups detection (Hanneman & Riddle, 2005). In the bottom-up approach, we are looking for subgroups that

[9] Other terms, such as “cohesive subgroups“, “clusters”, or “communities“, are used to label this type of sets of nodes within the network. Since the term “community” has other meanings across social sciences, “clusters” may create confusion with cluster analysis and for clarity purposes, we will simply talk about “subgroups” here.
[10] An elaborated and more technical review of these methods was provided by Fortunato (2010).

overlap (share nodes) and we may even be interested in how this overlap builds up to create the network. In the top-down approach, the subgroups are mutually exclusive (overlap is not permitted). Here, we will describe cliques and k-plexes from the bottom-up approach, and Girvan-Newman and Louvain methods from the top-down approach.

Cliques are formally defined as maximal complete subgraphs. This means that a clique is a group in which all nodes have ties to each other, but there is no other node that also has ties to all nodes in this group. Thus, the density within each clique equals 1, as all the ties which can be there are by definition present. The minimal number of nodes considered is usually three. One important property of cliques is that they can overlap, which means that one node can belong to multiple cliques. This way, cliques stack onto one another resulting in the overall structure of the network (Borgatti et al., 2013). The definition of cliques implies that in most usual networks, clique sizes are rather small, e.g., going up to four or five nodes. However, if we imagine a subgroup of seven actors, where everyone has ties to everyone else with the sole exception of one null dyad (a pair of actors with no tie between them), it is not a clique, but it still is considerably cohesive (density = 0.98). For this reason, alternative concepts have been proposed. One such alternative is a subgroup called *k-plex*. A k-plex, for a given value of *k*, is a group in which each node is connected to all other nodes except perhaps a subset of at most *k* nodes. So, in our earlier example, the group of seven actors with one null dyad is a 1-plex of size 7.

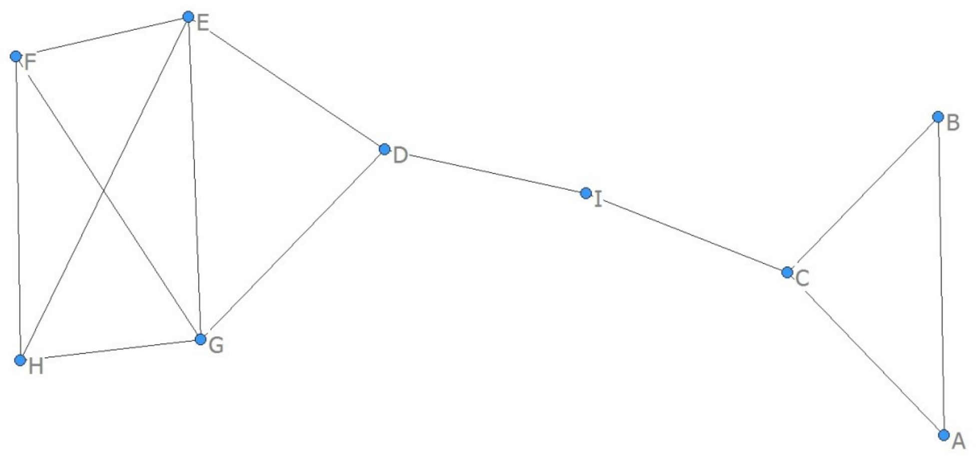


Figure 7: A network with 3 cliques – one contains four nodes (E, F, G, H), two contain three nodes (A, B, C and D, E, G)

A more computationally complex approach to subgroups detection is the top-down approach[11]. The main idea is that a network can be partitioned into subgroups, which internally contain as many ties as possible (so, ideally they are cliques) while between them, in contrast, there are as few ties as possible. The extent to which a network can be partitioned into subgroups fulfilling these criteria can be quantified by a measure called *modularity* (Newman, 2006). Modularity is the number of ties falling within subgroups in the network relative to the number of ties falling within subgroups in case the ties were randomly reshuffled. Modularity ranges from -1 to 1 with higher values indicating more resemblance to the subgroup structure. Networks with modularity above 0.3 can considered to be subgroup structured (DellaPosta, 2017), as it means the network is 30% more subgroup-structured than we would expect by random chance. It is up to researcher to determine the number of subgroups to be found this way and frequently, it is useful to try different numbers and see whether the results make substantive sense and what is the resulting modularity. One frequently used algorithm for top-down subgroup detection is called Girvan-Newman or edge-betweenness (Newman & Girvan, 2004) based on the fact that betweenness can also be calculated for edges. The algorithm successively deletes edges with the highest betweenness until the network breaks down into a prespecified number of isolated subgroups. Another algorithm is called Louvain (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). It starts with each node as its own subgroup and subsequently, it tries to group nodes into larger subgroups by increasing the value of modularity of the next assignment of nodes into subgroups. The algorithm does this repeatedly until there is no further increase in modularity.

[11] In statistical physics or computer science literature on networks, the term “community detection” is used for these methods.

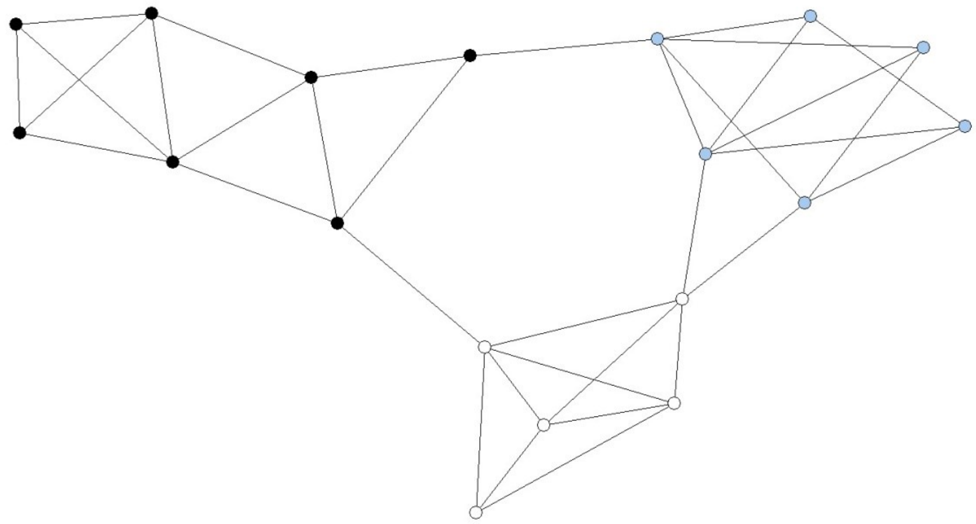


Figure 8: A network with 3 identified factions distinguished with different colors of nodes

The role of subgroups has also been investigated in criminal networks. An influential idea was proposed by Sageman (2004)who postulated that jihadist terrorist networks (Al-Quaeda particularly) are organized in what he called a "cell-structure". Terrorist networks are supposed to be built up from small clique-like subgroups, with only very sparse interconnections between these subgroups. This is a result of a purposeful design, where these small cells allow for carrying out complex tasks, but they also allow for remaining secure from infiltration as within these groups, everyone knows everyone else. Although this idea needs to be empirically tested, some other studies have shown this structure in other networks. An example is the study of British suffragette network, which became more cell structured with their engagement in militant activities (Crossley, Edwards, Harries, & Stevenson, 2012). In other studies using the factions approach, subgroups were found to be an important structural feature in Russian mafia outpost in Italy (Varese, 2012) or in Calabrian N'dranghetta, where they corresponded with formal organisation units called "locali" or their unions (Calderoni, Brunetto, & Piccardi, 2017). A sparse subgroup of brokers with high betweenness was identified as crucial for distribution of illegal steroids among other subgroups of professional athletes (Athey & Bouchard, 2013).

2.5. Statistical models of networks

Methods we have introduced so far are descriptive measures for the whole structure, substructures, and individual nodes in networks. However, there is also a large set of methods which go beyond description. These network models allow to capture irregularities in human behaviour and action, assess the influence of randomness on network structures, test various hypotheses on processes and mechanisms which form social networks, and simplify some highly complex network structures (Robins, Pattison, Kalish, & Lusher, 2007). The development of these models has been vigorous in recent years (Snijders, 2011) and researchers of criminal networks may greatly benefit from this development in order to provide more empirically based explanations of organized crime. Nevertheless, there is a huge gap between descriptive measures and models of networks, which are both conceptually and computationally more elaborate, and the application of which requires nontrivial knowledge of statistics. Hence, the following section only briefly introduces the most frequently used models, their principles and some criminological applications[12].

An immediate question may arise – why should we not just apply standard statistical models we use regularly in social sciences (e.g., various general linear models)? There are two main reasons why standard statistical models are not sufficient to model networks. The first reason is the violation of the assumption of independence of observations. This is a basic assumption of standard statistics, but it is by definition violated with network data – after all, networks are all about interdependencies of nodes. For instance, if we remove a node from a network, its removal also changes centralities of other nodes in the network. The second reason is the requirement of random sampling. In network analysis, we do not usually work with random samples drawn from a population. Instead, we are typically dealing with case studies of a few networks or even just one. However, inference may still be useful in such cases – we are just not trying to infer about a population of networks, but rather aim for inferences about certain mechanisms or processes in our studied cases (Snijders, 2011).

The simplest way to handle these difficulties is to accommodate regular statistical tools for inference to non-independent data. Methods for computation of effects remain the same (e.g., correlation or regression), we only use different way to estimate statistical significance. This is what the *quadratic assignment procedure* (QAP; Krackhardt, 1988) does. QAP works like permutation tests - it "reshuffles" randomly the labels of nodes in the network many times (usually from one to ten thousand times), which yields a distribution of possible outcomes (say, a correlation between the degree of nodes and their age). If there is just a small fraction of such randomly obtained results which are equal or more extreme than our empirical

[12] A very accessible brief overview can be found in the corresponding chapter of Borgatti et al. (2013). A more detailed overview of statistical models of social networks with technical details is provided by Snijders (2011).

correlation (5% is equivalent to the p-value of 0.05), we deem the result unlikely to just be a result of chance and therefore we consider it significant[13]. QAP based regression models may be useful, especially in modelling valued networks (Campana, 2016). An example of application of QAP multiple regression is given by Campana and Varese (2013), who studied the impact of kinship ties and violence on cooperation among Mafiosi from Russian and Neapolitan mafia groups. They found that both these factors enforce cooperation, although the effect of violence is much stronger than the effect of kinship. Another proof of usefulness of QAP is a study by Grund and Densley (2012), who found that ethnically similar gang members tend to commit similar types of offences.

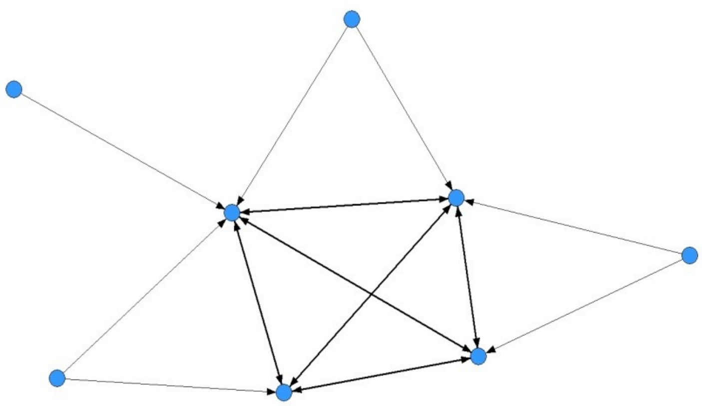
Models using the QAP deal with the network structure by accounting for it with different ways of determining statistical significance. However, no information is obtained about the structure as it is not explicitly modelled. We introduce three broader sets of models, which all explicitly model the structure of the network rather than merely control for it. These sets of models are blockmodels, exponential random graph models, and stochastic actor-oriented models.

In networks, two nodes may have ties of the same strength to the same nodes. If we would swap such nodes, the structure of the network would not change. We say that these two nodes are structurally equivalent (Lorrain & White, 1971) [14]. The principal idea behind *blockmodels* is that it is possible to reduce the network structure to mutually exclusive sets of equivalent nodes (called positions) and ties among them (called roles; Diviák, 2017; Doreian, Batagelj, & Ferligoj, 2004). Blocks are pairs of positions and ties between them – this way, we do not only model subsets of nodes (like in the subgroup detection), but also relations among them and thus the structure as well. This reduction yields a simplified picture of the network, which captures its essential features. It may even be visualised as an image graph, which is the graph of positions depicted as nodes and roles between them depicted as ties. Since exact structural equivalence is rare in empirical networks, in practice, we usually measure the extent of (dis)similarity of ties between each pair of nodes within the network and aim at finding a partition of the node set in positions that satisfy structural equivalence approximately. To find

[13] Detailed, yet very clear description of the whole procedure is given in Borgatti et al. (2013: 126 – 133) or in Robins (2015: 190).

[14] There are also other, less restrictive, definitions of equivalence, such as regular or stochastic. For the sake of simplicity, we will consider only the structural variant here. More on the other definitions can be learned in a chapter by Batagelj, Doreian, and Ferligoj (2011).

such a partition, we can apply one of many blockmodelling algorithms. These algorithms are in essence akin to what is known from standard statistics as cluster analysis or classification[15]. They partition the network into positions, within which nodes are similar to each other and between these positions, nodes are dissimilar. Subsequently, the quality of the resulting partition (that is the extent of internal homogeneity and external heterogeneity of positions) is assessed with so-called measures of adequacy. The entire procedure of blockmodelling can be done in two general ways. One way is exploratory, which is much like for example in hierarchical cluster analysis, where we try numerous different partitions and algorithms trying to come up with a meaningfully interpretable solution. The other way is confirmatory, where an analogy can be made with latent class analysis, where we start with a theory about how a network should be partitioned and then we investigate, whether this theoretical blockmodel fits our empirical data or not. To give an example, one very well explored blockmodel is the core/periphery structure (Borgatti & Everett, 1999). It consists of two sets of nodes – core and periphery. The core is ideally a clique – every member has ties to all others, also connected to all peripheral nodes. Peripheral nodes have, ideally, ties only to the nodes in the core and no ties within the periphery. In practice, it is used mostly in an approximate way. In criminal networks, this model has been found to capture the structure of the inner circle of the Provisional Irish Republican Army, where the core consisted of experienced members and was solidified over time (Stevenson & Crossley, 2014). Another case of core/periphery structure was a Czech political corruption affair, where politicians formed a dense core and ad hoc cooperated with businesspeople to manipulate public contracts (Diviák et al., 2018).



[15] As a matter of fact, clustering algorithms may be used for blockmodelling as well with some adjustments (Robins, 2015).

Figure 9: A core/periphery structured network (core is composed of the square of nodes in the middle) and its blocked image graph. Note that the image graph, unlike directly observed networks, contains a self-loop for the core, indicating that it is a cohesive subset, with many ties within the group.

A different approach to model the network structure is represented by *exponential random graphs models* (ERGM)[16]. Instead of grouping nodes on the basis of similarity in their ties, ERGMs are based on the idea that network structure is built by overlapping, intertwining, and cumulating micro network substructures called configurations. There are numerous hypothetical configurations which can be modelled, ranging from simple ties and reciprocated ties to various forms of triadic closure (see Figure 10 below). These configurations may represent theoretical mechanisms or processes, for example, reciprocated ties represent a tendency of actors to exchange transferred resources in the network, and triangles represent a tendency of actors to collaborate if they share a common third collaborator. Roughly, ERGMs work in a way similar to logistic regression (Grund & Densley, 2014) – predicting the empirical network based on the presence of ties patterned in configurations. If a parameter in this model is significant and positive, it means that the corresponding configuration is present in the network more than can be explained by chance given all other parameters in the model and if the parameter is significantly negative, then the corresponding configuration is present less than could be explained this way. A theoretically interesting benefit of ERGMs is the fact, that they can disentangle the network structure by separating the influence of competing mechanisms (represented by configurations) which may work simultaneously. We may for example have a drug distribution network, which is descriptively highly centralized, but when we fit an ERGM with a star parameter (representing the contrast between high activity of some actors and low activity of others) and a triangle parameter (representing closure, i.e., the tendency of two distributors to collaborate if they share a common third collaborator), we could get a result with insignificant star parameter and significant triangle parameter, suggesting that the observed centralization is not the effect of disproportionate activity of a few actors. Instead, the centralized network then may be a result of working together in closed structures (e.g., in order to keep each other "in check"), which frequently include particular actors making them in turn central. ERGMs have been used to show that co-offenders in a

[16] A comprehensive and detailed account of ERGMs is given in the book by Lusher, Koskinen, and Robins (2013). A more detailed explanation together with a utilisation of ERGM can be found in chapter 4 of this thesis as well.

street gang are more likely to commit illicit behaviour if they share an ethnic background and even more so, when their shared ethnicity combines with co-offending in closed structures (Grund & Densley, 2014). Another example is a study by Smith & Papachristos (2016) of the prohibition-era Chicago organized crime scene, where strong effects were found of both legitimate (e.g., business) and personal (e.g., kinship) ties on criminal activity. Hellfstein and Wright (2011) applied ERGMs to test two competing theories about the structure of terrorist networks and found support for neither of them – modelled networks displayed no tendencies towards heavily centralized structures and also no tendencies towards open non-redundant structures. Instead, they all exhibited strong tendencies towards decentralization and triadic closure. No matter how powerful ERGMs are, their estimation may be rather time-consuming due to simulations used for estimating significance of parameters.

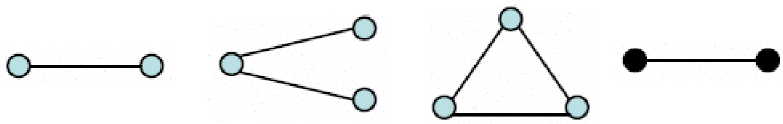


Figure 10: Some basic ERGM network configurations (from left to right) - edge, two-path, triangle, and interaction (homophily)

All the models we have introduced so far treat the network structure as static. However, networks are dynamic and change over time. A dynamic network is a network with the same set of nodes measured over multiple periods of time. This allows for tracking the change of the network over time. The question is to find which structural mechanisms, together with a dose of randomness, may explain such changes (the creation and dissolution of ties). *Stochastic actor-oriented models* (SAOM[17]; Snijders, van de Bunt, & Steglich, 2010) have been developed as a tool to model changes in the network over time. SAOMs are built up on the same underlying principle as ERGMs – network structure is modelled from configurations representing theoretical mechanisms/processes[18]. Changes between two successive time points are decomposed into a sequence of microsteps – the network is supposed to change gradually over time, in small steps where each actor is given an option to create or remove a tie. The probability of an actor creating or dropping a tie is then modelled in a similar way as in ERGMs. SAOMs have been for example applied to show how actors in a drug trafficking

[17] These models are sometimes referred to as SIENA (Simulation Investigation of Empirical Network Analysis) models due to the name of the software they were first implemented in.

[18] More detiled description and a utilisation of SAOMs can be found in chapter 6 of this thesis.

network tend to create closed triangles to facilitate trust and simultaneously build indirect connections to assure security (Bright, Koskinen, & Malm, 2018).

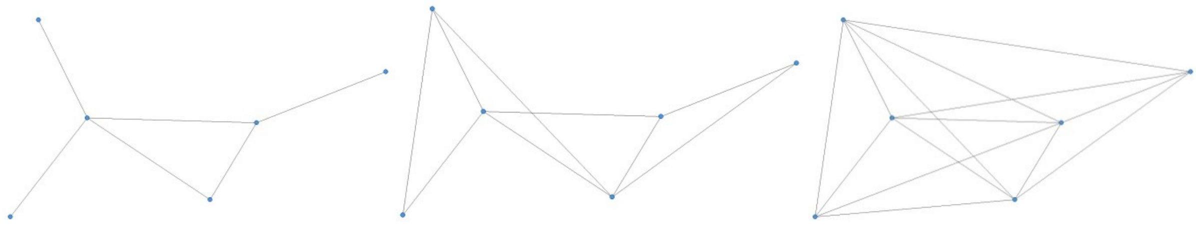


Figure 11: A dynamic network at three time points (from left to right) t_1, t_2, and t_3

2.6. Challenges for criminal network analysis

There are three challenges, which every researcher in the field of criminal network analysis as well as the field as a whole has to face (Morselli, 2014). The three challenges are data, methods, and theories. These challenges sometimes constrain the research to some extent, but finding solutions to these problems may help the development of this area of research and our understanding of organized crime.

The problem of data availability and validity is a severe one. For a network approach, this becomes especially problematic, because one Achilles' heel of this approach is its sensitivity to missing data (Krause, Huisman, Steglich, & Snijders, 2018). This is especially problematic for covert networks. If we miss important actors (such as brokers), the picture of the network may alter drastically and as a result, we will draw invalid conclusions from our analysis. Similarly, if we miss important ties (such as a bridge connecting two otherwise unconnected segments of the network), we may incorrectly deduce that there are unconnected groups which have no way how to cooperate. It is therefore important to consider the validity, reliability, and quality of possible data sources. Bright and colleagues (2012) compared five different data sources - offender databases, transcripts of physical or electronic surveillance, summaries of police interrogation, transcripts of court proceedings and online or print media. With the exception of online or print media, all these sources are not usually publicly or freely accessible. But even if they are, they are not flawless – some offenders might have not yet been caught and thus they are not in the databases, criminals may limit their communication using cover language (e.g., nicknames) and not mention crucial information in their phone calls, and during interrogation or trials offenders may lie or hold up information to avoid sentencing. If media-based sources are used, which may be freely available, extra caution needs to be taken in order assure data validity. In highly media-attractive cases (e.g., with the involvement of politicians or other public figures), media coverage may create a spotlight effect and reports may be disproportionately concentrated on the well-known offenders. This concentration may lead to the impression of a centralized network structure, but reality could be very different and, again, incorrect conclusions might be drawn. While this spotlight effect can be assessed in modelling (as shown by Smith & Papachristos, 2016), there is no specific way how to deal with it. The general advice is to process the data as carefully as possible. This can be helped by content analysis of the sources (van der Hulst, 2009), which allows for transparent coding, recoding, and comparisons of categories. Suspicious as well as solid information may become more visible and the reliability of the procedure can be checked by another independent coder (as in chapter 3 for instance).

Regarding the second challenge, the use of methods, there are two possible ways of improving the analytical tools at our disposal. One way is the use of statistical modelling of networks, the other is qualitative analysis as a complement to the SNA. We have briefly covered the basics of statistical modelling of networks and underlined its usefulness and potential for the field of criminal network analysis, which has been predominantly descriptive so far. Mixed methods approaches, where various qualitative analysis methods accompany SNA, have also been recently discussed as ways to improve how we study networks (Bellotti, 2014; Domínguez & Hollstein, 2014). The mixed methods approach is potentially fruitful especially when details can be obtained, from the actors themselves, from well-placed informants, or from intelligence sources on how actors themselves perceive, plan, and reflect their network positions and attributes (Hollstein, 2014). We have talked about strategic positioning from the network point of view, but the question is how actors experience such situation (do they really think about reducing redundant connections or are they just trying to not "go too far"?). Furthermore, combining qualitative findings (e.g., from interviews or an ethnographic study) with quantitative results of SNA may either corroborate our results, fill in some gaps, or may even lead to contradictions. Imagine a situation where we are studying networks of mobile phone communication of a criminal group at two points of time. With SNA alone, we may come to a result that at the first time point, the structure was dense and centralized, while in following time point, it changed drastically and became sparse and decentralized. We may conclude that such a change was caused by a lot of actors deciding to terminate their criminal activity in fear of being arrested amidst ongoing investigations. However, a qualitative analysis of interrogation records or maybe participant observation might reveal that participants just shifted their communication from mobile phones to face-to-face. Thus, mixed methods provides better understanding of the phenomena we study as it brings more insight into the context and meaning of what is going on in the networks we describe formally (Stevenson & Crossley, 2014). The difficulty with mixed methods studies is the fact that they are very demanding in terms of time, money, and skills of researchers (Hollstein, 2014).

The last challenge for network criminology is theory-building. There are some researchers who deem the whole field to be rather devoid of theory or primarily driven by data rather than theory (Bright et al., 2012; Carrington, 2011; van der Hulst, 2011). A proper theory should start with the individual action as the individual level is the locus of intentionality (Coleman, 1990; Robins, 2009). While SNA is all about structures of interactions, these are necessarily based in individual interactions and relations with others. One relatively new approach to theorizing about social world is analytical sociology (Hedström, 2005; Hedström & Bearman, 2011). Analytical sociology seeks to explain how social structures (in our case, criminal networks) are brought about by individual action and interaction (e.g., cooperation on a criminal task). It emphasizes that social scientists should look for mechanisms in order to formulate useful explanations of social phenomena. „Mechanism approach is that we explain a social phenomenon by referring to a constellation of entities and activities, typically actors and their actions, that are linked to one another in such a way that they regularly bring about the type of phenomenon we seek to explain." (Hedström, 2005, p. 2). As we can see from this definition, analytical sociology is often concerned with actors and their relations similarly to SNA. There is a synergy which could be explored further and help network criminologists in theoretical explanations of organized crime.

3. Structure, Multiplexity, and Centrality in a Corruption Network: The Czech Rath Affair[19]

In the last decade, there has been a growing interest in covert and criminal networks. Particular attention has been paid to terrorist, smuggling, and trafficking networks (Morselli, 2009; van der Hulst, 2011). In comparison, corruption networks have gained far less attention in research and have been generally understudied. However, the consequences of corruption in terms of security, trust, welfare and justice warrant a closer look to understand how corruption is structured and organized.

In this study, we examine a case of a corruption network with a specific focus on the structure of the network, multiplexity of relations (i.e., the existence of several different types of ties between actors), and centrality of actors. Specifically, we applied social network analysis (SNA) to a case of political corruption in the Czech Republic, known as the Rath affair, reconstructed with publicly available data, resulting in a small network of 11 persons, who were involved in large scale abuse of EU subsidies, bribery, and manipulation of public contracts. We analyze the overall structure of the network, the multiplexity of ties in this structure, and the centrality of actors. We investigate how certain micro-level features (overlapping of multiple types of ties and activity of individual actors) bring about macro-level outcomes, in this case the overall structure of the network (Coleman, 1990; Hedström, 2005).

3.1. Corruption

Corruption is generally defined as an "abuse of public power for private gain" (Funderburk, 2012; Silitonga et al., 2016; Uslaner, 2008). While this general definition of corruption does not entail any particularly relational or interactional features, corruption as a phenomenon consists of a wide range of activities and some of them are intrinsically relational. For instance, bribery and blackmailing are based on a transfer of various resources, which are either offered or demanded in return for a desired service. Another form of corruption

[19] This chapter is based on: Diviák, T., Dijkstra, J. K., & Snijders, T. A. B. (2018). Structure, multiplexity, and centrality in a corruption network: The Czech Rath affair. Trends in Organized Crime, 1–24. https://doi.org/10.1007/s12117-018-9334-y .

involving transfer or exchange of resources is the so-called kickback, which is a term for illegal provision of a public contract, which is “kicked”, i.e., boosted, to provide a share for the corrupted official. Nepotism and cronyism are based on pre-existing relationships with relatives or friends respectively, who are installed into influential or well-paid positions despite their incompetence. Although these are just the most common forms of corruption, there are more activities which could be labelled as such (for a detailed description, see Silitonga et al., 2016). What is shared by all the mentioned forms of corruption, however, is that these activities take place in human interactions and relationships.

Although some corruption involves just the exchange between two individuals in cases of abusing a single opportunity (Granovetter, 2004; Uslaner, 2008), there is also a type of corruption that disproportionately enriches a small number of rich and influential actors from the public as well as private sector. This form of corruption, labeled as grand corruption, involves far greater flows of financial resources or their material and immaterial equivalents, giving rise to severe envy, mistrust and perception of social inequalities (Uslaner, 2008).

The danger of grand corruption lies in its potential for sophisticated collaboration and coordination among multiple actors, who can act in an organized manner to maximize their profit and minimize their risks. Such conspiracies of multiple individuals acting in concert to reach illegal goals are cases of organized crime (Albanese & Reichel, 2014; Paoli, 2014). This cooperation creates a network of transfers and relationships among these actors. To such structures of joint activities, social network analysis can be applied as an analytical tool apt to capture the underlying organizational principles (van der Hulst, 2009). Here, we focus on the overall structure of the network and the way it is constituted by multiplex relations and by the activity of the individual actors involved.

3.2. Core/periphery structure

Research on criminal networks has generated a considerable body of knowledge (Carrington, 2011; Gerdes, 2015b; Morselli, 2009; 2014; Oliver et al., 2014). One network concept is especially relevant in the context of criminal networks: the so-called core/periphery structure (Borgatti & Everett, 1999). Networks displaying this structure are composed of two sets of nodes. The core is a densely interconnected group of nodes, whereas the periphery is a set of nodes with ties to the core, but few or no ties within the periphery. This structure has been described in a variety of empirical networks, such as economic networks and international trade, formal organizations, scientific citations or even animal collectives (ibid.). Borgatti & Everett (1999) developed a formal way of examining the core/periphery structure, by trying to find the optimal partition of the node set reflecting the division in core and periphery. This optimal partition is then compared to the ideal core/periphery structured network with the same number of nodes and their similarity yields a measure of goodness of fit.

In criminal settings, features indicative of the presence of the core/periphery structure have been described in a number of cases, such as several Spanish cocaine trafficking networks (Gimenéz Salinas-Framis, 2011), the Turkish terrorist organization Ergenekon (Demiroz & Kapucu, 2012), price fixing conspiracies in electrical industry (Baker & Faulkner, 1993), and the Watergate conspiracy (Faulkner & Cheney, 2013). Most of these studies did not formally fit the core/periphery structure to the available data; an exception is the study of the inner circle of the Provisional Irish Republican Army (Stevenson & Crossley, 2014). We follow a similar approach in modeling the network. In the case of corruption networks, a core/periphery structure resembles the structure of patron/client relationships, which are often thought to be the basis for political corruption with mutually beneficial quid-pro-quo exchanges between politicians (patrons – the core) and their supporters (clients – the periphery; della Porta & Vanucci, 2012; Funderburk, 2012; Granovetter, 2004). Consequently, the first research question is *to what extent does the corruption network in this study resemble a core/periphery structure?*

3.3. Multiplexity in criminal networks

Social relationships are often based on more than one dimension, for instance, two individuals may be friends and co-workers simultaneously. Multiplex[20] networks describe multiple relationships among the same set of actors (Hanneman & Riddle, 2005). The analysis of multiplex instead of simplex[21] networks provides a more realistic and more detailed picture of social reality and in turn deepens the understanding of the network under scrutiny (Bright et al., 2015; Faulkner & Cheney, 2013; Gerdes, 2015a; Hamill et al., 2008; Kivelä et al., 2014).

[20] Multiplex networks are sometimes referred to as multivariate, multidimensional or multirelational, which are different from multilevel networks or multilayer networks.

[21] For traditional networks with just one relation among nodes, the terms simplex, monoplex, or uniplex may be used.

Despite the attention to multiplexity in criminal networks given in the literature, starting already quite some time ago (Ianni, 1972; Krohn, Massey, & Zielinski, 1988), in many studies the relational information has been aggregated to a single network, without specifying the content of the relation, or of the exchanges taking place. The reason is the paucity of available information, so that the researcher already has made progress when there is evidence for at least some relationships between pairs of actors. However, multiplexity is a key component of the dyadic level of analysis in the network perspective (Robins, 2009). Organized crime is in principle an embedded and multiplex phenomenon, created by individuals nested within multiple social relations held together by information, activities, obligations, and exchanges (Papachristos & Smith, 2014). Distinguishing between these relational contents is essential for understanding criminal activities and how networks play a role in their organization. Papachristos and Smith (2016) suggest that multiplexity of relations is an important factor in illegal settings where it compensates for the lack of formal institutions. Therefore, when going more deeply in the explanation and analysis of the social organization of crime, a differentiation between different types of relations is important.

There are some published examples of multiplex criminal network analyses. Most prominently, a study by Krebs (2002) of the 9/11 terrorist attacks followed the example of overt organization analysis in mapping different types of ties, resulting in four types or dimensions; trust, tasks, money & resources, and strategy & goals. Another example is Faulkner's and Cheney's (2013) study of the Watergate conspiracy, where they distinguish five separate dimensions, emphasizing negative ties of enmity among actors, which could have been a stronger cause of eventual collapse of the conspiracy than an external disruption. In a study by Everton (2012) on the Indonesian terrorist network of Noordin Mohammad Top, trust (friendship, kinship or shared affiliation) and operational ties (communication, financing, common training) were distinguished. Papachristos and Smith (2014; 2016) analyzed a large network of criminal and legitimate actors surrounding the infamous gangster Al Capone, resulting in three types of relations; criminal, personal (e.g., kinship) and legal (e.g., non-criminal cooperation). Bright and colleagues (2015) base their analysis on the concept of tangible (e.g., money or material) and intangible (e.g., skills or information) resource transfers among co-offenders in the case of drug smuggling. They also underline the importance of multiplexity by warning for potentially misleading results of simplex analysis of aggregated networks as this may lead to over- or underestimation of prominence of individual actors. For example, an actor may be central in one dimension but peripheral in others, incorrectly making him seem unimportant in the overall aggregated simplex network. Finally, a review by Gerdes (2015a) described ten possible dimensions; direct operational links, logistic links, planning links, financial links, training links, ideological links, family, friendship, enmity and uncertain links.

Based on the previous research described above, we propose three dimensions. For each dimension, we provide a brief description, the content of ties, and a justification for its inclusion.

1) *Pre-existing ties*. There has been a great emphasis on the importance of trust within covert networks (Erickson, 1981; Krebs, 2002; Milward & Raab, 2006; Oliver et al., 2014; Robins, 2009; van der Hulst, 2011). By trust, we mean the expectation of reciprocation and of not defecting, that is, not breaking the concealment, in a covert environment (further see Campana & Varese, 2013; von Lampe & Johansen, 2004). Pre-existing ties, meaning ties established before the criminal act itself, may be crucial sources of trust, which makes their analysis important (Morselli & Roy, 2008). Specifically, pre-existing ties may take a form of kinship relations, friendships, or relations based on shared ideology or shared affiliation to the same organizations or institutions. Therefore, they are to a large extent overt, unlike the other types of ties presented below. In our case, pre-existing ties include marriage, being university classmates, and mutual membership in a board of directors of a company. However, it is important to acknowledge that the presence of such a tie does not automatically create trust between the two connected actors, and a pre-existing tie may only potentially facilitate a creation of a tie of another type; but we have no other information about trust between these individuals. The question is, to what extent was the criminal cooperation backed up by pre-existing ties. Ties in this dimension capture the notion of Krebs' (2002) and Everton's (2012) dimension of trust, Papachristos' and Smith's (2014; 2016) personal ties and partly legal ties and Gerdes' (2015a) links of training, ideology, family and friendship.

2) *Resource transfer*. Resource transfer or exchange (if reciprocated) is the main component of numerous forms of organized criminal activity. It includes the transfer of illegal profits obtained. Resources to be transferred may be both material and immaterial, tangible (e.g., equipment) as well as intangible (permissions, skills; see Bright et al., 2015). This dimension covers the logistic, training, planning and financial links proposed by Gerdes (2015a). In our

case, the main transferred resources are money in the form of bribes or kickbacks for politicians and manipulated contracts for businessmen.

3) *Collaboration*. Ties in this dimension can be broadly defined as purposeful interactions, involving communication that can be both direct (face-to-face) and indirect (e.g., phone calls, e-mails). This dimension also includes collaboration on tasks or co-appearance at the same time in relevant places, which is consistent with the task and strategy and goals networks in the concept of Krebs (2002), operational ties as defined by Everton (2012), and the criminal dimension of Papachristos and Smith (2014; 2016).[22]

For each of these three dimensions there could be negative ties, as in some cases, animosity or even outright enmity may exist among actors (Faulkner & Cheney, 2013; Gerdes, 2015a). These dimensions also allow tie weights to be taken into account. They also allow the specification of the direction of ties as directed or undirected based on the source of the data and the accuracy and detail of their recording. This framework is sufficiently general and flexible, which makes it potentially applicable to other cases of corruption networks. As will be mentioned below, in the analysis presented in this paper, we do not consider negative, directed, or weighted ties.

We examine different ties to assess the multiplexity in the corruption networks in this study. In a multiplex network, some dimensions may tend to overlap with other dimensions and this may also differ between the core and the periphery. Hence, the second research question is *how do different types of ties overlap in the aggregated network?*

3.4. Central actors in criminal networks

The analysis and identification of central actors is a crucial task for explanation of the structure of the criminal network, as it is the individual level where the intentionality (e.g., intention to remain covert or to maximize profit) resides (Robins, 2009). Organizing activities of central actors have been related to the organization of the whole group, fostering its ability

[22] In order to distinguish between the dimensions of collaboration and resource transfer, we consider an interaction to be a tie in the resource transfer dimension if it involves any transfer of resources. In order to be a tie in the dimension of collaboration, the interaction has to include any sign of collaboration different from a transfer of resources.

to adapt to a changing environment and to profit or survive in the face of disruption (see e.g., Bright et al., 2012; Morselli, 2009; Oliver et al., 2014). Centrality is a concept which captures to which extent the actor is connected to many others, or connects many others, and thus may be influential for the organization of the entire group. In the core/periphery structure, central actors are those in the core. Centrality of actors in the network can be measured in different ways (Freeman, 1979). Two of the most commonly used measures are *degree* and *betweenness*. Whereas degree is a simple count of all ties of a node, betweenness captures the number of shortest paths between other pairs of nodes on which the actor stands, enabling to bridge different segments of the network. Actors with high betweenness, so-called brokers, are considered crucial in keeping the network connected (Morselli & Roy, 2008). Degree and betweenness express the concept of centrality in quite distinct ways, and they do not necessarily correlate. It has been shown that in some cases leaders in criminal networks may hide in the background by having a low degree, as having high number of ties is easily detectible and thus vulnerable. By contrast, they compensate by having a brokerage position (a high betweenness score). Morselli (2010) calls this 'strategic positioning'. In addition, there may be three more types of actors depending on their degree and betweenness. Actors with low values for both degree and betweenness are marginal in the network. Actors with a low betweenness but a high degree are more visible and therefore more at the risk of detection. Finally, actors with high values on both indices are highly central and as such visible. Even though they have a high betweenness, this potential advantage may be outweighed by the risks of high degree (ibid.).

The concept of centrality is more complicated when taking multiplexity into account. Battiston, Nicosia, and Latora (2014) point out that nodes may differ in terms of how dispersed their ties are between different dimensions of a multiplex network. They theorize three possible types of nodes in this regard. Focused nodes have ties in only one dimension and thus are unconnected in others. Multiplex nodes have ties spread evenly across all the dimensions. Lastly, mixed nodes have ties in multiple dimensions, yet their dispersion across them is uneven, that is, they have more ties in one dimension compared to other dimensions (ibid.).

We combine this approach with the strategic positioning introduced above. By doing so, we can identify central actors and take multiplexity of their ties into account. Some actors may be central in one dimension, but marginal in other dimensions, suggesting specialization in the network in a certain task, while being marginal in others (Bright et al., 2015). Other actors may occupy average or even marginal positions in terms of centrality in each dimension separately, but may be crucial by integrating different layers of the network into one single coherent whole due to multiplex spread of their ties.

Hence, the third research question is *which actors are central in the corruption network and how do centralities of actors differ across network dimensions?*

3.5. Case description - The Rath affair[23]

In this study we analyze a political corruption scandal from the Czech Republic. The analyzed case consists of actors involved in an affair surrounding a long-term controversial figure of Czech politics – David Rath[24], a former minister of health, at the outbreak of this scandal a social democratic party (CSSD) deputy and governor of the Central Bohemia region. David Rath was arrested the 14th of May 2012 by anti-corruption police together with his close colleagues and two lovers, Petr Kott and Katerina Pancova, in the midst of being bribed. The main reasons for their arrest were embezzlement, kickbacks, abuse of EU subsidies, and manipulation of public contracts, mostly in the domain of hospital equipment and public estates reconstructions (e.g., chateaus or schools). As the investigation continued, it turned out that these three persons were not alone in their offences and another eight persons were arrested as well, mainly managers of firms involved in manipulated contracts or profiting on the abused subsidies. Together, these 11 actors were systematically cooperating on embezzlement, manipulation of contracts and abuse of EU subsidies and they mutually shared the profits of their action. The financial damage reached at least twenty million Czech crowns (almost one million Euros). Hence, this case matches the definition of grand corruption and organized crime presented above, as it entails both collaboration of a group of offenders and a large amount of transferred resources.

[23] For more information on this affair, see e. g. (both in Czech): http://www.lidovky.cz/infografika.aspx?grafika=korupcni-kauza-davida-ratha (Lidovky.cz, 2016) or: http://zpravy.idnes.cz/soud-s-davidem-rathem-05r-/krimi.aspx?c=A130806_141944_krimi_klm(iDNES.cz, 2013)

[24] Czech names usually contain letters with diacritics such as “á“, “š“, or “č“. In order to be consistent with the visualizations, which are made with a software package not supporting such letters, we do not include them in the text.

In order to alleviate otherwise severe problems of boundary definition in criminal networks, we adopted a nominalist approach (Borgatti et al., 2013, p. 33 - 34). The criterion for including an actor into the network is based on criminal justice circles (see Morselli, 2009, p. 44 - 45). We define the criminal justice circle for the Rath affair as “being charged”, including as a node in the network everyone who was charged with any criminal act in connection to this affair. This resulted in the following eleven actors;

David Rath, – governor of the Central Bohemian Region and a deputy of the social democratic party (CSSD);

Petr Kott, Katerina Pancova (after marriage - Kottova) – a politician (CSSD) and his wife and the director of Kladno city hospital;

Pavel Drazdansky, Lucia Novanska, Martin Jires, Ivana Salacova, Tomas Mlady, Vaclav Kovanda, Jindrich Rehak, Jan Hajek – managers and representatives of various construction or medical equipment providing firms.

3.6. Methods

Data collection and coding

One of the most challenging tasks in research on covert networks is the collection of data (Morselli, 2014b; van der Hulst, 2009). Bright and colleagues (2012) compared five different data sources: offender databases, transcripts of physical or electronic surveillance, summaries of police interrogation, transcripts of court proceedings and online or print media. Apart from online or print media, most data sources are not publicly or freely accessible.

An objection against using online or print media is their lower validity, as they are always a secondary source of information dependent on the perspective and knowledge of the journalists, who produce it. This also limits researchers’ options to control their quality and credibility. Another possible pitfall of media-based data is the tendency of journalists to focus on what or who they deem to be interesting and, consequently, focusing their reports on specific persons, making the data derived from these reports centralized as a result. Nevertheless, if the reported information is sufficiently detailed and carefully processed, it may yield meaningful results (see e.g., Athey & Bouchard, 2013; Bright et al., 2012; Krebs, 2002; Milward & Raab, 2006; Silitonga et al., 2016). However, it is important to keep the limitations of the data in mind when interpreting the results and drawing conclusions.

In our study, we rely on online and print media as a data source. We extracted the data from a Czech media database called Newton Media Search, searching for online or print articles containing the names of each pair of actors simultaneously (e.g., "David Rath" AND "Petr Kott" or "David Rath" AND "Lucia Novanska" and so on) and also for "kauza Rath", which is the Czech name of the analyzed case. We then sorted out 20 most relevant articles for the whole case as well as for each pair of actors (based on the Newton Media Search criterion called relevance) from the period from 2011 to 2015 (i.e., from a year prior to the outbreak of the scandal), resulting in a total of 240 unique articles[25]. We have checked all these reports. In case there was a statement about a connection between any of the involved actors, we saved the source as well as the exact wording of the statement. After deleting multiplicities, for instance multiple mentions of Kott and Pancova being in an intimate relationship, we ended up with 49 records of ties between the actors, which is the total number of ties for all dimensions in the network.

Subsequently, we coded all ties into the three dimensions: pre-existing ties, resource transfer, and collaboration, based on their content. All coding was again conducted by a second, independent researcher. Only three ties were coded differently, which were then recoded based on mutual agreement between coders. Therefore, we consider the coding to be reliable.

Measures

Pre-existing ties are relations based on shared affiliations of actors (e.g. being members of the same party or of the directorial board of the same company) or their mutual involvement in a personal relation (e.g. being married or being university classmates). *Resource transfer* ties were derived from information about bribing, kickbacking or placing a manipulated contract

[25] The total number of articles searched this way was 1120 (20 articles for 55 pairs of actors and 20 articles for the case as a whole), but due to overlap between the articles, some of the articles were found repeatedly. For example, a review article on the case contained "kauza Rath" and it also contained the names of each of the 11 actors and thus it appeared in results for the search for each pair (55 times) and in the search for the whole case (once). Hence, the number of unique papers is 240.

between the actors. *Collaboration* ties were coded accordingly when two actors were reported to be meeting together, communicating with each other or cooperating on a certain task.

Because the *pre-existing ties* dimension is based on shared attributes or similarities between actors, this dimension is undirected by definition. Although ties in the *resource transfer* and *collaboration* dimensions can be thought of as directed, we decided to code these ties as undirected due to insufficient information about the direction of ties. Specifically, the data sources were rarely detailed enough to specify the direction of ties, for instance, who called whom or who encouraged a personal meeting with whom. Rather, these interactions are typically simply described as just happening, e.g. person A and person B met each other or were in contact with each other. Similarly, in some cases of *resource transfer*, it is possible to distinguish who bribes whom, but in other cases such as sharing profit from a manipulated contract, the direction is indistinguishable. The same reasoning leads to considering all ties as binary (i.e., absent or present) rather than weighted as detailed information about frequency of collaboration or volume of resource transfers is rarely, if ever, specified. Thus, all three dimensions are undirected and binary.

Analytic strategy

To obtain a first view of the network, the multiplexity is provisionally left out of consideration and these several dimensions are aggregated into a single simplex network. We aggregated the dimensions with the use of logical expression of union (Hanneman & Riddle, 2005). This means that if there is a tie between two actors in at least one of the dimensions, then it exists in the aggregated network. This yields an aggregated network where ties represent any connection between the actors. This gives us a picture of the overall network structure. Subsequently, we decompose the aggregated network by looking at each dimension separately.

First, we describe all the three dimensions and the aggregated network by the number of participating (connected) nodes, number of ties, density, centralization, average degree and its standard deviation, average geodesic distance and diameter, using corresponding computations in the UCINET (Borgatti, Everett, & Freeman, 2002) software and the statnet (Handcock, Hunter, Butts, Goodreau, & Morris, 2003) package in R.

In order to answer the first research question concerning the core/periphery structure, we fitted the ideal core/periphery model to the data and compared its fit using the categorical core/periphery routine in the UCINET software package (Borgatti & Everett, 2000). Put simply, this attempts to optimally partition nodes into two sets (i.e., core and periphery) and simultaneously uses (dis)similarity measures (e.g., correlation or Hamming distance) to show the goodness of fit of the empirical data to the ideal model, in which the core is a complete graph (a clique) and periphery is an empty graph. A good fit indicates that the observed network exhibits the core/periphery structure. We ran the routine with varying starting configurations in order to see if the resulting solution is robust.

To answer the second research question, about the multiplexity of ties, we analyzed overlapping ties between dimensions in two steps. First, we calculated similarities between the dimensions. For this purpose, we computed the Jaccard coefficients for each pair of dimensions, which is a ratio of ties being present in both compared networks to the number of ties present in at least one of them. This is 1 if the networks are identical and 0 if they have no ties in common. Second, we analyzed the overlap of ties in a similar way as Bright and colleagues (2015). We used the multiplexity coder function in the UCINET, which assigns different codes to each different combination of dimensions between each pair of actors. This allows us to see which dimensions overlap between which nodes.

For the third research question, about centrality and multiplexity of the individual actors, we first computed the standard degree and betweenness centrality measures. Degree of a node is a simple count of all adjacent nodes. Betweenness of a node is the proportion of shortest paths between all other nodes that include the given node. In order to identify strategic positions, we also calculated means of both these measures. Following the same procedure as Morselli (2010) and Bright et al. (2015), we then deem nodes strategically positioned if their betweenness value is higher than the mean value and degree value lower than the average. Subsequently, we term actors with below average betweenness and above average degree as “visible”. Actors with values for both measures exceeding their mean are called “central”. Lastly, those with both values below the mean are labeled as “marginal”. In the second step, we computed the multiplex participation index (further see Battiston et al., 2014). Essentially, this index measures how ties of a node vary across different dimensions and is standardized with values ranging between 0 (absence of multiplexity with concentration of ties in one dimension) and 1 (perfect multiplexity with ties equally spread across all dimensions). If this range is divided into thirds, then the lower third values belong to uniplex or focused nodes, middle range values cover mixed nodes and the highest values reflect multiplex nodes (ibid.).

Visualization

As is usual in SNA, we use sociograms to visualize our network. The inclusion of multiplexity calls for some adjustments. We decided to adopt the visualization strategy for multiplex networks proposed by Kivelä and colleagues (2014). Their idea is to visualize the aggregated network first, save coordinates of the nodes in the aggregated network and then visualize each dimension separately with nodes anchored in these coordinates. This allows for easy visual comparisons between different dimensions and is less cluttered than visualizing all the dimensions in one graph with the use of different line colors or line types. Concerning the analysis of overlap, we decided to visualize the result using the well-known Venn diagram, which is suitable for capturing overlapping sets of objects (see e.g., Papachristos and Smith, 2014).

We also present a permuted core/periphery matrix as a result of the model fitting. It is an adjacency matrix rearranged in such way that nodes belonging to the core are grouped together and nodes belonging to the periphery are also grouped together. These two groups are just visually distinguished by a dividing dashed line drawn in the matrix. For networks with small number of nodes, this is clear and offers the advantage to closely inspect particular ties or actors.

In order to display the strategic positioning, we also use a scatterplot of degree and betweenness with dashed lines representing the means of both these measures (Bright et al., 2015; Morselli, 2010). This divides the graph into four parts corresponding to the "strategically positioned", "visible", "central" and "marginal" types of actors.

3.7. Results

Descriptive statistics

Table 1 shows descriptive statistics of all the three dimensions and the aggregated network (see also Figures 1 to 4). Note the absence of average geodesic distance and diameter for the *pre-existing ties* network. Both measures are based on path lengths and connectivity of the network, but this particular network is disconnected and most of the shortest path lengths are undefined (or infinite) as a result, making it meaningless to include these calculations. This is the least dense and the least centralized dimension. It is also the only dimension in which some nodes do not participate (have no ties). There are five such nodes. The densest and most centralized dimension is *collaboration*. The high density reflects the small number of nodes, but the average degree indicates frequent activity of actors in this dimension. Centralization is high in the collaboration dimension, suggesting that all the activities were concentrated around a few influential actors. This makes the network effective in terms of cooperation due to good flow of information, yet vulnerable due to potential disintegration with removal of central actors. The *resource transfer* dimension is less dense and less centralized than *collaboration*. It has also longer geodesic distances on average. Nevertheless, all nodes are connected in this dimension, but due to lower average degree and longer distances, the flow of resources is less cohesive than collaboration. It is also worth mentioning that aggregating all the ties does not lead to dispersion or lesser centralization for the actors but even stronger centralization. Therefore, the network as a whole is neither polycentric (centralized around a few different locally central nodes) nor flat (with evenly spread centralities), which is consistent with findings from other studies (e.g., Varese, 2012).

Network descriptives								
network	nodes	ties	density	avg degree	SD degree	centralization	avg geodesic	diameter
aggregated	11	32	0.58	5.82	2.75	0.51	1.42	2
pre-existing ties	11	5	0.09	0.91	1.04	0.26	-	-
resource transfer	11	15	0.27	2.73	1.56	0.28	2.12	4
collaboration	11	24	0.44	4.36	2.46	0.44	1.66	3

Table 3.1: Network descriptive statistics for all dimensions and the aggregated network

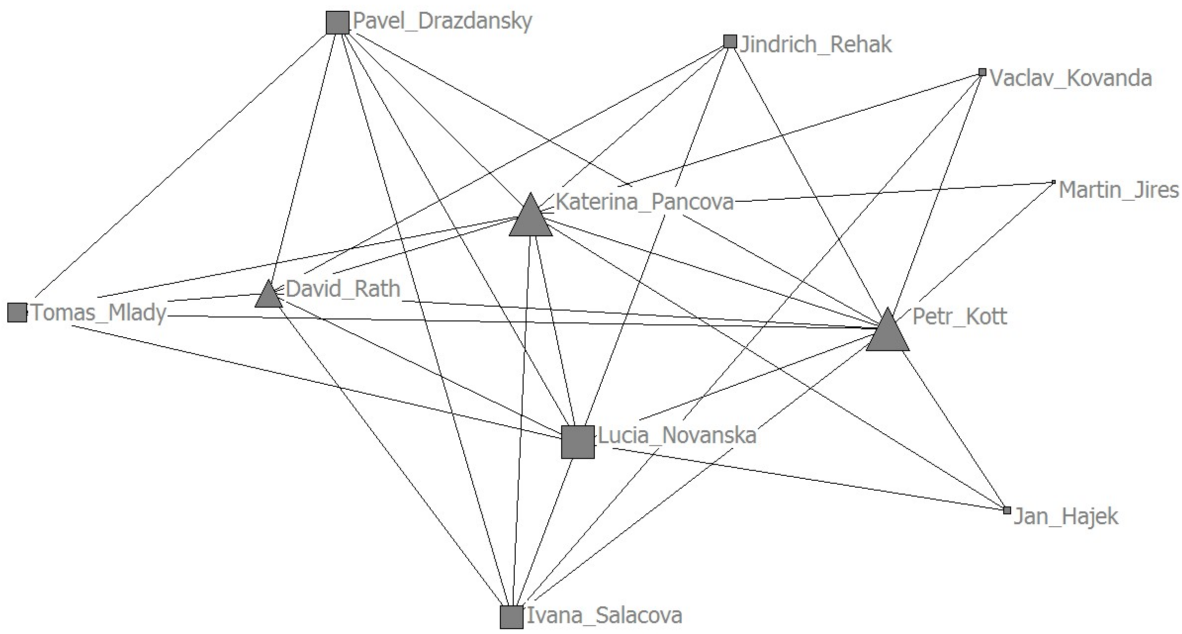


Figure 3.1: Aggregated network. Triangles represent politicians.

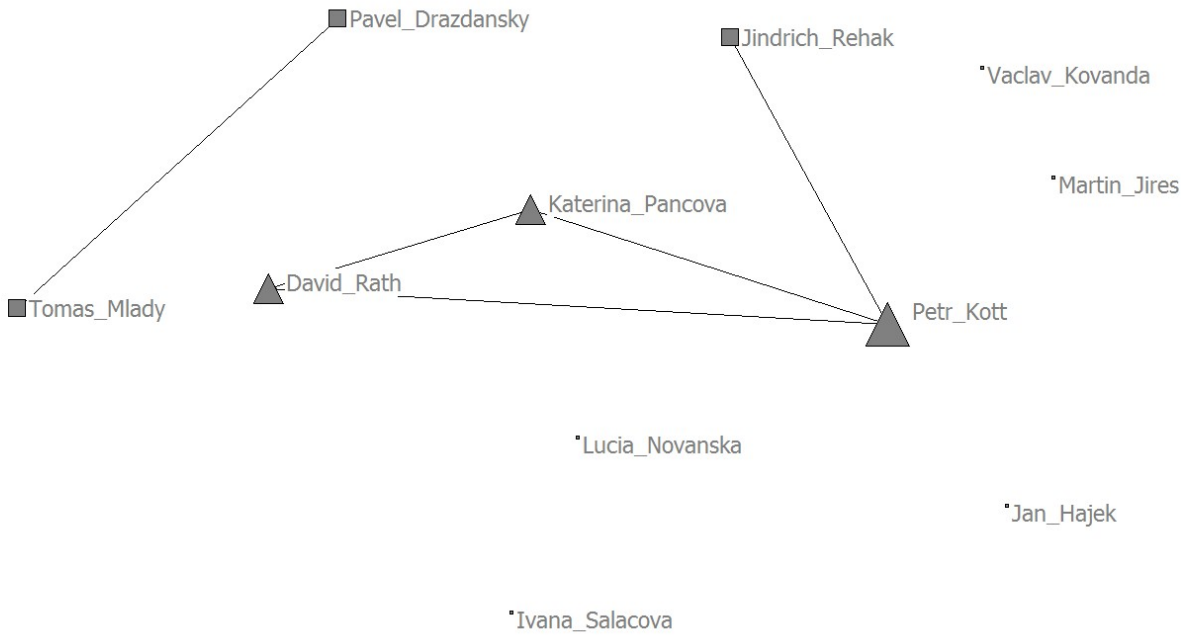


Figure 3.2: Pre-existing ties dimension network. Triangles represent politicians.

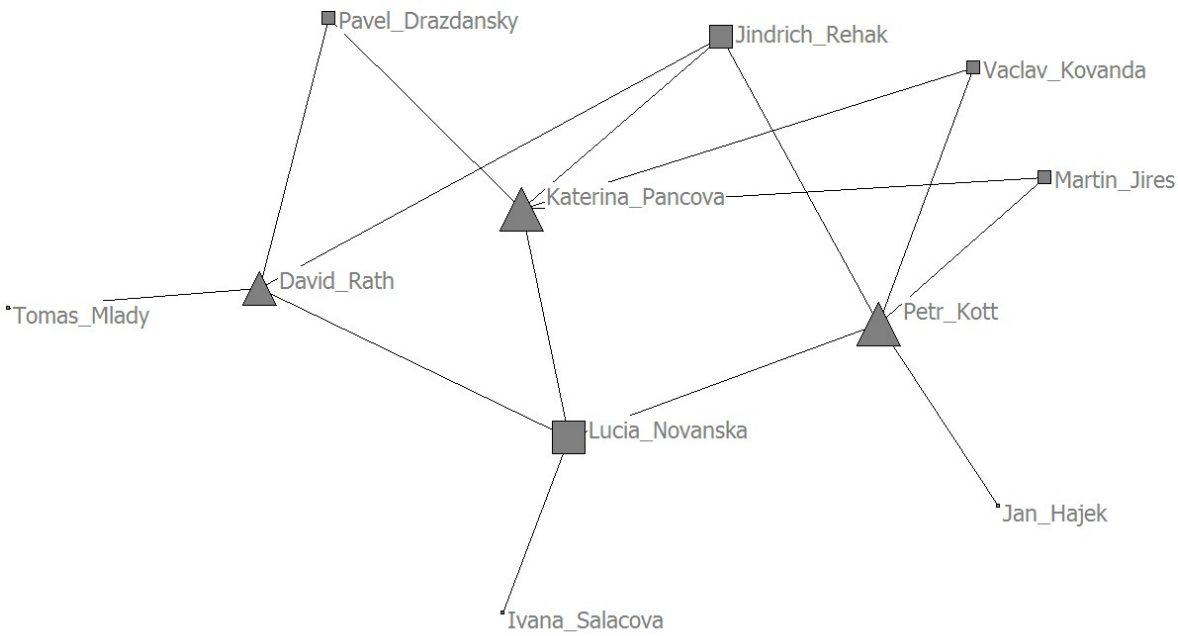


Figure 3.3: Resource transfer dimension network. Triangles represent politicians.

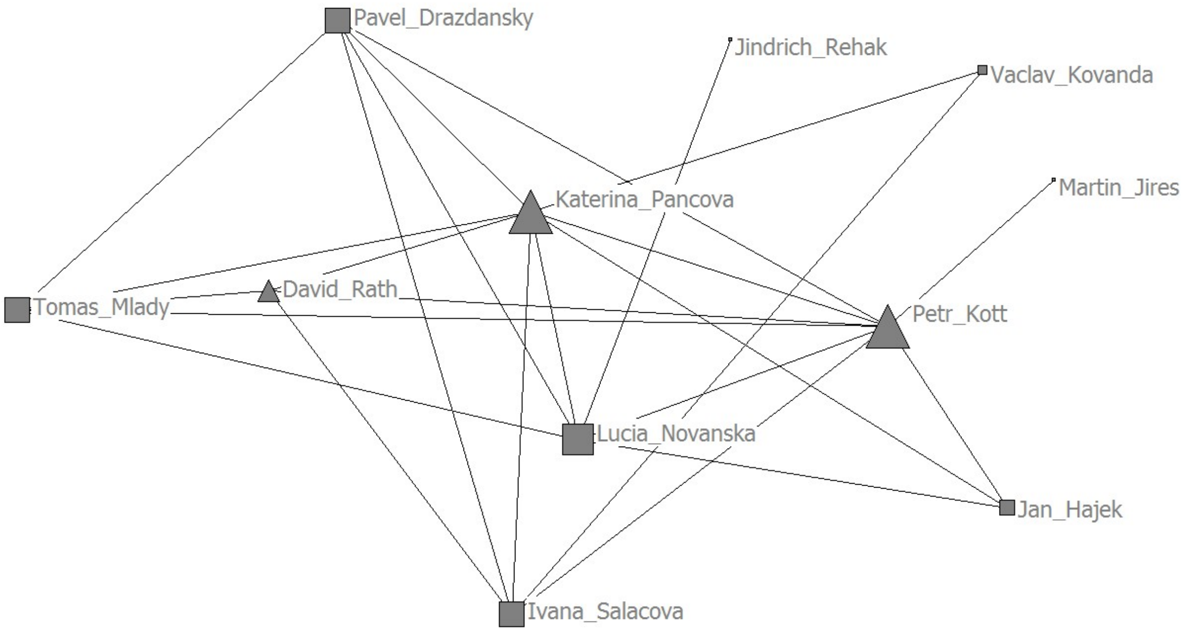


Figure 3.4: Collaboration dimension network. Triangles represent politicians.

Core/periphery

To answer our first research question about the core/periphery structure in the network, we fitted the ideal core/periphery matrix with the observed aggregated matrix and then looked at their correlation. This correlation was 1.0, showing that this network exhibits a perfect core/periphery structure. This is also shown in the permuted core/periphery matrix (Table 2). We see that indeed the core is fully connected, and the periphery is an empty graph. Further, no periphery member is connected to all core members. The core is composed of, first, the three politicians, Rath, Kott and Pancova, who were handing over all the corrupted contracts. Kott and Pancova are the only actors who are connected to all others in the network. The three were helped in manipulating these contracts by another member of the core – Novanska. The remaining two actors from the core are the most central managers, Drazdansky and Salacova, who were frequently connecting other actors from the core and from the periphery and cooperated on more than one manipulated contract with other members of the core (Deník.cz, 2013; parlamentnilisty.cz, 2013). The periphery consists of the remaining businessmen, who (unlike Drazdansky and Salacova) were involved in criminal activities only occasionally or ad hoc in order to exploit a single opportunity for kicking a contract or participating in a manipulated competition. This interpretation substantively validates this partition of the core and periphery as there is a clear dividing line between densely interconnected and active actors in the core and marginal actors in the periphery with only connections to the core. In corruption networks, politicians and officials who are in possession of demanded services and power, may become highly attractive and/or active and thus central. This is a mechanism of generalized social selection, where individuals with certain qualities tend to occupy adequate structural positions within the network (Robins, 2009). This gives rise to the centralized network structure. In this case, the core has more members than the periphery, contrasting to what is mostly seen for core/periphery structures. We do not know if this is a true characteristic of this case; it is also possible that the periphery is larger and contains some more individuals, as yet undetected. It is also important to note that the perfect core/periphery structure in this case may be to some extent an artefact of the media-derived data. Specifically, there might be some ties missing among the peripheral actors in the network as a result of the "spotlight effect" (Smith & Papachristos, 2016), that is, disproportionate attention of journalists towards the core actors of the case. However, because the core is so dense, the overall core-periphery would still be present, albeit not in perfect form, even if there were some ties present among the peripheral actors.

Permuted core/periphery matrix												
	actor	1	2	3	4	5	6	7	8	9	10	11
1	David Rath		1	1	1	1	1		1		1	
2	Petr Kott	1		1	1	1	1	1	1	1	1	1
3	Lucia Novanska	1	1		1	1	1		1		1	1
4	Katerina Pancova	1	1	1		1	1	1	1	1	1	1
5	Pavel Drazdansky	1	1	1	1		1		1			
6	Ivana Salacova	1	1	1	1	1				1		
7	Martin Jires		1		1							
8	Tomas Mlady	1	1	1	1	1						
9	Vaclav Kovanda		1		1		1					
10	Jindrich Rehak	1	1	1	1							
11	Jan Hajek		1	1	1							

Table 3.2: Permuted core/periphery matrix

Multiplexity

As it can be seen in Table 3, the low values of Jaccard coefficients reveal that the three different dimensions do not overlap very much. The sparseness of pre-existing ties leads especially to low Jaccard coefficients for this network. In order to disentangle the overlap between dimensions, it is necessary to analyze the patterns of overlaps more closely. Results of this analysis are shown in the Table 4 and depicted in a Venn diagram (Figure 5).

In total there are 55 dyads, pairs of actors, in the overall undirected network. These 55 dyads can be arranged into 8 different types based on their composition, that is, from empty null dyads to fully multiplex dyads containing a tie of each dimension and every possible combination in between (Figure 5). 23 of all dyads are null, having no ties at all. The majority of the present ties are uniplex (20 out of 32, i.e., 62,5%), which corresponds with previous research findings (Bright et al., 2015; Papachristos & Smith, 2014; 2016). Even though there are only five ties overall in the pre-existing ties dimension, none of them is uniplex. This means that ties in this dimension are not functional by themselves, but rather serve as a basis or facilitation for ties in other dimensions, mostly (four of them) in the collaboration dimension.

On the contrary, collaboration was possible to be carried out mostly without a combination with any other type of tie. In seven dyads, it was also accompanied by transferred resources. Pure resource transfer without further cooperation or communication, and not combined with pre-existing ties, appeared in seven instances. Lastly, there is no fully multiplex dyad in the network. This together with the low number of pre-existing ties means that the dimensions of collaboration and resource transfer are vital to the functioning of the network as a whole, while the role of pre-existing ties is in reinforcing other relations and interactions.

	1	2	3
1 Pre-existing ties	-		
2 Resource transfer	0.05	-	
3 Collaboration	0.16	0.22	-

Table 3.3: Jaccard coefficients of dimension networks

Core/periphery matrix with dimension overlaps												
	actor	1	2	3	4	5	6	7	8	9	10	11
1	David Rath		5	1	5	1	2		4		1	
2	Petr Kott	5		4	5	2	2	4	2	1	3	4
3	Lucia Novanska	1	4		4	2	1		2		2	2
4	Katerina Pancova	5	5	4		4	2	1	2	4	1	2
5	Pavel Drazdansky	1	2	2	4		2		5			
6	Ivana Salacova	2	2	1	2	2				2		
7	Martin Jires		4		1							
8	Tomas Mlady	4	2	2	2	5						
9	Vaclav Kovanda		1		4		2					
10	Jindrich Rehak	1	3	2	1							
11	Jan Hajek		4	2	2							

Table 3.4: Core/periphery structure including multiplexity. 1 = only resource transfer; 2 = only collaboration; 3 = pre-existing ties & resource transfer; 4 = resource transfer & collaboration; 5 = collaboration & pre-existing ties

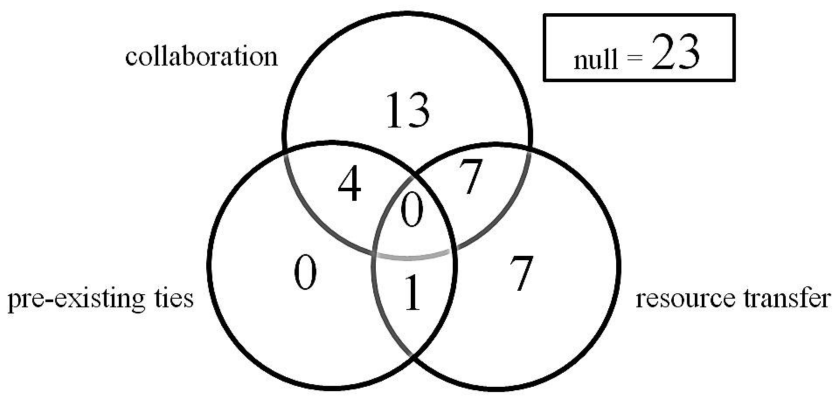


Figure 3.5: Venn diagram of dimension overlaps

Additional analyses

As an additional step, we combined the dimension overlaps with the core/periphery structure of the network. This shows which of the overlapping ties fall into the core, which into the periphery, and which cross between them. Table 4 shows all tie overlaps. First of all, the pre-existing ties are not exclusively located only in the core block – three of them are, but the remaining two are located in the core/periphery block. Although these ties link some of the important figures in the core, there is no evidence that these ties are exclusive to the most central actors. Specifically, some of the most central actors are not connected in this dimension (Novanska and Salacova) and other core members are, but there are also some peripheral actors participating in this dimension (Rehak and Mlady).

Collaboration ties are evenly spread across the network segments – exactly half of them are located within the core and the other half is a part of ties between core and periphery. However, this is not true for the dimension of resource transfer. Exactly two fifths of these ties (40 %) are a part of relations between the core actors, whereas the remaining 60% of resource transfer is going on between core and periphery nodes. This further supports the theoretically expected notion of patron-client relationships (della Porta & Vanucci, 2012; Funderburk, 2012; Granovetter, 2004), where patrons provide “favors” for clients in return for their support or resources. Therefore, even though we don’t have directionality of ties, we can say who is a patron and who is a client based on actors’ network position and their attributes. High density of collaboration among patrons in this regard may be explained as mutual attempts to strengthen their position and to protect themselves. It is also indicative of their organizing and coordinating efforts in terms of the activity of the whole group.

The overall core/periphery structure thus is built up from a dense collaboration within the core and a slightly sparser collaboration between the core and the periphery. The collaboration is cemented with the resource transfer between the members of the core and periphery, in accordance with the notion of patron-client relationships. While pre-existing ties reinforce other relations, they are not necessary for them – only a handful of resource transfer or collaboration ties were underlined by them. The multiplex overlap of collaboration and resource transfer is an important building block of the macro-structure.

Centrality measures

Table 5 shows the degree and betweenness of each actor in the aggregated network together with their multiplexity participation index. Surprisingly, Rath himself is not the most central actor in the overall network. The most central actors in terms of both degree and betweenness are the married couple Pancova and Kott, followed by Novanska. Kott and Pancova were behind all the manipulated contracts and bribes, which is reflected by their degree of 10. This means they have a tie in at least one dimension to every other actor in the network. Novanska was involved mainly because of her expertise in handling and corrupting contracts (Lidovky.cz, 2014). The eponymous actor, Rath, was very well informed and consulted by Kott and Pancova, but this couple also took care of the majority of all the work (Lidovky.cz, 2013). This probably also explains why they are more central and arguably also more important for integration of the group as a whole. Less central positions are held by managers and businessmen. This is quite logical, as they were mostly involved ad hoc for one specific task or contract. Furthermore, all the peripheral actors have a betweenness of zero, which is in fact a consequence of a perfect core/periphery structure.

The role of Rath begs the question whether he is strategically positioned within the network or not. As it turns out, there is neither a strategically positioned actor (with above average betweenness and below average degree) nor any actor close to being strategically positioned. The two centrality measures are highly correlated ($r = .85$), indicating that nodes are either central in both measures or not. This implies considerable visibility of central actors and thus also high exposure and the risk of detection.

The analysis of multiplexity of ties of each actor complements this picture. Overall, none of the actors is uniplex or focused. On the contrary, the majority of actors is multiplex as indicated by the multiplex participation index which exceeds the value of 0.66. On the one hand, with the highest values of this index, ties of Rath and Kott span across all dimensions and thus these actors bring the network together. On the other hand, Hajek and Jires are the least multiplex nodes. They are the only nodes with mixed ties and they also have low overall degree.

To gain further insight, we also combined the centrality measures with this multiplexity measure. Combinations of positions and multiplexity of nodes in the network are shown in Table 6. As we have already stated above, nodes are neither focused nor strategically positioned. The three multiplex and central nodes are Kott, Pancova and Novanska. They are the most active actors and furthermore, they are active across dimensions. Another set of three nodes are those, who are highly visible (high degree) and multiplex. This set consists of the remaining actors from the core – Rath, Drazdansky and Salacova, although Salacova's multiplex participation index is borderline (= 0.67). The last set of nodes is composed of the five marginal actors from the periphery of the network, who are either multiplex or mixed in terms of their multiplexity. In general, the centrality measures further confirm the fact that the network is core/periphery structured with the core consisting of politicians and officials, and the periphery of business people. All the central actors exhibit a strong tendency towards multiplexity, yet none of them exhibits tendencies towards the security of strategic positioning.

actor	degree	betweenness	participation
David Rath	7	0.95	0.96
Petr Kott	10	9.12	0.93
Lucia Novanska	8	2.62	0.72
Katerina Pancova	10	9.12	0.88
Pavel Drazdansky	6	0.2	0.86
Martin Jires	2	0	0.42
Ivana Salacova	6	1	0.67
Tomas Mlady	5	0	0.67
Vaclav Kovanda	3	0	0.75
Jindrich Rehak	4	0	0.84
Jan Hajek	3	0	0.56
mean	5.82	2.09	0.75
standard deviation	2.75	3.56	0.17

Table 3.5: Centrality measures

	multiplexity		
positioning	multiplex	mixed	focused
central	3	0	0
strategically positioned	0	0	0
visible	3	0	0
marginal	3	2	0

Table 3.6: Positioning and multiplexity

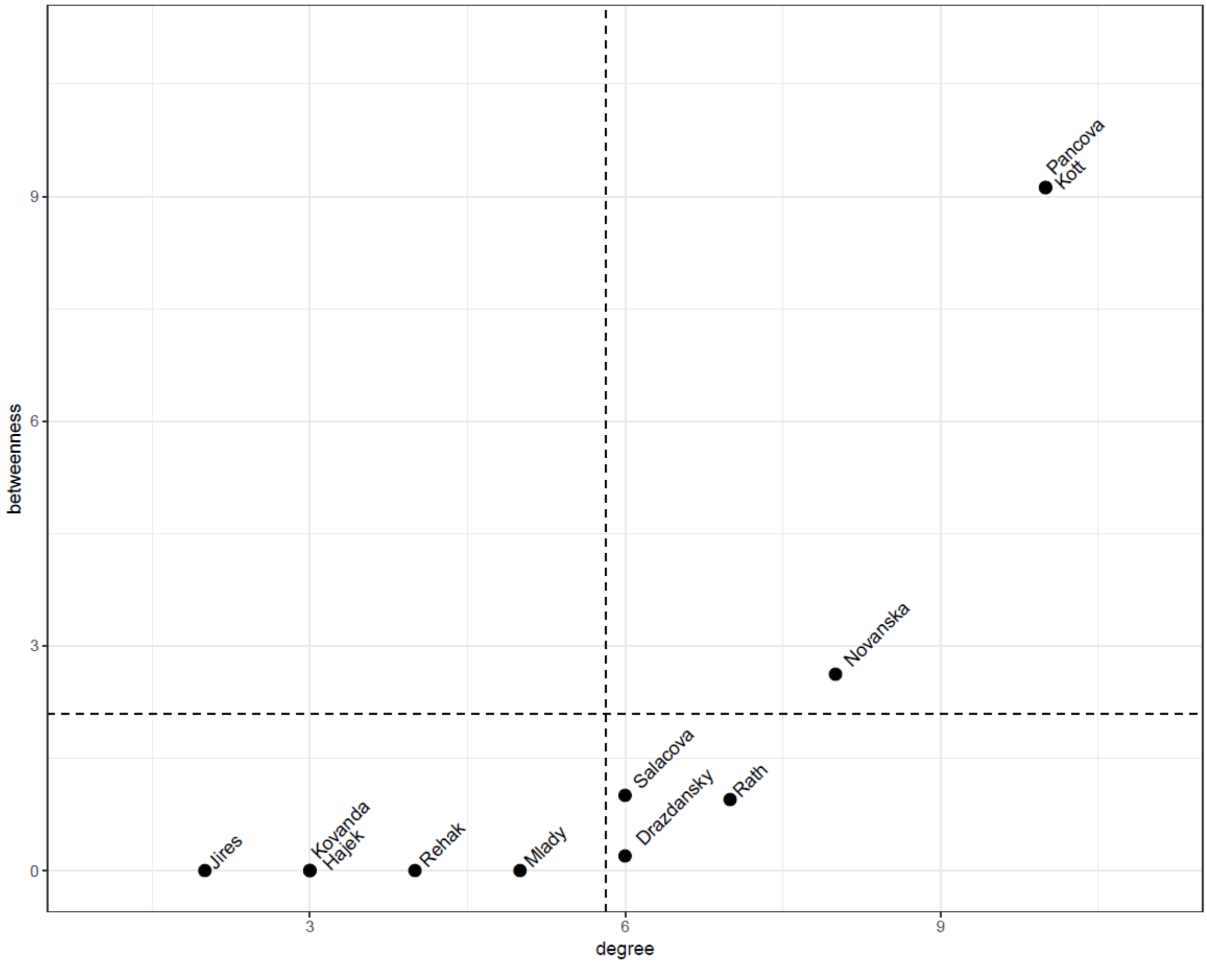


Figure 3.6: Positioning of actors

3.8. Discussion

One question arising from our analysis is related to the theoretical discussion about the importance of trust in organized crime and covert networks. While the dimension of pre-existing ties − which in the literature is supposed to be the basis for trust − underlies and reinforces other types of ties, in the Rath case it seems very sparse, and dissimilar to other dimensions. Thus, our findings suggest that this criminal network operated without being firmly based on pre-existing ties, which contradicts results or assumptions of other researchers (e.g., Erickson, 1981; Krebs, 2002; van der Hulst, 2011; Battiston et al., 2014). Which other bases for trust are there in the absence of pre-existing ties? Varese and Campana (2013) mention, for example, third party enforcement, cutting of options to defect, taking hostages, or threat and potential use of violence. For cases like the one studied here, the influence of third parties and cutting of the options by knowing about illegal deeds of others come to mind as ways to enforce cooperation and to prevent defection. Alternatively, von Lampe and

Johansen (2004) show cases where there is no fundamental need for trust at all in order to cooperate in criminal networks and defection is considered as a real possibility. Such cases may be for example purely risking the cooperation in adverse conditions with no feasible alternatives, or just accepting the possibility of others defecting as a natural or even thrilling part of the criminal activity. One especially important base for trust is worth mentioning in the light of other findings of our study. Smith and Papachristos (2016) argued that it is in fact the overlapping of multiple types of ties which builds trust and reduces uncertainty among the offenders in the network by rooting the relation in multiple bases. So in cases where pre-existing ties are not extensive, overlapping of resource transfer and collaboration may possibly be a mechanism compensating for the lack of pre-existing ties or other trust-enhancing mechanisms. If two actors engage in a lot of common activities, they may lose a lot by defecting in one of them. However, these modes of cooperation as well as the role of trust itself need to be further empirically investigated.

Another question arises from the results about the core/periphery structure of the network. Why did these persons act in a way that made their interactions so centralized and frequent, even though this was dangerous as it made the network vulnerable to the disruption in the core? From the network point of view, none of the actors tried to reduce the risk by seeking a strategic position, that is, by minimizing redundant connections. Of course, it is highly problematic to assume that actors themselves actually think about their activities in network terms, but they are still able to reflect upon their actions and tell whether they are not "taking it too far". One possible explanation for this may be their reliance on their elite membership status (Demiroz & Kapucu, 2012) such as being an official or a politician (for instance, Rath had the deputy immunity[26]). This elite membership status in turn led actors to foster a belief and a strong confidence that they might not be arrested or even investigated at all (ihned.cz, 2013). The core-periphery structure has an important implication for the disruption of such corruption networks. While actors in the core may be easier to detect, it is necessary to capture all the members of the core in order to effectively incapacitate the network, because all the members of the core are structurally equivalent and thus a single removed actor may be quickly replaced by another one. However, such network interventions should always take the shortcomings of the data into account. For example, prior to the intervention, the results

[26] In the Czech Republic, deputies are protected by the law from being arrested or sentenced unless they are caught immediately after committing a crime.

obtained from one data source should ideally be triangulated with data obtained from other sources.

An interesting point connected to the “visible” actors is the fact that it allowed the police investigators and law enforcement representatives to take the advantage and make two crucial steps in the investigation – arresting Rath red-handed while taking a bribe, and later turning Salacova to become a star witness and subsequently provide critical evidence in the trial (ihned.cz, 2013). We suppose this was made possible by the highly visible positioning of these two actors within the network. Because of their high degree, the role of Rath was easily traceable and Salacova could provide essential information about other actors in the network.

3.9. Conclusion

The goal of this study of a Czech political corruption network was to understand its structure by focusing on its characteristics as a multiplex network, distinguishing the three network dimensions of collaboration, resource transfer, and prior existing ties. Specifically, we aimed at answering three interconnected research questions – whether the network has a core/periphery structure, how the multiplex dimensions overlap in its structure, and which actors are central in the network. First, the aggregated network exhibits a close to perfect core/periphery structure with all the involved politicians located within the core, and businessmen in the periphery. Second, ties in the collaboration dimension are evenly split between the core block and core-periphery block, while resource transfer ties are mostly located between core and periphery. The dimension of pre-existing ties is very sparse and all of the pre-existing ties are combined with at least one of the other dimensions. Most of the ties are either collaboration or resource transfer, not both; not a single tie covers all three dimensions. Last, there is a clear distinction between prominent and marginal actors, but none of the more prominent actors occupies a strategic position in the sense of trying to hide by minimizing redundant connections. A vast majority of actors are multiplex in terms of spread of their ties across multiple dimensions.

We reviewed previous studies that employed the notion of multiplexity in covert settings. The findings of these studies together with ours show that the multiplex point of view may reveal important information. However, this gives rise to the question why there are not more studies of criminal networks highlighting multiplexity. This may be on the one hand due to difficulties of data availability and data validity. In the context of criminal networks, it is much more difficult to distinguish several network dimensions, because it is already so difficult just to determine if there is a tie or not in the first place (Gerdes, 2015a). Most research about criminal networks is data-driven (Bright, Hughes, & Chalmers, 2012; Carrington, 2011), and if the available data do not allow to specify different dimensions of interaction, the multiplex analysis is simply impossible. The other reason may be a lack of suitable methods for description of multiple dimensions simultaneously – while conceptually and computationally more elaborated network analysis methods such as exponential random graph models (Robins et al., 2007) or stochastic actor-oriented models (Snijders et al., 2010) have their extensions to multiplex data, simple descriptive measures such as centrality or cohesion measures for multiplex networks are in their "infancy" (Kivelä et al., 2014). And since the field of covert and criminal network analysis is mostly based on these more simple measures (probably because of unfamiliarity with statistical models as well as theoretical interest in network description; see Campana, 2016), the possibility to include the aspect of multiplexity into the analysis might have been overlooked. We believe that the multiplex participation index of Battiston et al. (2014) and the dimensions overlap analysis are two of such potentially fruitful measures for description of multiplex networks.

An evident difficulty for our approach is data quality and reliability, as data on covert networks are in principle impossible to collect by standard means of observation or questionnaires. Thus, a researcher in this area is left to rely upon other sources of data, which may vary in their availability and validity (Bright et al., 2012). We have used publicly available open-source data from media. Clearly, data obtained from this source suffer from problems with validity and reliability. Therefore, the results should be taken with a grain of salt, as there may be some information missing. As was already pointed out above, such missing information may to some extent alter the results. In order to make the most of the available information, it is necessary to process the data carefully. We performed a content analysis with pre-specified coding categories. Content analysis not only fulfils requirements for careful data processing with its reliability check (see also Stevenson & Crossley, 2014). Van der Hulst (2009) also recommends content analysis as a suitable complement to SNA in criminal networks research, because it allows taking a more detailed look at the data and thus gaining more solid understanding of the studied case and its context and making the interpretation more valid (further see e.g., Campana & Varese, 2012; Natarajan, 2006). We complemented our quantitative findings with qualitative insights based on our content analysis. From this point, one possible extension for this research could be to incorporate qualitative methods even more with a fully mixed-methods design. Qualitative analysis allows to derive the meaning from the network or as Crossley and Stevenson (2014) aptly expressed it – if network analysis captures the structure, then qualitative methods complement it by capturing the agency.

Related to the discussion of proper methods for the analysis of multiplex criminal networks is the issue of theory-building to overcome the lack of feasible theoretical explanations in the field (Carrington, 2011; van der Hulst, 2011). The case presented in this study was analyzed with mechanism-based explanations in mind. This can be elaborated in further research. Mechanism-based explanations have been pioneered within analytical sociology (Hedström, 2005; Hedström & Bearman, 2011) and this analytical approach to the explanation of organized crime may be of good use to criminology. The mechanism approach seeks to explain a social phenomenon by identifying a constellation of entities and activities, typically actors and their actions, that are linked to one another in such a way that they regularly bring about the type of phenomenon in question (Hedström, 2005, p. 2). There is an evident synergy between this approach and SNA, as they both are concerned with actors and their relations. Furthermore, analytical sociology explicitly relies on actor-oriented explanations (ibid.), which counterbalances the overemphasis on network topology in the analysis of criminal networks (Robins, 2009). A synthesis of these approaches may help the field of criminal networks studies both in theorizing as well as in modelling. This study shows that looking at mechanisms such as multiplex overlap of ties is an important factor in explaining the structure of criminal networks and may help to advance our understanding of corruption.

4. Poisonous connections: A case study on a Czech counterfeit alcohol distribution network[27]

4.1. Introduction[28]

Studies about trafficking and smuggling of illegal commodities have aimed to unravel the overall network structures. In comparison to co-offending networks and also to their legal counterparts, these networks tend to exhibit a lower number of ties (density) and less concentration of ties around key actors (centralization). Moreover, trafficking and smuggling networks also reveal stronger centralization than terrorist networks (Bichler, Malm, & Cooper, 2017). For instance, Natarajan (2006) found that the network of heroin distribution in New York City was composed of small compact groups which were loosely interconnected. There is also evidence that drug trafficking networks may be evolving over time in response to supply/demand, and to the activity of law enforcement agents (Bright & Delaney, 2013). Hughes, Bright, and Chalmers (2017) mapped the functional and structural differentiation of poly-drug distribution networks operating simultaneously with multiple types of drugs. This differentiation may take different forms, such as outsourcing production to another drug syndicate, accompanied by the emergence of clear management structures with centralized oversight. A study by Lord and colleagues (2017) on a counterfeit alcohol distribution found that the network was considerably resilient and adaptive due to a number of brokers who managed and oversaw the processes associated with production and distribution.

Despite the wide application of SNA, it has been criticized, particularly for two issues. First, network research on organized crime often lacks proper theoretical foundations (Carrington, 2011; van der Hulst, 2011), being driven by available data rather than by theory (Bright, Hughes, & Chalmers, 2012). Second, research on criminal networks strongly relies on descriptive measures, neglecting complex interdependencies among actors and ties and more in-depth explanations of criminal network structures (Campana, 2016; Carrington, 2011).

This paper aims to overcome both issues by using the theoretical approach of analytical sociology (cf. Hedström, 2005; Hedström & Bearman, 2011; Manzo, 2014) and analytical

[27] This chapter is based on: Diviák, T., Dijkstra, J. K., & Snijders, T. A. B. (2019). Poisonous connections: A case study on a Czech counterfeit alcohol distribution network. Global Crime, 1–23. https://doi.org/10.1080/17440572.2019.1645653

[28] We are grateful to Miroslav Scheinost for his help with getting access to the data.

criminology (Matsueda, 2017; Wikström & Sampson, 2006) in combination with statistical models developed for network data (Robins, 2013; Snijders, 2011a). The analytical approach is based on identifying micro-level mechanisms which result in outcomes at the macro level. Specifically, we aim to identify relational mechanisms that bring about the observed network structure. Statistical models for social networks synergize with this aim, as they allow to disentangle the network structure into micro-elements representing relational mechanisms. There are several examples of previous studies of criminal networks using mechanism-oriented theory and statistical models for networks (Bright, Koskinen, & Malm, 2018; Grund & Densley, 2014). We build upon this work by explicitly formulating a theory of action for criminal networks and deriving hypotheses on relational mechanisms. Subsequently, we test the hypotheses with a statistical network model.

We study a case of a counterfeit alcohol distribution network from the Czech Republic which has become publicly known as the methanol affair. This network was uncovered in the second half of 2012 after its activities resulted in numerous cases of deaths and permanent medical consequences for tens of victims due to drinking methanol-diluted spirits. The poisonous mixture had been efficiently distributed to a lot of consumers across the whole country in a process of cooperation and coordination among actors who manufactured, distributed, and sold it. We aim to shed more light on this specific case combining a general theoretical and rigorous methodological framework.

4.2. Background of the case: The methanol affair

The case studied in this paper is a network of actors involved in the production and distribution of illegal alcoholic beverages mixed with poisonous methanol. In September 2012, this affair was under widespread attention from police and media in the Czech Republic when series of deaths and serious health damages, most prominently poisoning induced blindness, occurred after consuming a poisonous mix of alcoholic beverages with methanol. In the aftermath, around 140 people suffered health damage and more than fifty died. Because of the rapid outbreak and increase in the number of victims, Czech state officials decided to impose temporary prohibition across the whole Czech Republic and temporary restrictions on alcohol export from the Czech Republic. These restrictions together with tax evasions associated with production and distribution of untaxed spirits resulted in strongly negative economic consequences.

During the investigation, it became apparent that the whole affair can be divided into two branches. The first one was based in the Zlín region in the eastern part of the Czech Republic and consisted of a long-term active organized criminal group led by RB, an entrepreneur and local *éminence grise*. This group developed an organized division of labour, provided a cover for illicit activities with legal business, and some of the actors routinely used intimidation, coercion, or physical confrontation in order to protect their illegal profits. These profits were mostly coming from tax evasion via production and distribution of untaxed alcoholic beverages. The second branch was located around the city of Ostrava and revolved around manufacturing and distribution of the incriminated lethal mix of alcohol and methanol. This mixture was originally created by a pair of actors, TK and RF, from whom it was distributed by JV, previously a legal distributor of spirits. The actors involved collaborated on the mixing of the poisonous drinks, storage, and distribution to small convenience stores or to potential customers directly.

4.3. Analytical sociology and network mechanisms

In this study we build upon analytical sociology (Hedström, 2005; Hedström & Bearman, 2011; Manzo, 2014a). The three pillars of this approach are mechanism-based explanations, the micro-macro link, and a theory of action. Regarding the first pillar, analytical sociology seeks to identify micro-level social mechanisms by identifying a constellation of entities and activities, typically actors and their actions, that are linked in such a way that they regularly bring about the phenomenon under study (Hedström, 2005: 2). This approach can be fruitful for SNA which concerns actors and relations among them. In SNA, the mechanisms of interest are the relational mechanisms connected to patterning ties in networks (Rivera, Soderstrom, & Uzzi, 2010). These mechanisms reflect tendencies of actors to act in the network in certain ways by creating, maintaining, or dissolving ties. However, actors in the network are seldom able to oversee the entire structure of the network as their information radius is limited mostly to their personal network, that is, the other actors to whom they are directly connected, with some further information about the connections of their connections. Hence, the macro-level network structure arises as a consequence of the accumulation, overlap, and collision of individual actions via relational mechanisms (Robins, Pattison, & Woolcock, 2005; Snijders & Steglich, 2015). This is the core of the second pillar of analytical sociology – explaining how macro outcomes are brought about by their micro foundations.

The analytical distinction between micro-relational mechanisms and macro-level outcomes is crucial here, as a particular characteristic of the whole network (a macro outcome), such as centralization, is not necessarily the consequence of one relational mechanism of concentration of ties because multiple mechanisms operate simultaneously either reinforcing or cancelling each other out (Hedström & Ylikoski, 2010). A strong centralization of a drug distribution network might suggest that the central actors mobilized resources and efforts into organizing and coordinating this network. However, this explanation may be incorrect if we also consider another mechanism such as triadic closure, in which three actors all become directly connected to each other. Hence, the centralization of the network might have arisen as an unintended consequence of creating closed triads which incidentally overlap due to the inclusion of particular individuals, making them in turn central. A descriptive analysis of the network does not allow to untangle these competing mechanisms. Therefore, it is necessary to use suitable statistical models for social networks to separate the contribution of several relational mechanisms to the structure (Campana, 2016; Robins et al., 2005). Such statistical network models employ computer simulations to effectuate the micro-macro link.

4.4. Theory of action

The third pillar of analytical sociology is a theory of action (Hedström, 2005; Manzo, 2014b). The theory of action specifies motives, constraints, and capabilities of actors, that is what happens at the micro level. For our case, we need to clarify our assumptions on how actors will act (i.e., create, maintain or dissolve ties) in certain ways (representing relational mechanisms). We assume that actors act purposefully in order to reach their goals (J. Coleman, 1990; Lindenberg, 2008). The primary goal here is to make financial profit. In this illegal spirit distribution network, it is reasonable to assume, which is further supported by the court testimonies of the offenders themselves, that the actors attempted to reach financial profit by the sub-goal of decreasing the cost of production through mixing alcohol with cheaper methanol and, subsequently, selling the beverages to consumers.

However, this goal is accompanied by an additional sub-goal, which constitutes a definitional feature of criminal networks, namely, the aim of actors to avoid detection and remain concealed (Morselli, 2009; Oliver, Crossley, Everett, Edwards, & Koskinen, 2014). In general, creating and maintaining ties is costly as actors need to mobilize resources, such as time or cognitive capacity (Snijders, 2013). The additional constraint of trying to avoid detection in criminal networks places “extra costs” on ties as each tie in a criminal network increases visibility and thereby comes with a larger probability of being detected. This is the most important imperative of actors in criminal networks; subject to this constraint, they try to achieve the goals they had for joining the network.

The tension between both goals is captured in the efficiency/security trade-off (Morselli, Giguère, & Petit, 2007). This trade-off refers to the fact that the more the network is efficiently structured towards reaching its goals by having numerous ties, the less it is secure because of the increased visibility introduced by the increasing amount of ties. Conversely, the more securely the network is structured, the less efficient it is in reaching its goals. This conflict between efficiently reaching the illicit goal while maintaining security introduces tension into individual action. Whenever there would be a conflict between remaining concealed and generating profit, we assume actors would prefer security. The argument for this claim is that the violation of security would lead to the inability to pursue any financial profit as being arrested actors cannot manufacture and distribute illicit alcohol in the market.

4.5. Network as a channel for flows

The network of the methanol affair raised public and law enforcement attention because of how quickly the poisonous beverages spread and killed or injured considerable numbers of victims. How is it possible that a network of 32 actors, with only one pair of them capable of manufacturing the mixture, was so deadly? Networks have been regarded as channels for flows of various types of resources (Borgatti, 2005; Borgatti, Mehra, Brass, & Labianca, 2009). From this point of view, one question is how the individual actors contributed to the distribution of poisonous spirits based on their position within the network and within the distribution flow. A major aspect of network position is actor centrality (Freeman, 1979) – the more central actors are, the more influential they are for the distribution. This does not necessarily overlap with the actors' position within the distribution chain, where the importance of actors is based on how close they are to the pair of manufacturers. The closer actors are to the manufacturers the sooner they may profit from selling a batch of poisonous spirits either to other involved actors or directly to consumers.

Next to individual actors, who can be assessed in terms of their contribution to flows in the network, the structure of the network as a whole can also be characterized in similar way. The longer path a batch of bottles has to travel in order to reach a consumer, the more time it takes and the more expensive it is and likely to be uncovered. Thus, an ideal distribution network from this point of view would have the shortest possible paths from the manufacturers to the remaining actors, which implies that the pair of manufacturers would have direct ties to all the other actors. In terms of the efficiency/security trade-off, this would maximize the efficiency, but it would maximize the vulnerability at the same time. The two manufacturers might have had some naïve conception of this, when they started to look for others to distribute the mixture. The question here is to what extent the observed network of this case optimized the closeness of the manufacturers to their co-offenders, enabling the quick distribution of the potentially lethal mixture. We subsequently aim to test which relational mechanisms can explain this overall network structure.

4.6. Structure of criminal networks

The structure of the network may arise from endogenous structural mechanisms, independent of any other exogenous factors, reflecting a process of network self-organization. This simply means that creation or dissolution of ties depends on the existence and/or absence of other ties in the network (Robins, 2015; Robins et al., 2005). The term ‘flexible order’ has been used in criminal networks with a similar meaning, denoting the proposition that there is no need for an architecture or plan for criminal network structure; rather, it emerges from interactions and relations among members of the network (Morselli, 2009). The most fundamental structural endogenous mechanisms are preferential attachment, closure, and brokerage. While these mechanisms are general, we argue how they might have specifically influenced our case.

Preferential attachment describes how initial differences between actors in their numbers of ties cumulate over time to produce a highly skewed degree distribution with a few highly central actors and a lot of marginal ones (Barabási & Albert, 1999; de Solla Price, 1976). According to this mechanism, the initial number of ties triggers a cumulative self-reinforcing process, where the probability that an actor creates/receives a new tie depends on the number of ties actors have – the more ties an actor has, the more likely new ties will be made to this actor in the future, which in turn increases the probability of having even more ties. This accumulation happens when having many ties increases visibility to other members, or potential members in the network, and also when it signifies power or a lucrative position.

In criminal networks, however, accumulation of ties has a clear disadvantage as each tie also increases the risk of visibility of the actor to law enforcers, thus undermining the aim of remaining concealed. In other words, while preferential attachment may increase efficiency, it decreases security. While the profit returns from every new tie may diminish rapidly, the chance of exposure may actually grow faster with each new tie, and the costs of maintaining ties in terms of time or effort are more or less constant. The literature on strategic positioning in criminal networks suggests that actors in criminal networks actively restrict their direct ties in order to avoid detection (Bright, Greenhill, Ritter, & Morselli, 2015; Morselli, 2010). Furthermore, actors joining the network may not even be aware of who is the central actor, as they would need to see the whole network in order to fully assess this, which is a doubtful assumption in covert settings.

Hypothesis 1: Actors display tendencies against preferential attachment.

Closure is a tendency of actors to close open micro-structures or, in friendship terms, to befriend the friends of current friends. Closure is manifested in the network by the presence of triangles, that is, triads in which all ties are present. The creation of closed triangles is associated with increased social control, trust, and cooperation, because actors embedded within closed structures can oversee one another, control and support each other, and easily coordinate their efforts (Bright et al., 2018; Coleman, 1990; Erickson, 1981; Robins, 2009). All these effects strengthen the security of the network as they help to prevent defection and infiltration. These advantages of closed micro-structures may be a reason why actors display positive tendencies towards closure, despite the fact that the proliferation of ties makes the network as a whole more susceptible to detection due to increased visibility. However, actors themselves may not be aware of macro structural consequences of strong closure as that would require them to have a "bird's eye view" over the entire network and mutually coordinate ties in some network-optimal way. But even in organizations with clearly defined formal organizational structures, parallel networks of informal ties emerge which may sometimes greatly differ from the officially prescribed structures (Robins, 2009). Hence, a much more realistic assumption about actors is that they try to improve their position within their network neighbourhood by forming ties in a way they see as sufficient to achieve their goals (Snijders, 2013). Because the advantages of closure at the micro-level are directly experienced by actors rather than the disadvantages at the macro-level and they add to the security of the network by fostering trust and social support while enabling cooperation (and thus efficiency), we expect positive closure tendencies.

Hypothesis 2: Actors display tendencies towards closure.

Closure in a network with a given density is highest for networks composed of small densely connected clusters of actors that are not interconnected. For interconnecting these subgroups and limiting the extent of closure, the mechanism of brokerage may be important, as it is the tendency of actors to bridge between closed regions (Burt, 1992, 2005; DellaPosta, 2017; Robins, 2009). Brokerage thus allows unimpeded flows in the network and it also provides the brokers with a competitive advantage, which has been repeatedly documented in networks legal as well as criminal. The reason is that whatever flows in the network needs to pass through the broker in order to get from one part of the network to another (Burt, 1992, 2005; DellaPosta, 2017; Morselli & Roy, 2008; Morselli, 2010). It is certainly possible to imagine the inclination towards brokerage in the counterfeit alcohol distribution network, because this would enable the generation of profit, which undoubtedly is of interest in profit-oriented organized crime. Nevertheless, such profit serves mainly the broker and not the brokered actors. Moreover, it does not necessarily translate into the profit of the whole group. The arguments for brokerage assume an opposition between the aim of the individual and those of the group, potentially leading to free-riding, decreased control, and defection, which would violate the security of the group. Substantial free-riding or defection were arguably not viable alternatives for actors involved in this case, as they were not able to produce nor distribute any larger amount of counterfeit alcohol on their own; also many of them were embedded in the network by being tied to other actors not only in terms of the illicit activities in the methanol affair, but also by being legitimate business partners or employers/employees. For these reasons, we would not expect a tendency for brokerage among actors in the network.

Hypothesis 3: Actors display tendencies against brokerage.

4.7. Individual attributes of actors in criminal networks

In addition to considering endogenous relational mechanisms, it is also necessary to account for individual attributes of actors involved in this type of network, because attributes reflect differences between actors in their abilities to contribute to reaching their goals and the collective goal, which will influence which ties they create (Coleman, 1990; Robins, 2009). Specifically, for a case of illegal manufacturing and distribution of alcohol, tie formation might be influenced by previous experiences of actors in legitimate business with spirits. There is a theoretical stream in the literature which points out the similarities between organized crime and legitimate organizations such as firms (Gimenéz Salinas-Framis, 2011;

Kenney, 2007; Milward & Raab, 2006). In this light, such experience with legitimate organizations and skills acquired therein may be useful for criminal activity.

This projection of business experience and corresponding skills and resources into criminal activity may happen through two relational mechanisms – generalized social selection and homophily. Generalized social selection designates a situation in which actors who possess certain attributes display the tendency to acquire certain network positions, such as being central or peripheral (Robins, 2009). Actors with strategic skills and resources may be important for the successful operation of the whole network thanks to which they may hold specific positions in its structure (Bright, Greenhill, Reynolds, Ritter, & Morselli, 2015). In this case, it is possible that resources and know-how gained in entrepreneurship may predispose their bearers to more central positions. A case in point may be the ability to manage employees, translated into managing co-offenders in a criminal network. Furthermore, actors with an entrepreneurial background may be more economic in the way they profit from their ties, as success in legitimate business requires good micromanagement of one's ties. Thus, the returns from ties in criminal networks may be less diminishing for entrepreneurs than for actors without this background. Hence, we would expect the entrepreneurs to be more active in the network.

Hypothesis 4: Entrepreneurs tend to be more active.

Another mechanism based on attributes is homophily (McPherson, Smith-Lovin, & Cook, 2001), which has been consistently shown to be a powerful driving force in many different empirical contexts, including criminal networks such as gangs (Grund & Densley, 2014). Homophily is frequently expressed with the saying that 'birds of a feather flock together' as it is a tendency of actors to form ties to those who are alike themselves – in other words, to those who share the same attribute. In organized crime and in crime in general, it is possible to make a case for an inverse mechanism to homophily: heterophily, the preference for choosing partners different from oneself in certain respects. The shortcoming of homophily is that mutually similar partners may frequently share the same resources and information, but contacts and ties to different others may also enable access to new resources and new information (M. S. Granovetter, 1973). This is particularly beneficial for collaboration networks where differences may be mutually complementary (Rivera et al., 2010). The overreliance on similar alters decreases efficiency, as access to unavailable resources, knowledge and skills. This works for both entrepreneurs and non-entrepreneurs. Whereas entrepreneurs may need actors with certain skills, such as operating machines or reliable drivers, to execute the production and distribution of illegal alcohol, non-entrepreneurs may rely on entrepreneurs to participate in the first place and to receive orders on storage and distribution of the mixture. Thus, we expect the network to exhibit signs of heterophily leading to ties between entrepreneurs and non-entrepreneurs.

Hypothesis 5: Entrepreneurs tend to associate with non-entrepreneurs.

4.8. Pre-existing ties

Pre-existing ties are legitimate or legal relations that were established between members of criminal networks prior to the criminal activity itself. In the case of the methanol affair, these ties take the form of kinship, prior friendship, being employees of the same firm, or being legitimate business partners. There are two reasons why pre-existing ties has been of interest among researchers of criminal networks for a long time. First, it has been argued that pre-existing ties are a basis for interpersonal trust, which is deemed to be crucial in criminal environment, where mistrust or untrustworthy partners may have fatal consequences (Erickson, 1981; Krebs, 2002; Morselli & Roy, 2008). Second, these ties represent the intertwining of the organized crime with legitimate business and legitimate social relations (cf. Felson, 2006; Paoli, 2014). Smith and Papachristos (2016) even argue that this overlap of pre-existing and criminal ties is a cornerstone of organized crime, as it compensates for the lack of formal institutions and organizations, which warrant enforceability of contracts and commitments in licit relations. While friendship or kinship may anchor criminal cooperation in shared commitments and experience, preceding collaboration in legitimate business or other legal activities may be seen as a sign of credibility and success of criminal collaboration. In this respect, social or physical settings in which criminals may find information, resources or accomplices for their illicit activities, so-called convergence settings, may facilitate or outright enable criminal organization and collaboration (Felson, 2006). Taken together, pre-existing ties have the potential to be translated into criminal ties.

Research on multiplex social networks considers the co-occurrence of ties of different types (Wang, 2013). The observation that multiple ties of different kind overlap (e. g., friendship and mutual help) may be brought about by different mechanisms. We postulate a mechanism of tie translation, that is, the tendency of actors to create operational ties on the basis of pre-existing ties. The presence of a pre-existing tie may increase the probability of the creation of an operational tie, but not the other way around. In this way pre-existing ties increase interpersonal trust, reduce uncertainty and risk, and thus, decrease the cost of creating operational ties. Embedding operational ties in pre-existing ties does not only increase security, but it also adds to the efficiency by making such connections more “economic”. For this reason, we expect positive effect of tie translation in the network under study.

Hypothesis 6: Actors tend to create operational ties on the basis of pre-existing ties.

4.9. Data collection and processing

This study relies on court files from three different courts which were judging the studied case in the Czech Republic. Court files have been used in previous studies yielding a valid representation of given network and providing a source data which has been deemed valid (cf. Bright et al., 2012). However, court files are not without their limits. A specific weakness of summaries of court proceeding is the fact that offenders themselves are interested in withholding as much information as possible in order to obtain the best possible sentence. This yields systematically incomplete data, which may or may not be uncovered by the investigation, court, or fellow offenders. Actors on the side of law enforcement, however, focus on trying to prove the guilt of the offenders, and thus scientifically interesting aspects, such as the evolution of offenders’ relations or their individual qualities, may be omitted unless they are of specific importance for the court.

The data file was extracted from nineteen court records provided by the courts themselves, which together add up to more than one thousand pages of text. We performed all the data coding manually identifying all actors associated with the case. For each actor, the name was noted and their experience with legitimate business. All actors who were reported to be involved in the affair (i.e., they knew they were collaborating in the distribution of illegal beverages) were included in the analysis. This yielded a total of 32 actors in the network. All mentions of interactions and relations among any pair of actors were recorded including the exact citation of the court file and a code for the content of that particular relation/interaction. By far the most frequent codes were cooperation on manufacturing the illicit spirits, cooperation on their storage or transport, and supplying or demanding some amount of the beverages. However, most of these codes were not distinguishable from one another (e.g., whenever actors exchanged alcohol, it also always entailed some instructions about logistics and planning). All the ties with these codes were eventually coded as operational ties, as they serve the purpose of cooperating on the organisation of the criminal activity. The only other type of ties that was distinguishable in the court files were pre-existing ties. These ties mostly referred to friendship, kinship, legal business partnership, or employment or cooperation within distilleries (convergence settings), in which incriminated commodities were manufactured or stored. All the pre-existing ties chronologically preceded the ties coded as operational. In sum, we analyse two undirected networks – one of operational ties and one of pre-existing ties together with a binary nodal attribute indicating entrepreneurship.

4.10. Methods

Cohesion measures are used in order to assess the properties of a network as a whole (cf. Borgatti et al., 2013; Prell, 2011). Density is a proportion of ties present in the network relative to the maximum number of possible ties in the network. Degree centralization is the ratio of the dispersion of the number of ties compared to a network with maximally concentrated ties (Freeman, 1979). Closure was measured by the clustering coefficient, which is a ratio of complete ("closed") triangles to all two-paths in the network, that is, to all triads connected only by two ties. All these measures have a range from 0 to 1, where the closer the value is to 1, the denser (resp. more centralized or closed) the network is. Density and centralization can also be expressed by average degree and the standard deviation of degrees respectively, which are also directly interpretable from the actors' perspective (Snijders, 1981). The cohesion of a network can also be expressed by the average geodesic (i.e., the shortest path length between a given pair) and diameter (i.e., the longest geodesic in the entire network). The shorter the geodesics and the diameter, the more cohesive the network. A descriptive measure of observed homophily/heterophily is the E-I index (Krackhardt & Stern, 1988), which ranges from -1 to 1, where -1 indicates that all ties are homophilous, whereas 1 indicates that all ties are heterophilous.

Geodesic distances are also important for characterizing the importance of actors within the flow in the network and the speed of flows in the network as a whole. We computed the geodesic distances from the two actors who manufactured the poisonous beverages to all other actors, which indicates how long distances the beverages had to travel in order to get to each actor. For interpretation purposes, we computed the reciprocal of all these values (cf. Gil & Schmidt, 1996) so that higher values indicate shorter distances, i.e., higher importance. We then averaged these reciprocal distances to have an actor-level measure. The larger this number, the less important the actor is as it takes more time until the batch of bottles reaches him/her. The network-level characteristic derived from this measure (based on its average) indicates to what extent the network is similar to an ideally structured one for distribution. As described above, distances of all actors to the distributors in such an ideal network are equal to one. If the observed reciprocal geodesic distances are divided by this number, the result indicates how similar the observed network is to an ideally structured one where a value of one means the observed network has the shortest possible geodesic distances from the manufacturers to all the other actors. To capture the centrality of each actor in the network, we computed their degree.

To disentangle effects of the micro-level mechanisms postulated in theory, it is necessary to apply statistical models designed for network data. Standard tools of statistical modelling and inference cannot be validly used for tie variables in networks for two reasons. The first reason for not using standard statistics is the fact that the latter is based on the underlying assumption of independence of observations. This assumption is principally violated in networks (further see e.g., Borgatti et al., 2013; Prell, 2011), because tie variables are interdependent. The second reason is the contrast that, while standard statistical inference is oriented towards making inferences about a population based on the knowledge of a sample drawn from it under certain conditions, inference in networks is usually oriented towards making conclusions for a given data set about its representation by a model (Snijders, 2011). For both reasons, it is essential to apply network models which were developed to address the interdependence among observations (Snijders, 2011; Robins, 2013).

An important class of models used to represent micro-level mechanisms in networks is the exponential random graph model (ERGM; Lusher, Koskinen, & Robins, 2013; Robins, Pattison, Kalish, & Lusher, 2007). ERGMs model the interdependence of tie variables with so-called configurations, which are basic building blocks of a network, for instance, closed triads of mutually interconnected actors or pairs of actors with the same value of a given attribute. The network structure is considered to be the result of accumulation, overlap, and collision of these configurations. Configurations can be used to represent theoretical local mechanisms and tendencies of actors to choose their ties, such as the tendency to cooperate in closed triads or to bridge open micro-structures. The estimation of the ERGM parameters determines which of these mechanisms were significant for the formation of the network structure. This allows to consider several micro-social tendencies at the same time and to disentangle their effect in the resulting network. These models have already been used in studies of criminal networks (e.g., Grund & Densley, 2014; Smith & Papachristos, 2016). Moreover, by explaining macro-level structures from their micro-level elements, ERGMs correspond with analytical sociology.

The dependent variables in ERGMs are the tie variables indicating the existence or non-existence of the ties in the observed network. These are binary variables like in logistic regression. The dependence between the tie variables is modelled by the aforementioned configurations, which capture many different ways in which the ties in the network may be dependent on each other. These configurations have a similar role as the explanatory variables in logistic regression. ERGMs are both computationally and conceptually considerably complex. Here, it is sufficient to say that first, the algorithm tries to find a distribution of networks which on average matches the observed frequencies of the configurations in the data. Based on the simulated distribution of networks, the model determines which of the configurations is statistically significant to explain the structure of the observed network. The output of the model is a list of parameter values, which express the conditional log odds of the probability of creating a tie in the observed network when, given the rest of the network, this tie would increase the frequency of the corresponding configuration by one. If the resulting parameter value is significant (in practice, at least twice as large as its standard error) and positive (negative), then the corresponding configuration is present (absent) more often than can be accounted for by the rest of the model. The configurations used to model the network of the methanol affair are summarized in Table 1. The accuracy of estimates is judged by their t-ratios for convergence, which should be smaller than 0.1 in absolute value to consider the model being converged.

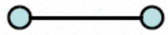
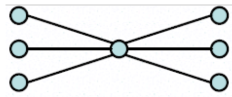
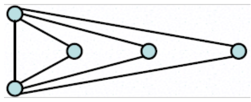
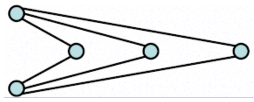
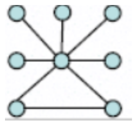
Exponential random graph model specification		
configuration	visual representation	interpretation
edges		Tendency to create ties (model intercept).
alternating star		Preferential attachment; H1 suggests negative effect.
alternating triangle		Closure; H2 suggests positive effect.
alternating two-path		Control configuration
alternating edge-triangle		Brokerage (Pattison & Snijders, 2013); H3 suggests negative effect.
attribute - activity		Generalized social selection; H4 suggests positive effect.
attribute - interaction		Homophily; H5 suggests negative effect.
tie entrainment		Tie translation; H6 suggests positive effect.

Table 4.1: ERGM specification

After the estimation of the model, it is also important to assess its goodness of fit to the data. In the ERGM framework, this is done by comparing the simulated distribution of networks with the observed network in terms of network characteristics that were not explicitly modelled, such as other configurations or global network properties. Specifically, for each of a set of such characteristics, its mean frequency in the simulated distribution is compared with its frequency in the observed network. If the absolute value of this difference divided by the standard error of the distribution is not too high (the usual cut-off is two), it can be said that the model has a reasonable fit to the data.

4.11. Results

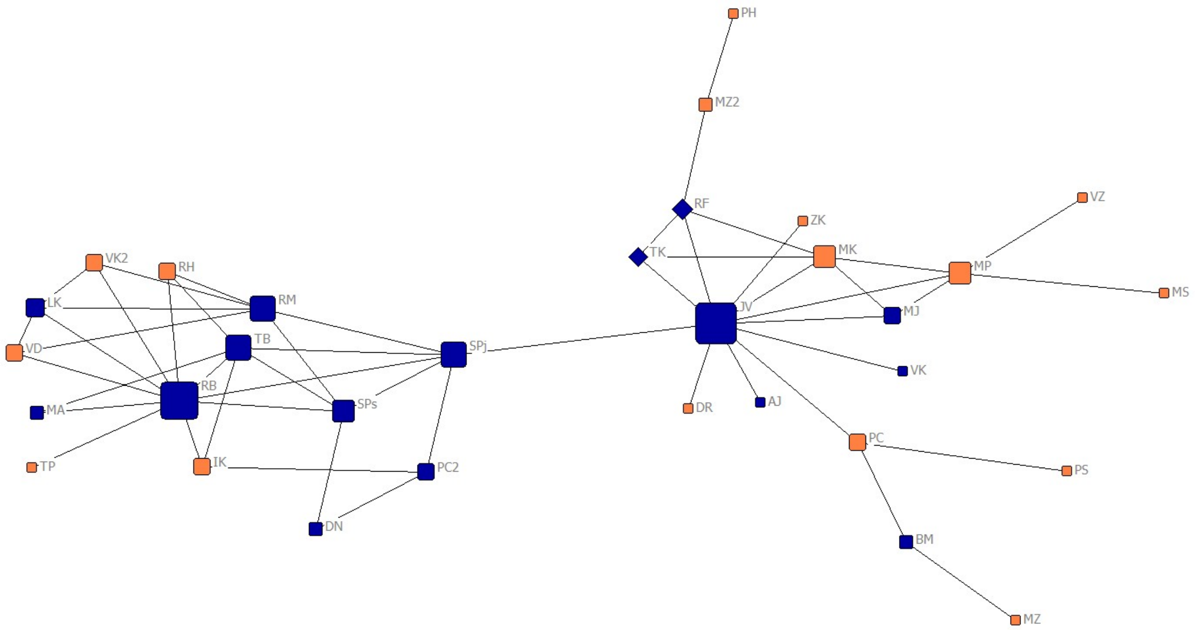


Figure 4.1: sociogram of the network. Node size is based on degree. Colour of nodes represents attributes (entrepreneur = blue). The left hand side corresponds to the Zlin branch, whereas the right hand side corresponds to the Ostrava branch. The two diamond-shaped nodes in the Ostrava branch are the manufacturers.

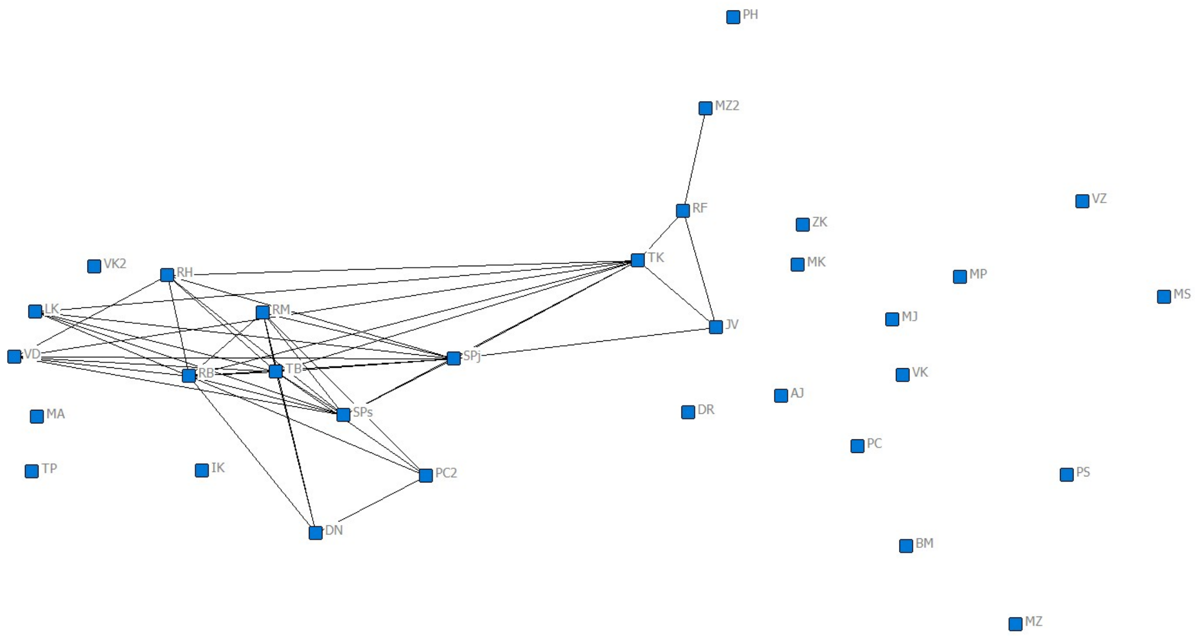


Figure 4.2: sociogram of pre-existing ties. The positions of nodes in the visualization is based on their position in Figure 1 for easy visual comparison.

Looking at Figure 1, it is apparent that the whole network is stitched together by the tie between actors SPj and JV. Without this connection, the whole network would fall apart into two mutually isolated components. Hence, it would be impossible to distribute the poisonous spirits among all actors as it was manufactured by a pair of actors (RF and TK), who both belong to the component around JV. According to the court files, JV had later become the main distributor of these illegal and poisonous alcohol drinks. Concurrently, JV started to cooperate with SPj, whom he knew from previous business activities and they considered each other to be good business partners (a case of tie translation), thereby connecting both branches and getting the poisonous spirits to the group around RB. This group was previously focused on profiting from tax evasions by manufacturing untaxed spirits. Therefore, it appears that in this regard, the network perspective collates with the conclusions from the investigation and court proceedings.

Whole network descriptive measures	
statistic	value
number of nodes	32
number of ties	52
density	0.11
degree centralization	0.27
average degree	3.25
standard deviation of degree	2.51
closure	0.28
average geodesic path length	3.15
diameter	6
number of entrepreneurs	16
E-I index (entrepreneur)	-0.04

Table 4.2: whole network measures

Table 2 summarizes the network descriptive measures. In total, there are 32 actors in the network connected by 52 ties, which together yields a density of 0.11. Hence, 11% of the theoretically possible ties are actually present in the network. While this number may not seem very high, we see from the sociogram that it is sufficient to keep the network connected in one component. Despite the fact that the network may appear centralized in the visualisation, there are multiple high degree actors and the centralization is only 0.27. This information is complemented by the average and standard deviation of the degrees. On average, each actor has slightly more than three ties, but the degrees show non-negligible variability, which means that there are highly central as well as marginal actors in the network. Looking at the average geodesic path length and the diameter, the distances between actors are quite long considering the number of actors in the network. On average, information or resources flow between any pair of actors through more than three ties, while the longest distance is six “steps”. The closure is 0.28, meaning that a bit more than one fourth of all potential triangles are closed, which means that the network is descriptively more open than closed. The value of the E-I index is –.04 indicating neither homophily nor heterophily.

Network and flow positions			
actor	degree	actor	distance
JV	11	RF	source
RB	10	TK	source
RM	6	JV	1
SPj	6	MK	1
TB	6	MZ2	0.75
MP	5	SPj	0.5
MK	5	MP	0.5
SPs	5	AJ	0.5
LK	4	DR	0.5
RF	4	MJ	0.5

Table 4.3: actor importance measures

Table 3 displays the results of actor importance measures, capturing the top ten actors with highest degree centrality and shortest distances to the two manufacturers. As it can be seen, there is some overlap. The most prominent distributor JV and SPj have high values of both measures. An interesting fact is that while one of the manufacturers, RF, had above average degree and the other manufacturer, TK, had below average degree, neither of them was very central in the network. If they would have been more central, the speed of distribution of the poisonous beverages and thus the lethality of the network would be even higher. So while the distances from these two actors were short overall (2.8 on average, maximum of 4), the structure could have been even more efficient with regards to distribution of the lethal spirits. This is also reflected by the network-level measure, average reciprocal geodesic distance to the manufactures, which is 0.59, suggesting that the network reached 59% of its distributive potential. Other actors who combined considerable degree with closeness to the manufacturers were MK and MP. Again, if more actors would have had higher degrees and been in short distance to the manufactures, the network could have been more effective with the distribution.

Exponential random graph model results			
configuration	parameter	S.E.	t-ratio
structural effects			
edges	-1.240	1.256	-0.030
alternating star	**-1.060**	**0.493**	-0.041
alternating triangle	**0.726**	**0.310**	-0.045
alternating two-path	0.080	0.073	-0.039
alternating edge-triangle	0.003	0.092	-0.037
individual effects			
entrepreneur - activity	0.829	0.575	-0.060
entrepreneur - homophily	-0.689	0.693	-0.049
dyadic effects			
pre-existing ties	**1.654**	**0.414**	0.013

Table 4.4: ERGM results. Statistically significant effects are in bold. The t-ratios are the t-ratios for convergence.

Table 4 shows the results of the ERGM. T-ratios of each modelled parameter were < 0.07 in absolute value indicating good model convergence and thus sufficient accuracy of the estimates. A first conclusion is the remarkable lack of an effect of the two configurations related to entrepreneurship. Thus, there is no evidence that the network structure was systematically patterned by the experience of the actors in the sphere of legitimate business, which is in contrast with Hypotheses 4 and 5. The parallel between organized crime and legal organizations (Gimenéz Salinas-Framis, 2011; Milward & Raab, 2006) is not exhibited in this case. What does significantly shape the network, however, is the presence of pre-existing ties. The positive sign here indicates that a pre-existing tie between two actors increases the probability of an operational tie. This supports Hypothesis 6 and also the results from previous research (Erickson, 1981; Smith & Papachristos, 2016). Further, two structural effects are significant; alternating star and alternating triangle. Alternating star models the preferential attachment. A negative value of this parameter suggests that actors in the network display the opposite tendency, that is, they try to spread their ties evenly across alters in the network, as with every tie actors have, the probability that they will create another one decreases, in line with Hypothesis 1. The alternating triangle captures the tendency towards creating closed micro-structures. This parameter is positive in the network, so there is evidence for this tendency, which supports Hypothesis 2. If there is a triad of actors in the network with two ties among them, the probability that they will create the remaining tie is larger than if the two ties were not there. The alternating edge-triangle effect indicating brokerage from closed regions is not significant, hence there is no evidence to support Hypothesis 3. Overall, the formation of the network structure can be seen as the result of the combined operation of the mechanisms of triadic closure, tendency against preferential attachment, and the translation of pre-existing ties into operational ties.

As for the goodness of fit, all of the 25 statistics representing configurations implemented in MPNet show adequate fit of the model to the data (t-ratios < 1.2 in absolute value for effects not included in the model and < 0.1 for those included in the model). Additionally, Table 5 displays the goodness of fit of our model to the global properties of the network which are implemented in the MPNet software package – standard deviation of degree, skewness of degree and clustering coefficient. All the t-ratios are well below 1 in absolute value, indicating satisfactory fit of the model to these global properties of the observed network.

Goodness of fit for global network properties				
statistic	observed	simulated mean	simulated SD	t-ratio
standard deviation of degree	2.51	2.33	0.43	0.43
skewness of degree	1.48	1.25	0.56	0.41
clustering coefficient	0.28	0.28	0.05	0.07

Table 4.5: Goodness of fit results

We also re-analysed the two branches of the network separately to inspect whether there are differences between the two branches in terms of ERGM results. However, even though the models converged, none of the theoretically postulated effects were significant and standard errors were considerably high due to the lack of statistical power[29]. This is not surprising, as these two sub-networks are smaller than the networks usually considered to be well analysable by ERGMs.

4.12. Discussion and conclusion

This study revealed several findings from the analysis of the network of actors involved in the methanol affair. First, the structure of the network was quite specific in that it consisted of two components connected only through one bridging tie. At first sight, the network does not show any obvious further structural features. That is, it is not remarkably dense nor sparse, heavily centralized nor decentralized, built on closed structures nor it is in any other way compartmentalized. Although the two manufacturers were not located particularly close to others, there are a few highly central actors in the network and some of them are also close to

[29] These ERGM results together with further goodness of fit results are not shown here. However, they are available in the online supplementary information.

the two actors who manufactured the poisonous beverages. The ERGM results suggest that the structure of the network was brought about by the mechanisms of closure, inverse preferential attachment, and translation of pre-existing ties into operational ties. We also hypothesized a tendency to avoid brokerage and heterophily with respect to being entrepreneurs, but found no support for this.

We demonstrated the utility of combining analytical sociology with statistical models for social networks. Analytical sociology provides a theoretical framework for postulating relational mechanisms as explanations for the observed network structure, which can in turn be empirically tested with an appropriate statistical model for network data. Our results show a strong effect of pre-existing ties on the creation of operational ties. Besides corresponding to extant theory (Erickson, 1981; Smith & Papachristos, 2016), the effect of pre-existing ties may have policy implications, as investigators may use this finding in an investigation and track potential co-offenders along the lines of already existing connections in legitimate spheres or personal domain, such as friendship. To our knowledge, police investigators already proceed frequently this way and thus our findings confirm the importance of such procedures. Despite the strong theoretical foundation (Kenney, 2007; Milward & Raab, 2006; Morselli, 2010; Morselli & Roy, 2008), brokerage, generalized social selection, or heterophily with regards to entrepreneurship did not systematically shape the network structure. In our view, this demonstrates the strength of our analytical approach. As we could have interpreted the sociogram showing an instance of brokerage (i.e., the bridging tie) or the prominence of entrepreneurs, these mechanisms tested within a coherent framework against other competing explanations turned out not to affect the network as much as it may seem upon first sight.

One mechanism worthy of further investigation might be propinquity (Daraganova et al., 2012). Propinquity is a tendency to create ties based on physical/geographical proximity. Usually the closer actors are to one another, the more likely it is that they will share a tie, as the shorter the distance, the easier it is to create and maintain a tie. This mechanism is of obvious explanatory importance for distribution networks as distribution unfolds in physical space. The role of physical distances alongside network distances may bring new insights into how the distribution network is structured.

Another avenue of research would be to consider the temporal dynamics of the network. Criminal networks are adaptive and dynamic as actors involved respond to their changing environment and the opportunities and threats it poses (Bright & Delaney, 2013; Kenney, 2007), which will be manifested by the changes of the structure or change in actors' attributes over time. The question is then what relational mechanisms drive the evolution of the network (Bright et al., 2018) and how do actors respond in the face of critical turns of events such as law enforcement crackdowns or the emergence of competing criminal groups.

However, neither propinquity, temporal dynamics, nor a more detailed distinction between different types of ties (multiplexity) could be incorporated in this study due to the lack of information in the court files that we used as a data source. Although there are previous studies extracting even this fine-grained information from court files (Bright et al., 2012; Hughes et al., 2017), the level of available detail may vary across jurisdictions. It is possible that court documentation in some countries will lend itself to extracting more detailed information, while this may not be the case in other countries without reaching out to other sources of information (e.g., police investigation files). Even though court files bear higher face validity than data obtained, e.g., from media databases, data validity constitutes the greatest limitation of the present study; this is the case in research on criminal networks in general (Bright et al., 2012; Morselli, 2009, 2014). Yet, we are confident that no crucial actor was absent from the court files and that all important connections were uncovered.

For the description of the network, we defined our own measure of actors' importance as the geodesic distance from the two manufacturers. In general, the choice of centrality measures for analysis should mirror the nature of the flow in the network (Borgatti, 2005). For our case, the flow of poisonous beverages was substantively important. The identification of central actors is obviously interesting for criminal network analysis and thus the application of existing centrality measures or creation of new ones is likely to proliferate. In order to use existing measures and derive new in principled way, a common methodological framework for thinking about centrality measures may be helpful. A potential framework for this is proposed in the so-called positional approach (Brandes, 2016). This approach provides a way of conceptualizing network measures with the aim to integrate the notion of position of an actor in a network (e.g., centrality) with the notion of position of that actor in social space (e.g., socioeconomic status). This opens the possibility to integrate centrality measures with the attributes of actors and capture the prominence of actors in the network as based on multiple dimensions such as centrality and skills or centrality in multiple different types of ties (Bright et al., 2015; Diviák, Dijkstra, & Snijders, 2018). Similarly, the study of influential actors and outliers may be incorporated in the ERGM framework with newly developed methods (Koskinen, Wang, Robins, & Pattison, 2018).

5. The efficiency/security trade-off and beyond: testing a theory on criminal networks[30]

5.1. Introduction

Actors in all organizations, overt and covert alike, need to act and cooperate in order to achieve their organizational goals. To this end, actors need to create ties with others for communication and cooperation, resulting in a network structure. However, a straightforward increase of activity and thus a higher number of ties may not simply result in better cooperation, especially not in criminal networks. A defining feature of criminal networks is the need of their participants to remain concealed (cf. Morselli, 2009; Oliver, Crossley, Everett, Edwards, & Koskinen, 2014). This puts constraints on interactions, because increasing activity becomes a liability as it comes with increased risk of being detected and consequently dismantled. Thus, criminal network participants must always oscillate between achieving their goals and keeping their activities hidden. Hence, Morselli, Giguère, and Petit (2007) postulate that "criminal network participants face a consistent *trade-off* between organizing for efficiency or security"; the so-called efficiency/security trade-off (Morselli et al., 2007, p. 143). Efficiency would imply that participants in criminal networks interact and communicate with each other frequently and have a large number of ties. At the same time, this undermines the security[31] of the network as it increases visibility and thus susceptibility to detection and disruption. Morselli and colleagues subsequently deduce systematic structural differences between criminal networks oriented towards profit and towards ideology, as they require different temporal planning. Consequently, the trade-off is supposed to be different between these types of networks.

Although this idea has become widely accepted in the field of research on covert and criminal networks, it has been rarely empirically tested until recently (Crossley et al., 2012; de Bie, de Poot, Freilich, & Chermak, 2017; DellaPosta, 2017; Ünal, 2019). This paper aims to test this theory by examining the implications of the efficiency/security-trade-off for different network

[30] This chapter is based on: Diviák, T., Dijkstra, J. K., & Snijders, T. A. B. (2019). The efficiency/security trade-off and beyond: Testing a theory on criminal networks. Under review.

[31] By security, we mean the absence of risk. This is different from resilience of the network, which is the ability of the network to withstand external shocks and attempts to disruption (cf. Bright, 2015; Duijn, Kashirin, & Sloot, 2014).

characteristics across nine ideology-driven and eleven profit-driven networks, using descriptive analysis and explore its implications with exponential random graph models (ERGMs). Although the theory is formulated on the network level, we contrast this with an individual actor level approach. This is because some network configurations may seem beneficial from the perspective of actors but detrimental when considered from a network perspective.

5.2. The efficiency/security trade-off

The idea that participants in criminal networks trade efficient achievement of their goals for security has been more or less explicitly articulated also before Morselli et al.'s seminal paper (2007). Baker and Faulkner (1993) stated that actors involved in criminal networks have two conflicting needs: maximizing concealment and maximizing efficiency. They showed that the need for concealment overrode the need for efficiency in three price-fixing conspiracy networks in heavy electrical industry. Similarly, Milward and Raab (2006) theorized a trade-off between the capacity to act and the capacity to persist. They related this tension to the theory of organizations and the processes of integration and differentiation, stating that "the structure will become more differentiated to make them (criminal networks) more difficult to find and destroy and thereby less integrated. This trade-off makes it more difficult for the network to maximize its destructive capacity but leaves it less vulnerable to attack" (Milward & Raab, 2006, p. 343). In a similar vein, Enders and Su (2007) talked about a trade-off between security and communication in terrorist networks.

A principal addition to this idea by Morselli et al. (2007) is that the trade-off does not occur uniformly in all criminal networks, but depends on the goal its members pursue. A distinction is made between two primary goals of criminal network participants: financial profit (e.g., traffickers of drugs or other goods) and ideological goals (typically terrorists). Whereas the efficiency is symptomatic for profit-driven networks, the security side of the trade-off is a domain of ideology-driven ones (Morselli et al., 2007).

The argumentation why profit-driven networks exhibit efficient structures, whereas ideology-driven networks exhibit secure structures, is based on the different time frames in which these network operate (Morselli et al., 2007). The time-to-task, that is, the interlude between time and action, is shorter in profit-driven networks as actors involved in them desire rapid pay-off. This shorter time-to-task requires the network to be designed for more efficient communication, while assuring as much security as possible. By contrast, the time-to-task is longer in ideology-driven networks, as these operate within longer time frames, allowing the network to maximise security and assure as much efficiency as possible. Hence, ideology-driven network participants are supposed to aim particularly for assuring security to carry out a carefully planned action (e.g., an attack). To achieve this, they have to remain as secure as possible. The question is how the different time-to-task considerations affect the structure of the network. In other words, what are the structural implications of the efficiency/security trade-off. If the theory holds, we would expect that these two types of criminal organizations differ in their network structure.

Despite the prominence of this theory in research on criminal networks, two important issues deserve more attention. The first issue with testing the efficiency/security trade-off theory is its generalizability. Originally, the theory was proposed and illustrated using two cases of criminal networks (one profit-driven and one ideology-driven; Morselli et al., 2007). Other studies were also case studies of a single particular network. For instance, Crossley and colleagues (2012) studied a network of militant suffragettes and found support for the theory showing how the network becomes less dense and less centralized when it becomes more covert. DellaPosta (2017) studied a large-scale American mafia network, which exhibited a balance between efficiency and security by combining local closure and global openness. De Bie and colleagues (2017) studied a case of Dutch jihadists, showing that contrary to the theoretical expectations, the jihadi network was structurally more inclined towards efficiency, especially when its members aimed for dissemination of their ideology. The only study which went beyond analysis of one or two cases is Ünal's (2019) study which compares five illicit drug networks with five narco-terrorist networks within the Turkish context on their descriptive whole network and centrality measures, finding no systematic structural differences between these networks, especially in terms of clustering and path lengths between actors.

The second issue concerns the analytical level where the trade-off between efficiency and security takes place. The theory is formulated at the analytical level of the network. That is, it is the network, where the goal (profit or ideology) is defined and it is the overall network structure which is supposed to reflect it. However, intentions and goals are always properties of individuals, who may base their action on them (see e.g., Coleman, 1990; Hedström, 2005; Robins, 2009). Hence, network structures arise as a result of accumulation, intertwining, and crossing of individual interactions and relationships. This implies that, if the mechanism is located at the network level, actors are regarded as being quite rational and able to see the network from a "bird's eye view" in order to adjust their actions (forming ties) in a way that serves the purpose of the network optimally. However, this is not a very realistic assumption as the structure may not always correspond to the intentions of individuals that initially brought it about. In some cases, the structure may be even in contradiction with individual intentions and arise as an unintended consequence of individual actions (Boudon, 1982). For instance, actors aiming for security may rely on frequent cooperation and communication in order to prevent infiltration by their opponents or defection by their collaborators. Moreover, in the pursuit of security, they may prefer to create dense closed structures, aiming to promote trust (cf. Coleman, 1990; Kadushin, 2011). Trust is supposed to be important for cooperation in high risk activities, such as organized crime (Erickson, 1981; Robins, 2009; von Lampe & Ole Johansen, 2004). However, as an unintended consequence of this behaviour, structures with dense ties may become easily visible and detectible, thus undermining the original intentions of its creators.

We aim to overcome both issues as follows. First, we test this theory on a large number of profit-driven and ideology-driven networks by examining network characteristics of both types of networks. In so doing, we aim to obtain more general conclusions about differences between them. Second, to our knowledge previous studies only used whole-network descriptive measures to test the efficiency/security trade-off. However, networks are known for their complex structures, where similar structures may result from different underlying mechanisms (Robins et al., 2005). For instance, network-level centralization may be brought about by a variety of mechanisms, not only by a tendency to concentrate ties around several actors at the actor level. Thus, we apply statistical models for social networks to disentangle the network structures to their constituent elements at the actor level represented by configurations, such as triangles (i.e., three fully interconnected actors). In so doing we are also able to distinguish tendencies of actors from their consequences for network structures.

5.3. Network-level properties

We test hypotheses about four basic structural features of networks, that is, density, centralization, closure, and brokerage. Note that density and centralization are explicitly formulated in the original theory, whereas closure and brokerage are only implied. However, since not only density and centralization, but also closure and brokerage are important for patterning ties in networks and thus for making them efficient or secure, we also derive hypotheses from the efficiency/security trade-off about closure and brokerage. In the following section, we briefly review each of these four concepts. Because our aim is to test the efficiency/security trade-off (formulated at the network level), we derive our hypotheses for the network level. To obtain greater clarity and understanding, we also explore the implications of the efficiency/security trade-off at the actor level in the following section.

Density

As a network property, density is the proportion of ties existing in the network compared to all potentially existing ones[32]. High density facilitates the flow of information and resources and enables fast diffusion (Janssen et al., 2006). Dense ties also form a basis for social support and social control (Coleman, 1990; Kadushin, 2011). Nevertheless, high density may not always be beneficial, as both extreme density and extreme sparsity are disadvantageous. In all types of networks including criminal networks, higher density initially increases its flexibility and the potential for interaction among its members. However, beyond a certain point, increased cohesion may stifle these advantages (Everton, 2012, p. 141), as overly dense network structures are supposed to lead to too much social control among the actors (Janssen et al., 2006; McGloin & Kirk, 2010), which hampers their ability to perform complex tasks and adapt to changing conditions. By contrast, very low density results in insufficient cooperation, coordination, social control among the actors and thus the inability to reach goals. At the network level of the efficiency/security trade-off (Morselli et al., 2007), efficiency is associated with a high number of ties and thus with high density as this is supposed to help generate value for profit-driven networks, whereas security is associated with a loose structure and subsequent low visibility and vulnerability (Enders & Su, 2007). Therefore, we expect profit-driven networks to be denser than ideology-driven networks.

Hypothesis 1: Profit-driven networks are denser than ideology-driven networks.

Centralization

High density is not the only way to assure efficiency. Actors in the network may also be efficiently connected if the ties are concentrated around a few central nodes, even though there is a low number of ties in total. Central actors in such networks directly exercise control over their neighbours and over a large proportion of flows in the network (Berardo & Scholz,

[32] Different terms may be used to denote what we refer to as 'density' here, such as cohesion, density or average degree. We understand density as a concept referring to the number of ties in a network, which can be measured by a measure called density or by average degree.

2010; Jackson, 2014; Janssen et al., 2006). These advantages are at the expense of dependence on the performance of the central nodes. In criminal networks, centralization comes with another drawback: high vulnerability to the removal of central nodes (Bright, 2015; Helfstein & Wright, 2011). Thus, increased centralization adds to the efficiency of the network, whereas decreased centralization adds to the networks' security (Morselli et al., 2007). Hence, we expect profit-driven networks to exhibit more centralization than ideology-driven networks.

Hypothesis 2: Profit-driven networks are more centralized than ideology-driven networks.

Closure

Closure or transitivity reflects the existence of closed structures (triangles) as a network property. Unlike density, which is about creating ties in general, closure is about connecting those, who are not yet directly connected. At the network level, closure increases efficiency by shortening the distances among actors (Berardo & Scholz, 2012). By closing an open triplet, two actors reach each other with one tie instead of having to use an intermediary. However, closure introduces redundant ties as two ties are enough to connect three actors and hence the third closing tie is redundant (cf. Burt, 1992; 2005). This redundancy in turn increases the risk of being detected (Robins, 2009), which decreases security. Following the original proposition of Morselli and colleagues (2007), increasing the efficiency by shortening the distances may be more salient in profit-driven networks, whereas the increase in visibility may be avoided by ideology-driven networks. Therefore, we expect more closure in profit-driven networks than in ideology-driven ones.

Hypothesis 3: Profit-driven networks show more closure than ideology-driven networks.

Brokerage

At the network level, brokerage is manifested by the presence of open structures, also known as structural holes. Brokerage introduces structural differentiation into the network as in open triads, there are two structurally equivalent actors who are interconnected by the actor in the position of broker. Milward and Raab (2006) argue that such differentiation increases the security of the network, because while it reduces the ability of actors to coordinate their actions, it makes them more difficult to detect and target. Furthermore, structural holes imply a low number of redundant ties, making the network less visible and more secure. Therefore, in line with the efficiency/security trade-off (Morselli et al., 2007), we suppose that ideology-driven networks exhibit more brokerage than their profit-driven counterparts, as that allows to maximize security.

Hypothesis 4: Ideology-driven networks display more brokerage than profit-driven networks.

Balance between efficiency and security

In addition to Morselli et al. (2007), we propose to take into account a balance between the conflicting ends of efficiency and security, which can be identified both at the actor-level and at the network-level. At the network level, this balance is very similar to what is known as the small-world phenomenon (Watts & Strogatz, 1998). A small-world network is characterized by high closure and short geodesic distances, which provides actors both the advantages of closed local clusters associated with trust and cooperation, and at the same time access to resources and ideas from other clusters through bridging ties. Small-world networks have been thought to be the balance between efficiency and security (DellaPosta, 2017; Robins, 2015, p. 31). This is also supported in research on criminal networks by revealing so-called cell structures or compartmentalized structures (DellaPosta, 2017; Faulkner & Cheney, 2014). The cell structure resembles the small-world network model as it is also composed of a number of small dense subgroups (cells) interconnected by sparse bridging ties, the difference being that the bridging ties are produced by a moderate amount of randomness in the small-world model, whereas in compartmentalized cell structured networks, the bridging ties are assumed to be resulting from strategic considerations. This compartmentalization is supposed to protect against infiltration and disruption, while assuring connectedness among the actors in the network. As the efficiency/security trade-off does not explicitly mention the balance between the two ends, we do not test it at the network level. However, we argue that it is important to discuss this possibility.

5.4. Actor-level mechanisms

In this section, we argue that the loci of action are actors, whose tendencies to relate to others in specific ways are captured by different mechanisms. The basic tendencies for network structures that we investigate are propensity to create and accumulate ties, to close open triads, and to leave triads open. As none of these tendencies is explicitly postulated in the efficiency/security trade-off, we do not derive hypotheses. However, we aim to explore their implications. Note that there is a potential tension between motives of individual actors and the purpose of the network and that as we said above, actor-level tendencies do not necessarily translate into corresponding network-level outcomes.

Tie creation

Actors in profit-driven networks may differ from actors in ideology-driven networks in their general propensity to create ties, that is in their propensity to cooperate and communicate with each other. Creation and maintenance of each tie has its cost in the form of time, effort or energy (Snijders, 2013). In criminal networks, there is an extra cost to each tie in the form of increased visibility. If the goal is profit, actors would probably be inclined to cooperate with others in order to make profit and achieve the desired good. If actors are involved in ideology-driven activities, only a few trusted contacts may suffice to get the necessary information and support. Thus, the actor level explanation aligns with the network level perspective.

Tie accumulation

The actor level mechanism associated with concentration or accumulation of ties is called cumulative advantage (also known as preferential attachment; Barabási & Albert, 1999; de Solla Price, 1976). This mechanism entails a self-reinforcing process making the probability that an actor creates or receives a new tie dependent upon the number of ties an actor already has. This may go together with disproportionately frequent activity of some members of the network (Milward & Raab, 2006), who may even try to organize the group to assure greater security. However, in doing so, they inadvertently undermine their own effort at the network level as they make the network centralized around themselves. If this is the case, intentions of individuals are counterproductive to the network level structural outcome. Centralization may also arise as an effect of popularity of central actors because of their highly demanded resources or skills (Robins, 2009). The accumulation of ties has diminishing returns (Rivera et al., 2010), which is more pronounced in criminal networks where it increases the visibility of central actors and their neighbours (Bright, Koskinen, & Malm, 2018) and provides the central actors with opportunities they may exploit for their personal advantage (Berardo & Scholz, 2010; Jackson, 2014). For both these reasons, actors in both profit-driven and ideology-driven networks may actively try to avoid accumulation of ties.

Closure

Closure refers to closing open triangles or, colloquially, to befriending friends of friends. Individuals form these structures to reinforce trust, control, and support as actors in the network can check on how they deal with each other (Berardo & Scholz, 2010; Coleman, 1988; Jackson, 2014; Rivera et al., 2010). In doing so, they may reinforce norms, for instance, pertaining to covertness and loyalty. Actors embedded in these closed network structures are thus less likely to defect (Jackson, 2014). As trust is supposed to be crucial in criminal networks (Erickson, 1981; Robins, 2009; von Lampe & Ole Johansen, 2004) and together with the fact that closure helps prevent defection and infiltration (Bright et al., 2018; Helfstein & Wright, 2011), actors may close triads to increase security rather than efficiency in contrast to the network level proposition. Consequently, this may result in increasing visibility by creating redundant ties and as an unintended consequence, it may expose the network to detection.

Brokerage

At the actor level, brokerage is the tendency of actors to create structural holes, to bridge between unconnected actors. From the perspective of individual actors, the closed structures may be disadvantageous because actors who are embedded within them constrain each other, as they have access to similar resources and capabilities (Burt, 1992, 2005). Brokerage over structural holes provides a competitive advantage, because it allows reaching out for new resources and ideas (Burt, 1992, 2005; Kadushin, 2011, p. 63). This tendency to exploit structural holes serves the profit of the brokers, sometimes captured by the notion that "brokers do better" (Morselli & Roy, 2008). The role of brokers and their competitive advantage is well documented in criminal settings, showing that more sophisticated criminal organizations display more brokerage (DellaPosta, 2017; McGloin & Kirk, 2010; Morselli, 2010; Morselli & Roy, 2008). From the actor's perspective, the intention to broker may also be driven by the motivation to obtain material profit and as such will be more salient in profit-driven networks.

Tendencies to balance efficiency and security

From the actor level perspective, the aim to balance efficiency and security has been described in both overt and covert settings. For instance, Uzzi (1996) showed that entrepreneurs in legitimate business in the apparel industry try to keep a mix of both weakly tied contacts to access innovation, and strongly tied contacts for situations which require trust and coordination. This is further supported by Burt (2005, p. 164), who claimed that while brokerage enables to create value, closure enables to deliver it. Brokerage provides access to new information and resources, whereas closure creates opportunities to make use of them.

Actors may also try to balance centralization and decentralization. Related to this, the concept of strategic positioning has gained considerable attention in the study of criminal networks in recent years (Morselli, 2010). Strategic positioning is the tendency of actors in criminal networks to limit their direct connections (i.e., below average degree), while seeking network positions on important flows (i.e., high betweenness). In this way strategically positioned actors decrease their visibility but retain some control over flows of information and resources in the network.

5.5. Data

We tried to find as many criminal networks as possible which were available for re-analysis and in which the content of ties as communication or cooperation can be clearly distinguished from other tie contents; this was required as it reflects the kind of ties the efficiency/security trade-off is referring to. This resulted in twenty networks: nine ideology-driven and eleven profit-driven. The profit-driven networks consist of cases of human trafficking, drug trafficking, and illicit vehicle resale, whereas ideology-driven networks contain terrorist networks. Networks where communication/cooperation ties were impossible to clearly distinguish from other tie contents were not included in the analysis.

Because most of the networks were undirected, we symmetrized the directed networks by making all the ties undirected (whenever there was a tie in at least one direction, it was considered to be in both directions) to allow for comparison between networks. Similarly, most of the networks were initially binary, so we dichotomized the remaining networks as well. All the networks, their sources, brief description, and the way we processed them prior to the analysis are summarized in the appendix. Table 1 provides the descriptive statistics for each network and the appendix provides further information on the datasets we used.

5.6. Methods

Descriptive analysis

To test our hypotheses, we compared the network characteristics of density, centralization, closure, and brokerage between ideology-driven and profit-driven networks. To account for the differences in size of the networks, ranging from 17 to 86 nodes, we used measures which are not sensitive to these differences.

Density. We used the average degree as an indicator of density instead of density itself. The reason is that network's density is inversely related to its size (Everton, 2012; Snijders, 1981). Moreover, average degree is directly interpretable in terms of activity of the actors in the network. The higher the average degree, the denser is the network.

Centralization. We used the variation coefficient of degrees as a measure of centralization of the network. Similar to density, centralization measures are sensitive to the size of the network. The variation coefficient is defined as the standard deviation divided by the mean, which allows for comparison of networks with different number of nodes as variation coefficient is by its definition dimensionless. The higher the variation coefficient of degrees, the more dispersed the degree distribution, indicating that there are a few high-degree and many low-degree nodes (cf. Snijders, 1981).

Closure. To measure closure, we started with the frequently used clustering coefficient. This coefficient is the ratio of closed triplets to three times the number of connected open triplets, so called two-paths. This measure ranges from 0 to 1, where 0 indicates no closed triangles and 1 indicates no open two-paths. However, the clustering coefficient is sensitive to the density, because the expected value of random networks with a given size and density is just the density itself. Thus, we subtracted the density of the network from its clustering coefficient to take out the potential distortion caused by different densities.

Brokerage. As an inverse measure of brokerage, we used Burt's (1992, p. 55) measure of aggregate constraint averaged across actors within each network. This measure expresses the extent to which an actor is tied to others who are themselves interconnected. If an actor's neighbours are not mutually interconnected, the actor is unconstrained and sits atop of a lot of structural holes. Well interconnected neighbours imply a small amount of structural holes, i.e., high constraint, and thus leave little opportunities for the focal actor to exploit. Higher values of this measure indicate higher constraint and thus less brokerage.

network	type	nodes	avg degree	variation c. degree	clustering c. - density	avg constraint
Togo	PD	33	2.85	1.23	0.06	0.58
Heroin Distribution	PD	38	4.58	0.91	0.09	0.54
WomenTraff B	PD	18	2.89	1.09	0.12	0.51
MAMBO	PD	31	3.74	0.94	0.17	0.47
Siren	PD	44	4.68	1.19	0.30	0.47
WomenTraff C	PD	19	2.63	0.96	0.16	0.47
JUANES	PD	51	3.65	0.88	0.20	0.44
Ciel	PD	25	2.8	1.00	0.05	0.41
ACERO	PD	25	2.96	1.07	0.07	0.38
WomenTraff E	PD	20	1.90	1.21	0.30	0.29
JAKE	PD	38	2.63	1.24	0.07	0.19
Mali	ID	36	3.72	0.77	0.28	0.73
Al-Qaeda WoT	ID	35	5.31	0.63	0.32	0.55
Ergenekon	ID	86	9.35	0.88	0.29	0.47
Noordin Top	ID	79	5.06	1.14	0.20	0.47
November17	ID	22	6	0.61	0.24	0.42
Al-Qaeda preWoT	ID	83	10.96	0.67	0.29	0.40
Jewish Underground	ID	26	2.77	1.21	0.08	0.35
IS-E	ID	62	2.45	1.43	0.02	0.31
Jemaah Islamiyah	ID	17	7.41	0.40	0.33	0.25
average PD		31.09	3.21	1.07	0.14	0.43
average ID		49.56	5.89	0.86	0.23	0.44

Table 5.1: Networks in our dataset and their descriptive statistics. Note: PD = profit-driven, ID = ideology-driven.

In order to compare the ideology-driven networks to their profit-driven counterparts, we conducted a two-sample one-sided Wilcoxon-Mann-Whitney permutation test for each of these measures using the coin package in R (Hothorn, Hornik, Wiel, & Zeileis, 2008). Note that our sample of networks is not a random draw from a well-defined population, but rather a set of available cases with the content of ties corresponding to the theory. Therefore, inferences based on our permutation tests pertain only to our set of networks and differences between the two types of networks therein.

Statistical models

As stated above, the efficiency/security trade-off has been originally proposed only with regard to descriptive network statistics. Although these measures provide a good basis for testing the efficiency/security trade-off on the network level, they do not capture the actor level. In order to explore the mechanisms at the actor level, we use exponential random graph models ('ERGMs'; Lusher, Koskinen, & Robins, 2013). These models represent global network structure in terms of local network configurations, that is, micro-level network patterns. By estimating and testing such models we assess which configurations contribute significantly to the overall structure of the network. In this way, ERGMs allow to capture the actor level elements which bring about the observed network structure.

We fitted an ERGM with a configuration for each of the discussed network mechanisms. As the efficiency/security trade-off is concerned only with structural effects, we did not include any node attribute parameters or dyadic covariates. We employed the alternating statistics in our models (Snijders, Pattison, Robins, & Handcock, 2006). Alternating statistics progressively weight down higher-order multiples of their corresponding configurations, which prevents the distribution of networks to be highly concentrated at a combination of nearly complete and nearly empty graphs, the so-called near-degeneracy problem. We fitted the models using the MPNet software for estimation of ERGMs (Wang, Robins, & Pattison, 2009).

We included the following effects in the model. The *edge parameter* models the overall propensity of actors to create ties. The *alternating star parameter* models the tendency of a few actors to have many ties, reflecting accumulation of ties. The *alternating triangle parameter* captures the tendency of actors to form closed structures (triangles), whereas the *alternating two-path parameter* captures the preconditions for closure. A positive two-path effect alongside a positive triangle effect in the model may be interpreted as brokerage as it suggests there is a tendency toward creating connected structures which are not part of closed triads (Garry Robins, personal communication). Finally, the *alternating edge-triangle* parameter, defined by a triangle in which one of the nodes has multiple other ties, models the tendency to combine efficiency and security, as it captures both closure and openness (see Figure 1; Pattison & Snijders, 2013). If the resulting coefficient is at least twice as high in absolute value as the corresponding standard error, we consider parameters significant (Lusher et al., 2013). Positive values of significant parameters indicate, that the given configuration is significantly more present given other parameters in the models, while negative values of significant parameters indicate they are significant less present.

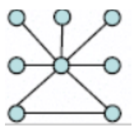


Figure 5.1: Alternating edge-triangle configuration

Many of the networks are too small to be analysed separately according to an ERGM in this specification. Therefore, all networks of the same type (profit-driven and ideology-driven) were combined in one large network, using structural zeros between individual networks representing that ties between networks are impossible to (Kalish & Luria, 2013)[33]. For the two combined networks, parameter estimation was iterated until satisfactory model convergence was obtained (convergence t-ratios for all fitted parameters < 0.1 in absolute value). We also checked the goodness of fit of each model to see whether it represents the data adequately by the method of Hunter, Goodreau, and Handcock (2008) as implemented in the MPnet software.

Modelling all networks of one type together with one model assumes that the model is homogeneous across all the networks, neglecting within-group differences. This is not tested by the standard goodness of fit checks for the ERGM. To investigate the homogeneity across networks, we did an additional goodness of fit check. This used three statistics that are not systematically dependent on number of nodes, applied to each network separately: average degree, variation coefficients of degrees, and clustering coefficients minus density[34]. To apply this to each network separately, we included dummy variables indicating the membership of a node in particular network. These statistics were also used in the goodness of fit procedure according to the method of Hunter, Goodreau and Handcock (2008). A poor fit (t-ratios > 2 in absolute values) suggests that the specific network is far from the model "average" in terms of the statistic in question. If this happens for many networks, it indicates internal heterogeneity within the given type of criminal networks.

5.7. Results

Descriptive measures comparisons

Table 1 contains the results of descriptive analyses. The comparison between profit- and ideology-driven networks in terms of the relevant descriptive measures is displayed by violin plots in Figure 2. In terms of the number of nodes, both the largest and smallest network are

[33] We initially started with case-by-case modelling with the intention to subsequently summarize the results with a meta-analytic technique (Lubbers & Snijders, 2007). However, this approach resulted in problems with poor convergence or degeneracy with a number of cases, which eventually rendered this approach inapplicable.

[34] These three statistics can be calculated with the simulation output from MPNet.

ideology driven, that is, the Turkish terrorist network Ergenekon (N = 86) and the Indonesian terrorist group Jemaah Islamiyah (N = 17). In general, ideology-driven networks in our dataset tend to be larger than profit-driven networks ($p = 0.06$ in a two-sample permutation test).

Hypothesis 1: Looking at cohesion, the densest network in the dataset is the Al-Qaeda pre-War on Terror network (average degree = 10.96), whereas the sparsest is a Dutch women trafficking network E (average degree = 1.9). There is considerable variability among ideology-driven networks, whereas the average degree varies less in profit-driven networks, as evidenced by Figure 3. We found no support for the hypothesis that profit-driven networks are denser than their ideology-driven counterparts ($p = 0.99$), however the p-value implies a significant difference opposite to Hypothesis 1, that is, ideology-driven networks have a higher average degree instead of profit-driven networks.

Hypothesis 2: The variation coefficient of degree, capturing the dispersion of the average number of ties among actors, is highest in the case of the European branch of the Islamic State terrorist network (1.43), and lowest in the Jemaah Islamiyah network (0.4). Similar to average degree, we found considerable variance in ideology-driven networks for this network measure. We found support for Hypothesis 2 ($p = 0.04$), which states that profit-driven networks are more centralized.

Hypothesis 3: The network which exhibits the highest clustering coefficient minus density (0.33) is the Jemaah Islamiyah, while the lowest value is for the European branch of the Islamic State network (0.02). Again, there is high variability among ideology-driven networks, but also among profit-driven networks. The difference between ideology-driven and profit-driven networks is not statistically significant in the predicted direction ($p = 0.96$). However, similar to average degree, this finding contradicts the efficiency/security trade-off as the p-value implies the opposite difference to what the theory predicts. Hence, we found no support for Hypothesis 3.

Hypothesis 4: Looking at brokerage captured by average constraint, the Malian-Tuareg terrorist network has the highest value (0.73), whereas the lowest value is displayed by a Spanish drug trafficking network JAKE (0.19). Both these networks are outliers of their respective types. Overall, the ideology-driven networks are not exhibiting statistically significantly more brokerage than profit-driven networks ($p = 0.45$). This is in contrast with the assumption at the network level of the efficiency/security trade-off that ideology-driven networks have a lower number of redundant ties. Hence, there is no support for Hypothesis 4.

In sum, only we found support for the trade-off theory only in Hypothesis 2 about network centralization. In the case of density and closure, our results are in the opposite direction to what the theory would imply.

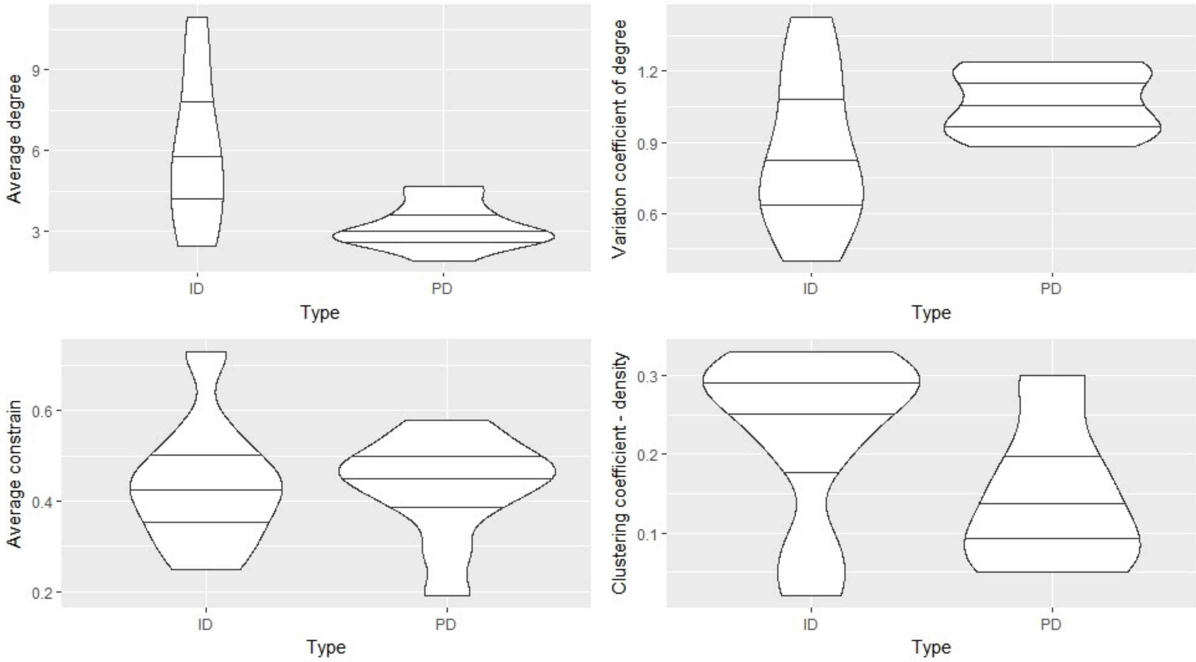


Figure 5.2: Violin plots comparing ideology-driven (ID) and profit-driven (PD) networks. Horizontal lines represent lower quartile, median and upper quartile respectively.

Exponential random graph model results

Table 2 displays the results of the exponential random graph models with one model for each type of network. In general, profit-driven and ideology-driven networks are rather similar in terms of ERGM results. First, the *edge* parameter is significant and negative in both cases, meaning that networks are sparse: actors do not have the tendency to proliferate their ties. Second, in both types of networks we found a significant, negative *star* parameter. This is consistent with general expectations about criminal network participants, who are supposed to avoid vulnerable centralized network structures. The *triangle* parameter capturing triadic closure is significant and positive in both types of criminal networks. Although closure results in more visibility and at least actors in ideology-driven networks should avoid it according to the trade-off theory, actors in both types of networks display tendencies towards it. The last similar feature is the positive and significant *edge-triangle* parameter. This can be seen as evidence for tendencies of actors in both types of criminal networks to balance brokerage and closure.

The only parameter that is not in the same direction for profit-driven and ideology-driven networks, is the alternating *two-path*. This effect is positive and significant in the case of profit-driven networks, but non-significant in ideology-driven networks. The positive two-path effect together with the positive triangle effect suggest that actors in profit-driven networks tend to create more open structures than actors in the ideology-driven networks, where the alternating two-path effects is not statistically significant. The non-significant effect in ideology-driven networks is contradictory to the expectation from the efficiency/security trade-off, which suggests that leaving two-paths open assures security while maintaining connectivity.

In terms of goodness of fit, the model for ideology-driven networks fits the data acceptably on 16 out of all 17 structural effects implemented in MPNet, with the exception of clustering coefficient (t-ratio = 8.35). The model for profit-driven networks slightly misfits five structural effects (goodness of fit t-ratio in all cases a bit above 2 in absolute value), but in the case of skewness of degrees, the t-ratio is -4.02 suggesting misfit.

	Profit-driven networks			Ideology-driven networks		
effect	estimate	SE	t-ratio	estimate	SE	t-ratio
edge	**-1,97**	**0,24**	-0,04	**-0,64**	**0,27**	0,06
alt star	**-0,56**	**0,09**	-0,03	**-1,40**	**0,08**	0,05
alt triangle	**0,63**	**0,09**	-0,02	**1,73**	**0,07**	0,02
alt two-path	**0,09**	**0,01**	-0,03	0,005	0,004	0,03
alt edge-triangle	**0,04**	**0,01**	-0,01	**0,015**	**0,001**	0,03
	11 networks, n = 342			8 networks, n = 363		

Table 5.2: Exponential random graph model results. Statistically significant effects are bold. Note: one network (pre-War on Terror Al Qaeda) has been excluded, because its inclusion caused problems with convergence of the model.

Figure 3 shows the comparison of goodness of fit for average degrees, variation coefficients of degrees and clustering coefficients minus density for each network. The bars represent *t*-values, which indicate the (dis)similarity between the mean counts of given statistics in the simulated sample of networks and the count of that statistic in the observed network. If the bar exceeds 2 or –2, this is an indication that the model does not adequately capture the corresponding network statistics. The statistics of the majority of networks in our sample are captured adequately by the model. However, we see different networks being highly over- or underestimated in each studied statistic. This is most clearly visible in the case of average degree, which the model overestimates in six profit-driven networks (one is underestimated) and three ideology-driven networks (one is underestimated). In terms of variation coefficient of degree, the results are very similar to average degree, although the deviations occur for different networks. Again a number of values are overestimated by the model, and one ideology-driven network is underestimated. In terms of clustering coefficient minus density, most of the networks are captured adequately by the model, but the outliers here are the farthest away from them (the t-ratio for the Ergenekon network is almost 60).

These results indicate two things. First, the efficiency/security trade-off theory as a structural theory does not yield a model which adequately explains criminal networks structures as indicated by its poor fit to a number of networks in our sample. Second, the post-hoc goodness of fit procedure reveals within-group differences which question whether the distinction between profit- and ideology-driven network is meaningful in terms of their actor-level relational mechanisms.

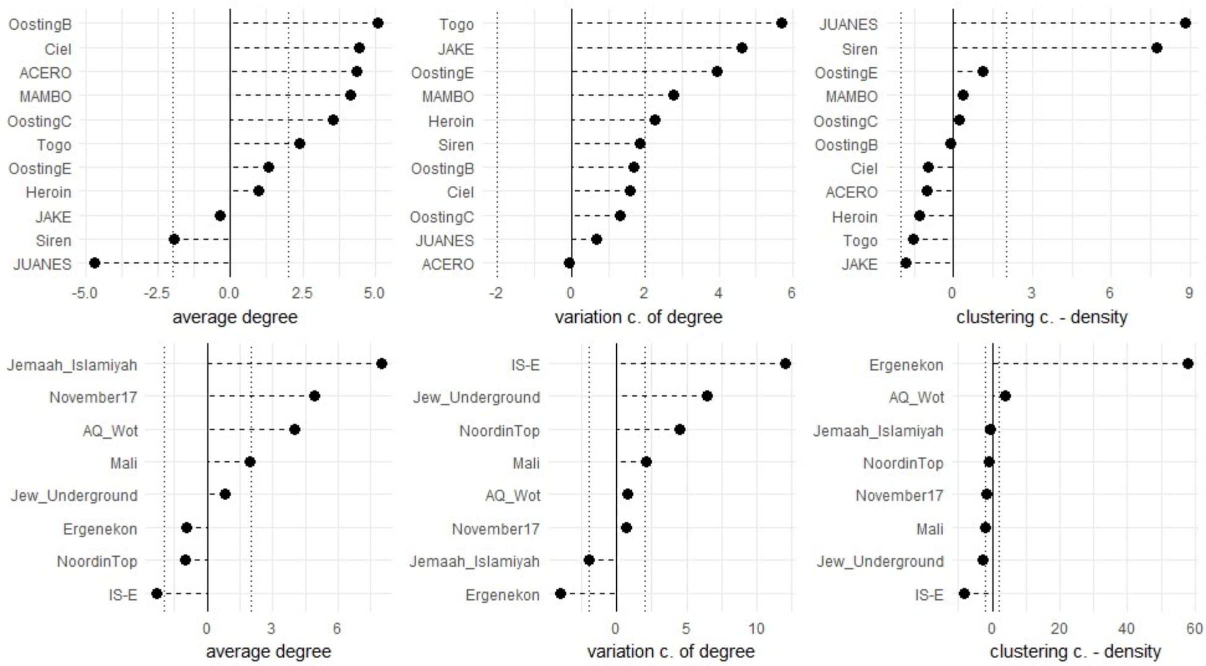


Figure 5.3: Goodness of fit t-ratios for average degrees, variation coefficients of degrees and clustering coefficients minus density in each network (upper row: profit-driven networks) based on 10,000 simulated networks of the same size and model parameters obtained from models in table 2.

Overall, the results of the ERGMs suggest that both profit-driven and ideology-driven networks are driven by the same underlying structural mechanisms; negative propensity to create ties, negative tendency towards centralization, positive closure, and positive tendencies towards balance between open and closed structures. The only clear difference is the positive brokerage tendency in profit-driven networks, which is absent in ideology-driven networks. The post-hoc goodness of fit analysis reveals that there are large within-group differences.

5.8. Discussion

The efficiency/security trade-off (Morselli et al., 2007) is an influential theory about the structure of criminal networks. We proposed several consequences of this theory on the network level, which we tested. However, we also argued that it is necessary to investigate the implications of the theory on the level of individual actors as network structures may not always align with individual intentions and even result in unintended, contradictory consequences. As such our study tries to respond to criticism for a lack of theoretical foundation in the field of criminal network studies (Carrington, 2011).

We focused on four properties of networks on which we tested the theory and, subsequently, explored the actor level mechanisms with exponential random graph models. Even though our tests found some differences between profit-driven and ideology-driven networks, these differences were only in one case in the direction predicted by the theory. Some differences were even opposite to the theory: ideology-driven networks displayed higher density (as measured by average degree) and closure than their counterparts. Our models suggest that both types of networks are brought about by similar actor level mechanisms with the exception of brokerage, for which there is statistical evidence only in profit-driven networks. Furthermore, the post-hoc comparisons based on these model reveals considerable within-group differences. We attempted to approach the profit-driven and ideology-driven networks as sets of criminal networks that, in spite of the size differences between individual networks, are internally homogeneous to a sufficient extent to allow a "collective" treatment and comparison at the group level. Our results show that the two groups are too heterogeneous internally for an unequivocal comparison, and that as far as clear-cut comparisons could be made, some of the differences found between the groups were opposite to the prediction of the efficiency/security trade-off theory.

Although there are some differences both descriptively and in terms of model parameters, these cannot sufficiently and satisfactorily be explained by the goal (profit or ideology) of the networks, as these differences do not align with the direction the trade-off theory would suggest. Moreover, there is also high variability within both types of criminal networks. These findings call into question the distinction between ideology-driven and profit-driven networks in the first place. Some cases have been documented where terrorist networks opted for drug dealing or other profit-driven activity as a part of their strategic toolkit (Asal, Milward, & Schoon, 2015; Ünal, 2019). This may also happen the other way around, when profit-driven networks try to intimidate their opponents by performing terrorist acts, for instance narco-mafias. Furthermore, it is certainly not impossible to imagine a profit-driven network in which actors sacrifice immediate profit for maximal security leading to a higher profit in the long-term, such as in the case of long-term planned bank robberies.

This is not to say that actors in criminal networks do not face the efficiency/security trade-off. Rather, there is very little support in our data that this trade-off is fundamentally different in profit- and ideology-driven networks. Theoretically, there are some inconsistencies between the analytical levels of actors and networks. One way in which the theory may be extended is the further conceptual clarification of the central concepts – security and efficiency. Currently, security is conceptualized as a need to stay away from detection. However, as suggested by theoretical arguments underpinning the mechanism of closure (e.g., Coleman, 1988), there may be another, and at least equally relevant, notion of security for actors in criminal networks, specifying security as the need to cooperate with trusted others. Similarly, efficiency is conceptualized as the amount of communication among actors. Some network theoretical literature suggests (cf. Snijders, 2013), that efficiency may also be thought of as trying to minimize the costs of creating and maintaining ties, which could motivate some actors to actually prevent the proliferation of ties or to be rather selective about which ties and with whom to create or maintain. Another way for extending the theory is explicitly theorizing the balance between efficiency and security. We have outlined several different forms this balance can take such as strategic positioning or balancing openness and closure. Furthermore, our model results suggest that actors have these balancing tendencies in both profit- and ideology-driven networks, which calls for further research on how these balancing tendencies unfold at both actor and network levels.

In the light of our findings and the theoretical issues discussed above, it is important to find some factors that might be better suited to explain variations between criminal networks. The dynamics and evolution of criminal networks over time is an intensively debated issue (see e.g., Bright et al., 2018; de Bie et al., 2017; Duijn, Kashirin, & Sloot, 2014; Stevenson &

Crossley, 2014). It is possible that the efficiency/security trade-off happens over time rather than across different types of activity. Actors observe their environment and they respond to perceived threats or opportunities. For instance, if actors feel threatened by law enforcement or by a competing criminal group, they may try to maximize security, while when they feel unthreatened or have plenty of opportunities to reach their goals, they may want to maximize efficiency. Studies by Crossley and colleagues (2012) and de Bie and colleagues (2017) point in that direction, when they show how the structures of ideology-driven networks change over time in response to change in the broader social context, whereas Bright and colleagues (2018) focused on changes at the actor level in a drug-trafficking network.

The efficiency/security trade-off as it is formulated now is a purely structural theory. Although endogenous self-organizing mechanisms may be critical parts of the explanation of emergence of criminal networks, it is unlikely that they will be sufficient explanations. The study of individual attributes and psychological predispositions of actors has been rather neglected in criminal networks (Robins, 2009). Nevertheless, motivation and intentions are properties of individuals, which intersect with their abilities and personal traits when actors create, maintain, or dissolve ties. The obvious question is how this happens, and to what extent it is modified by the attempts of actors to remain concealed. For example, there is some evidence suggesting that actors with high social status, such as politicians, have high self-confidence that they will not be detected or prosecuted, and thus create numerous ties which may result in high visibility and their eventual downfall (Demiroz & Kapucu, 2012; Diviák et al., 2018b).

More research on both the dynamics and individual attributes requires available data. However, the data availability, validity, and reliability is the greatest limitation of our study and perhaps of the entire research field of criminal networks. The comparison we conducted relies on clear and comparable content of ties, which discards much of the available data. Moreover, what was beyond our control was the definition of boundaries of the networks in our sample. Both these issues are frequently under insufficient consideration in the studies of criminal networks, yet the plausibility of conclusions from these studies directly depends on how the boundaries of the networks and the content of ties are defined. Morselli's (2009) criminal justice rings approach to boundary definition and the graph database framework for data collection proposed by Gutfraind and Genkin (2017) are promising in this regard. Transparent and unified schemes for data collection could enable more systematic comparison and generalization of findings across studies and in turn deepen our understanding of criminal networks.

We conclude that although there are structural differences among criminal networks, these differences cannot be accounted for by profit-driven or ideological motivation, as the differences *between* these groups are not marked and differences *within* the groups are non-negligible.

5.9. Appendix to chapter 5

Analysed networks:

Noordin Top – taken from the covert networks database of the Mitchell Centre for SNA (2019; available at: https://sites.google.com/site/ucinetsoftware/datasets/covert-networks), originally collected by Roberts and Everton (2011). N = 79; ideology-driven; only the ties in the dimension of communication are analysed. Indonesian jihadist terrorist network responsible for multiple acts of terrorism in South-East Asia.

November 17 - taken from the covert networks database of the Mitchell Centre for SNA (see above), originally collected by Rhodes and Jones (2009). N = 22; ideology-driven. Greek radical left-wing urban guerrilla.

Mali - taken from the covert networks database of the Mitchell Centre for SNA (see above), originally collected by Walther & Christopoulos (2015). N = 36; ideology-driven. Network of Islamist terrorists and Tuareg rebels in Mali.

Jemaah Islamiyah - taken from the covert networks database of the Mitchell Centre for SNA (see above), originally collected by Koschade (2006). N = 17; ideology-driven. Dichotomized. Indonesian terrorist network known for bombings in Bali in 2002.

Al-Qaeda pre-War on Terror – originally collected by Ouellet and colleagues (2017). N = 83; ideology-driven. Network of cooperation among members of Al-Qaeda prior to the War on Terror. Nodes do not overlap with Al-Qaeda War on Terror network.

Al-Qaeda War on Terror – originally collected by Ouellet and colleagues (2017). N = 35; ideology-driven. Network of cooperation among members of Al-Qaeda during the War on Terror. Nodes do not overlap with Al-Qaeda pre-War on Terror network.

Ergenekon - originally collected by Demiroz and Kapucu (2012). N = 86; ideology-driven. Symmetrized. Turkish political conspiracy and terrorist organization.

Islamic State in Europe – originally collected by Gutfraind and Genkin (2017). N = 62; ideology-driven. Only ties labelled as "met with" analysed. Network Islamic State supporters in Europe responsible for attacks in Paris and other Western-European locations.

Jewish Underground – originally collected by Asal, Nagar, and Rethemeyer (2014). N = 26; ideology-driven. Ties based on recruitment analysed. Israeli terrorist network which planned attacks on Muslim targets.

MAMBO - taken from the covert networks database of the Mitchell Centre for SNA (see above), originally collected by Gimenéz Salinas-Framis (2011). N = 31; profit-driven. Spanish-Colombian drug trafficking network.

JUANES - taken from the covert networks database of the Mitchell Centre for SNA (see above), originally collected by Giménez-Salinas Framis (2011). N = 51; profit-driven. Cocaine smuggling network between Mexico and Spain.

ACERO - taken from the covert networks database of the Mitchell Centre for SNA (see above), originally collected by Giménez-Salinas Framis (2011). N = 25; profit-driven. Spanish family-based drug distribution network.

JAKE - taken from the covert networks database of the Mitchell Centre for SNA (see above), originally collected by Giménez-Salinas Framis (2011). N = 38; profit-driven. Spanish drug distribution network.

Ciel - taken from the covert networks database of the Mitchell Centre for SNA (see above), originally collected by Morselli (2009). N = 25; profit-driven. Drug smuggling network from Jamaica and Canada.

Siren - taken from the covert networks database of the Mitchell Centre for SNA (see above), originally collected by Morselli (2009). N = 44; profit-driven. International network of stolen vehicle transportation.

Heroin distribution - taken from the covert networks database of the Mitchell Centre for SNA (see above), originally collected by Natarajan (2006). N = 38; profit-driven. Symmetrized. Drug dealing network from New York.

Togo - taken from the covert networks database of the Mitchell Centre for SNA (see above), originally collected by Morselli (2009). N = 33; profit-driven. Stolen vehicle resale network from Canada.

WomenTraffB (N = 18), WomenTraffC (N = 19), and WomenTraffE (N = 20) – three cases of woman trafficking in the Northern part of the Netherlands, which were investigated by the police in 2013-2014 and analysed by Oosting (2016).

6. Dynamics and disruption: structural and individual effects of police interventions on two Dutch jihadi networks[35]

6.1. Introduction

Despite the broad-based claim that criminal networks are dynamic, flexible, and adaptable, empirical research on dynamics of these networks is scarce (Bright, Koskinen, & Malm, 2018; Campana, 2016). One reason for this lack of evidence might be the scarcity of longitudinal data about criminal networks. While it is difficult to collect data on criminal networks in the first place, incorporating the temporal aspect is even more complex. However, the change of criminal network structure over time is an important aspect, as the ability to adapt and respond to internal and external changes is crucial for their functioning (Bright & Delaney, 2013; Bright et al., 2018; Duijn, Kashirin, & Sloot, 2014; Kenney, 2007).

The dynamics of criminal networks is especially relevant in relation to activities of law enforcement agencies to disrupt these networks. Observational and simulation studies comparing the performance of different disruption strategies showed that removal of actors in various types of central positions is among the most immediately efficient strategies (Bright, 2015). What is necessary, though, is to assess how disruption of criminal networks affects their evolution over time (Fielding, 2016). Interestingly, disruption attempts, such as arrests, do not usually lead to the complete dismantlement of the network, but only to partial damage. In response, actors may change the way they create, maintain, or dissolve ties, which, in turn, leads to changes in the network structure.

Considering network disruption in dynamic criminal network analysis allows to empirically asses the effect of disruption on network structure and actors' responses to disruption. Understanding how disruption strategies affect criminal networks is crucial considering the fact that even a very carefully planned network intervention may result in contradictory unintended consequences (Duijn et al., 2014; Morselli & Petit, 2007).

[35] This chapter is based on: Diviák, T., van Nassau, C. S., Dijkstra, J. K., & Snijders, T. A. B. (2019). Dynamics and disruption: structural and individual effects of police interventions on two Dutch jihadi networks. Under review.

We aim to study how disruption of criminal networks affects the network dynamics examining a unique longitudinal dataset about two jihadi extremist networks operating between 2002 and 2006 in the Netherlands. Members of these networks perpetrated or planned several terrorist actions, which prompted law enforcement to act and disrupt both networks. We study how the structure as a whole changed after the disruption attempts, and also how individual actors responded in terms of creating, maintaining, and dissolving relations with others. This allows us to assess the underlying mechanisms driving the change in structure (Bright et al., 2018; Ouellet, Bouchard, & Hart, 2017). By doing so, we aim to answer two interrelated research questions; how did the structure of these jihadi extremist networks change after the disruption by law enforcement agencies, and how did the tendencies of actors to connect with others change after the disruption.

6.2. Changes in network structure after disruption

Law enforcement agents may target criminal and terrorist networks with disruption strategies to incapacitate and eventually dismantle the network. The impact of these disruption attempts depend on the structure of the targeted network and its capacity to recover afterwards (Duxbury & Haynie, 2019; Malm & Bichler, 2011). In this section, we review important structural properties of criminal networks and how they might be affected by disruption attempts.

Size

One basic structural property of networks is their size, that is, the number of participating actors. Smaller criminal groups have been shown to be more resilient against disruption by law enforcement agencies than larger groups, as smaller groups are easier to coordinate, to organize internally, and to secure from activities by law enforcement agencies due to lower visibility (Bouchard & Morselli, 2014). Disruption of criminal networks may result in a decrease in size not only due to members being removed (e.g., by arrest) or reluctance of their members to prolonged participation, but also because this may be strategically more advantageous. For instance, to reduce the chance of detection by law enforcement agencies.

Density

Related to the number of participating actors is the number of ties among them, which is expressed by the density of the network. Although it could be argued that density decreases after removal of central actors, some studies of drug trafficking networks revealed the exact opposite, that is, an increase of density in response to disruption (Bright & Delaney, 2013; Duijn et al., 2014). Usually, this latter is driven by the remaining actors in the network, who increase contact and communication in response to activities of law enforcement agencies.

Centralization

Criminal networks may also exhibit varying degrees of centralization, defined as the extent to which ties are concentrated around a limited number of central actors. Centralization of networks is supposed to facilitate efficient and frequent cooperation due to central actors being in control of the majority of flows and processes in such networks. This reliance on central actors comes at the price of vulnerability to their removal. Indeed, some studies showed that after the removal of central actors, networks tended to fall apart, for instance, in the case of Indonesian terrorist network centralized around Noordin Top (Everton & Cunningham, 2014) and a drug importation network (Morselli & Petit, 2007). At the same time, there are some other network studies showing the opposite (e.g., Stevenson & Crossley, 2014). One explanation for this opposite effect is that previously less central actors may take over the position of the central actors who were removed from the network.

Network composition

Criminal networks may also exhibit more complex structural compositions. Two prominent types of structural compositions are core/periphery and cell structure. A core/periphery structure consists of two parts. The core part of the network consists of highly central actors who are mutually interconnected, whereas the periphery part contains actors who are not mutually connected, but only connected to the core (Borgatti & Everett, 1999). A core/periphery structure is centralized, but does not rely solely on one central actor, as all the core actors can substitute each other in terms of their structural position. In their study on the Provisional Irish Republican Army, Stevenson and Crossley (2014) found that the centralized network structure was also increasingly converging to a core/periphery structure.

Next to the core/periphery structure, attention has been paid to so-called cell structures in criminal and especially terrorist networks. A cell-structured network is compartmentalized into smaller internally dense subgroups, which are sparsely interconnected to one another (Sageman, 2004). This division into cells is supposed to assure trust and compliance, while increasing the autonomy of cells and the resilience of the network to infiltration and removal of actors. A network of militant suffragettes was found to closely resemble a cell structure with increasing compartmentalization in response to disruption (Crossley et al., 2012). So, whereas core/periphery structured networks allow centralized control of the network and replaceability of their central actors, cell structured networks promote autonomy and replaceability of cells in case of disruption.

In sum, there is some evidence that the structure of criminal and terrorist networks changes in response to disruption attempts of law enforcement agencies. This leads to the first research question: What are the changes in structural properties of networks under disruption?

To understand how these changes emerge, however, it is necessary to focus on individual actors. What is observed at the network level may not necessarily correspond to the underlying intentions and tendencies of actors. Similar network structures may even be brought about by different underlying mechanisms (Robins, Pattison, & Woolcock, 2005; Snijders & Steglich, 2015). To this end, it is necessary to not only assess the structure of the network over time, but also the tendencies of actors, who are ultimately responsible for changes in the network via their individual actions. In order to explain this interplay between actor tendencies and structural network changes, we will theorize why and in what way actors may act in response to disruption attempts of law enforcement agencies.

6.3. Network dynamics and individual action

It is commonly assumed that actors involved in criminal networks primarily aim to avoid detection due to the risk of being arrested (cf. Diviák, 2018; Morselli, 2009). Every action, such as creating a tie by cooperating with someone, increases visibility and, consequently, the risk of being detected. While creation and maintenance of ties is costly in general as it requires investment in time, energy, or effort (Snijders, 2013), these costs are even higher in criminal networks as each tie increases the chance of being detected. However, actors in criminal networks also need to interact and cooperate with others to perform their tasks and reach their goals for which they participate in the network. The need to act but at the same time remain concealed creates a tension which is known as the efficiency/security trade-off (Diviák, Dijkstra, & Snijders, 2019b; Morselli et al., 2007).

The efficiency/security trade-off postulates that actors in criminal networks manoeuver between the aims of assuring security by remaining concealed and working efficiently in reaching their goals. The trade-off between efficiency and security is supposed to be different between networks oriented towards financial profit and networks oriented towards ideological goals. According to the trade-off theory, profit-driven networks are assumed to be inclined towards efficiency, whereas ideology-driven networks (terrorists) are thought to be inclined towards security. Although recent studies found little support for the efficiency/security trade-off theory by revealing almost no predicted structural differences between profit-driven and ideology-driven networks (Diviák et al., 2019; Ünal, 2019), this does not necessarily imply that the trade-off is not at play. Instead, actors may constantly manoeuver over time between efficiency and security in response to changes in the network and its external environment.

We assume that actors are to some extent able to perceive what is going on in- and outside their network, enabling them to modify their actions accordingly. This assumption is consistent with the approach of structural individualism which posits that individual actors are the loci of action, but this action is constrained or facilitated by cognitive and social circumstances (Coleman, 1990; Hedström, 2005; Lindenberg, 2008). In our case, this relates to the efficiency/security trade-off by assuming that actors create, maintain, or dissolve their ties based on their aims and their information, including balancing between efficiency and security.

Whenever the network or its environment provides opportunities and actors feel relatively safe (e.g., when there is no opposition or the risk of prosecution is low), they opt for efficiency. In case actors feel threatened, or the structure of the network or its environment become constrained and reveal risks, for instance, in the presence of competing criminal groups or active law enforcement, they opt for security. As a consequence, we would expect that actors who face criminal network disruption by law enforcement, pattern their ties to improve security. In the following section, we theorize how efficiency and security considerations motivate actors to structure their relations and interactions, referred to as relational mechanisms.

6.4. Relational mechanisms in dynamic criminal networks

Relational mechanisms embody the tendencies of actors to interact with others in particular ways that bring about the observed structures (cf. Hedström, 2005; Rivera, Soderstrom, & Uzzi, 2010). When interacting with others, actors have three options; create new ties, maintain existing ties, or dissolve ties (Rivera, Soderstrom, & Uzzi, 2010; Snijders, van de Bunt, &

Steglich, 2010). In this section, we argue about how different relevant relational mechanisms affect the creation, maintenance, or dissolution of ties given that actors seek to maximize security after an attempt to disrupt the network. In general, relational mechanisms may increase security by either enhancing trust between actors or by reducing risk of detection from outside the network. Whereas trust-enhancing mechanisms generally contribute to maintenance of ties or creation of new ones, risk-reducing mechanisms prevent creation of ties or contribute to dissolution of already existing ones. We argue that trust enhancement and risk reduction become especially salient when actors in criminal networks face disruption.

Trust-enhancing mechanisms

Closure

Closure, also known as transitivity, is the tendency of actors to form triangles in the network, that is, triads in which all actors are connected to each other (Coleman, 1988; Rivera et al., 2010). Within these triangles, actors can oversee and support each other, and are less likely to defect or behave opportunistically, which is supposed to promote trust and security in criminal and terrorists networks (see e.g., Bright et al., 2018; Grund & Densley, 2014; Ouellet et al., 2017). How does closure evolve over time in criminal networks? There is some evidence that increased pressure on criminal networks from law enforcement increases cohesion of the network (Bright & Delaney, 2013; Duijn et al., 2014). This may be attributed to the increased need for trust in face of increased risk (Coleman, 1988). By maintaining closed triangles, actors may assure collaboration with trusted partners. When the network is being disrupted and actors are choosing which ties to keep and which ties to drop, ties embedded within triangles may be more likely to be maintained than those without the additional backup by a third party. Similarly for tie creation, we could expect that actors under pressure would prefer to cooperate with actors who are already connected to their current contacts.

Homophily

Homophily is the tendency of actors to have ties to others with whom they share some salient attributes (McPherson, Smith-Lovin, & Cook, 2001; Snijders, 2013). One salient attribute may be ethnic background as sharing the same ethnicity may facilitate trust and communication between actors, resulting in the initiation and maintenance of a relationship (Snijders, 2013). For instance, in an ethnically heterogeneous gang, shared ethnicity was found to be a strong predictor of co-offending (Grund & Densley, 2014). A study on the

Provisional Irish Republican Army also revealed that brigade membership homophily contributed to the collaboration among its members (Gill, Lee, Rethemeyer, Horgan, & Asal, 2014). Shared ethnic background may facilitate cooperation as well. When facing a disruption attempt, actors in terrorist networks may opt for maintaining or, if necessary, creating ties with similar others, because such ties may be easier to keep concealed (e.g., by using ethnically specific language or communication practices) and may be more trustworthy.

Radical settings

Convergence settings denote spatial or social settings that provide criminal actors opportunities to meet and gain information and resources, which facilitate collaboration among them (Felson, 2006, 2009). In the context of terrorist networks, the concept of convergence settings has been referred to as radical settings (Malthaner, 2018; Wikström & Bouhana, 2017), which analogously enable actors who are interested in radical ideas and activities, to seek fellow radicals, disseminate radical ideas, and provide social support and access to a common pool of information and resources. Thus, joint exposure to radical settings may stimulate formation of ties. In the face of network disruption, actors may seek confinement within radical settings or prefer to maintain the ties embedded within radical settings, as such ties may be seen as more trustworthy and secure.

Pre-existing ties

Pre-existing ties are legal and legitimate relationships established prior to cooperation within a criminal network, such as being classmates, workmates, or family members (Diviák et al., 2018b; Diviák, Dijkstra, & Snijders, 2019a; Erickson, 1981). These ties provide a solid basis for trust as they build on shared histories, commitment, and expectations (Erickson, 1981; Krebs, 2002). This makes pre-existing ties crucial in criminal and terrorist settings as they compensate for the lack of formal institutions, which may assure compliance and enforceability of contracts (Smith & Papachristos, 2016). While the above-mentioned characteristics of pre-existing ties highlight their relevance for criminal collaboration, in the case of network disruption, the importance of pre-existing ties may even increase as actors seek to maximize security and, thus, rely only on actors whom they deem trustworthy.

Risk-reducing mechanisms

Preferential attachment

Preferential attachment is the tendency towards accumulation of ties by actors who already have a relatively high number of ties (Barabási & Albert, 1999; de Solla Price, 1976; Rivera et al., 2010). Although having many ties may be seen as more efficient as it allows central actors to cooperate with numerous other actors, from a security point of view, the accumulation of ties increases visibility of actors and thus their risk of being detected. Moreover, once central actors have been detected a large number of other network members may become visible as well. This is also supported by previous research showing that criminal and terrorist networks become more vulnerable when ties are increasingly concentrated around a few particular actors (Bright et al., 2018; de Bie, de Poot, Freilich, & Chermak, 2017; Everton & Cunningham, 2014; Ouellet et al., 2017). Therefore, we would expect actors in a terrorist network under pressure to drop their ties, especially to or from central actors, in order to prevent visibility rather than accumulate new ones.

Arrest deterrence

Some actors may have been investigated or arrested in association with jihadi activities prior to joining the networks in our study or during the first observation period. Both the awareness of surveillance and the restrictions induced by temporal arrests may motivate them to limit their activity. Moreover, they may also become regarded as risky partners by others, who, in turn, may want to avoid interacting with them as it would increase their own risk of detection and potential imprisonment. Thus, actors being arrested or interrogated may be themselves less likely to maintain existing or create new ties, whereas other actors may refrain from creating or even dissolve ties with them.

Together, we identified several mechanisms that potentially explain why and how actors in terrorist networks create, maintain, or dissolve ties with others in response to activities of law enforcement agencies. Specifically, we distinguished trust-enhancing mechanisms in which we assume that actors rely on specific ties (i.e., pre-existing, homophilous ties, friends of friends, and ties within radical settings) and risk-reducing mechanisms in which we assume that actors refrain from certain contacts (i.e., reducing the accumulation of ties and the avoidance of contact with those having been arrested) when facing disruption by law enforcement agencies. Hence, our second research question is: to what extent do trust-enhancing and risk-reducing mechanisms affect the evolution of the network under disruption?

6.5. Data

The data in our study follow from police files on terrorist networks operating in the Netherlands. The two networks in our study are part of a larger Jihadi scene active in the Netherlands between 2002 and 2006. The selection of networks is based on the assessment of police officers identifying both networks to be separately emerging and evolving within a broader Jihadi scene in The Netherlands and our assessment of the availability of information on the contacts among the involved actors. Information on the networks follow from 15 (partly overlapping) police investigations, covering a range of investigative procedures, including wire taps of telephone and internet communications, recordings of in-house communication, transcripts of suspect interrogations and witness statements, house searches, and observation reports. Additional information was added from court transcripts, interviews with leading police investigators, public prosecutors, and criminal defense lawyers (further see De Bie & De Poot, 2016). The dataset is not publicly available due to sensitive information, but we were allowed to work on it under the condition of assuring information security and anonymity of all involved actors.

Description of cases

The two networks of Salafi-Jihadi inspired actors operated over a five-year period and were at some stage disrupted by law enforcement. Network 1 was active between 2002 - 2005 and was initially formed by mainly young men and women inspired by two older (competing) Syrian men teaching their Salafi-Jihadi interpretation of Islam. They frequently met to read the Quran and discuss religion, politics, and possible actions. Some were related by kinship, grew up in the same neighbourhood and/or went to school together, whereas others had met in local mosques known for their Salafi interpretation of Islam. The radical settings in which they frequently met also served as a place where many actors initially met. For some of the initial actors, and some who joined later, participation became a full time occupation, actively reaching out to share their interpretation of Islam and stimulating others to join their activities. From the early start on these activities included illegal, ideologically driven activities, including a false bomb alert, the threatening of a politician and travelling to foreign conflict areas supporting the international Jihad.

Network 2 evolved over a two-year period (2005-2006) and included two small groups of actors who prepared for foreign fighting. Both groups were connected by an older man, who already was known in local communities as well as by law enforcement for his Jihadi sympathies and recruiting activities. He assisted both groups in both religious matters (calling for prayers etc.) and more practical affairs (financial resources, visas etc.). The second group within this network however became increasingly disappointed in his deliverance, leading eventually to his (much discussed) excommunication. Many of the actors involved in network 2 first met while attending the lectures of a firebrand preacher teaching a Salafi interpretation of Islam in a local mosque. They started meeting frequently outside this mosque as well, in the apartment of the aforementioned older man, and later also in the apartment of a married couple. This couple became central in discussing the Jihadi narrative. Although young, the male actor in this couple was respected for his knowledge of the Quran and the Arabic language, while his wife was actively involved in (digitally) spreading Jihadi material.

As for the number of actors involved, in the first network 57 actors were included and in the second network 26. The inclusion of these actors was based on the following criteria: (1) actor expresses extremist, Salafi-Jihadi sympathies (or is explicitly facilitating other actors who do so), (2) resides in the Netherlands (or in close vicinity, i.e., Belgium), (3) basic information is available on the actor's background characteristics (e.g., age, gender, ethnicity, place of residence) and (4) at least some information is available on contacts with other actors included.

For both networks, it was possible to distinguish two periods referring to the situation before and after the law enforcement disruption took place. Thus, the delineation between the periods in our networks is an event-based split (Campana & Varese, 2012) . For network 1, the terrorist action of one particular actor resulted in the police arresting over a dozen actors at the end of 2004, which constitutes the delineation between the first and the second period in network 1 (2002-2004 and 2005). Police officers pointed at the stimulating role of two specific actors, who were among the initial actors of the network. One was part of the group of arrested actors and swore revenge once he was released from prison. The second actor, who stimulated the network to continue its (terrorist) activities, reappeared a couple of months after the arrests took place. No new actors joined this network after disruption.

During this period (2005) in which the continuing activities of network 1 were observed, network 2 emerged, with three actors attempting to support jihad by travelling to a foreign conflict area at the end of 2005. Soon after they had left, they were put into local custody and sent back to the Netherlands. This event constitutes the delineation between the first and second time point in network 2. So while the disruption in network 1 consisted of larger shakedown in the form of numerous arrests, the disruption of network 2 was minor in terms of the number of directly affected actors. Within the cores of both disrupted networks, several married couples actively participated. Some by teaching and spreading the Jihadi narrative and planning other activities, others by offering material support, in sharing their apartments, cars, etc.

Measures

For all actors we recorded the information on contacts mostly related to jihadi activities or ideas with other actors included in our networks. These contacts constitute the basis of our dependent variable – a network of communication among actors. Thus, the ties in our networks represent that the two actors were in touch, either in person, by phone, or on the internet (during given period).

As an individual attribute relevant to our hypotheses, we included the *ethnic background* of each actor. The largest group in both networks is formed by Moroccans, followed by Syrian, Turkish, and native Dutch. The second individual attribute relevant for our hypothesis is a binary variable called *arrest* which captures whether the given actor had previous contacts with the police related to (possible) terrorist activities. These contacts include arrests and house searches. We use the arrest variable only in models for network 1, as there were no such actors in network 2 prior to its disruption and thus it was impossible to include it in the models. The last individual attribute, *police attention*, indicates that the actor was under *police attention* at the start of an investigation. The police attention variable is supposed to control for the initial focus of the police, which may positively bias the actor's observed involvement, sometimes called the spotlight effect (Bright et al., 2018; Smith & Papachristos, 2016). The spotlight effect might make the initially surveilled actors seem more active in the network, although this activity may just be artificially induced by their longer observation.

We also included three dyadic variables in our models. *Radical settings* refer to joint participation of actors in settings, such as phone shops, apartments, in which the actors met on a regular basis and shared information. *Pre-existing ties* denote familial or friendship ties from before the jihadi activities. *Shared location* was included as control variable, measuring actors who were jointly located in one of the five municipalities in our data and, thus, having higher probabilities to interact because of their spatial proximity.

6.6. Methods

We descriptively analysed both the networks, which is important in itself and allows us to answer RQ1 about the change at level of the whole network structure. We applied statistical models for network dynamics to investigate the effect of trust-enhancing and risk-reducing mechanisms on the change in the network, answering RQ2 about which mechanisms drive the change at the individual level. We subsequently used the information from the data source to contextualize our quantitative findings and to reflect on our interpretation of the results.

Descriptive measures

To capture the change in the overall network structure of the two Dutch Jihadi networks and thus to answer our first research question, we used the following network level indicators (see e.g., Borgatti, Everett, & Johnson, 2013; Cunningham, Everton, & Murphy, 2016; Prell, 2011). *Density* is the number of ties in the network relative to the maximum number of possible ties in the network. *Centralization* is the dispersion of the number of ties across actors compared to a network with maximally concentrated ties. *Transitivity* is a ratio of complete triangles to all two-paths (triads connected only by two ties). Hence, transitivity descriptively measures closure. All these measures range between 0 and 1, where values closer to 1 indicate a denser, more centralized or more closed network. The average degree and standard deviation of degrees are alternative ways to express the number of ties and their dispersion in the network. *Geodesic distance* is the shortest path length between a given pair of actors in the network and diameter is the longest geodesic distance in the network. Shorter geodesic distances indicate more cohesion in the network. *Isolates* are actors with no ties in the network, that is, with a degree of zero. Isolates were not included in the calculations of geodesic distances as the path length between actors without a path is undefined. We calculated all these metrics using the igraph R package (Csardi & Nepusz, 2006).

In order to assess the extent to which our networks resemble a *core/periphery* structure, we used the categorical core/periphery routine in the UCINET software (Borgatti et al., 2002). This procedure iteratively tries to partition the actors in the network into two sets (i.e., core and periphery). In so doing, it maximizes the similarity between the partitioned data and an ideal core/periphery structured network (with core being a complete graph, periphery being an empty graph, and remaining ties falling between core and periphery). Subsequently, the correlation between the resulting partition and its ideal core/periphery counterpart is calculated.

In order to assess the extent to which our networks exhibit a *cell-structure*, we first applied a subgroup detection algorithm and subsequently assessed the resulting subgroups by calculating their modularity. We used the edge-betweenness (also known as Girvan-Newman) algorithm[36] to define the groups (Newman & Girvan, 2004). This algorithm tries to identify subgroups in the network by successively deleting bridging ties from the network. Isolated components created by these deletions are then the subgroups, which corresponds to the concept of a cell-structure. Modularity is the number of ties falling within subgroups in the network relative to the number of ties falling within subgroups in case the ties were randomly reshuffled (Newman & Girvan, 2004). Modularity ranges from -1 to 1 with higher values indicating more resemblance to the community structure. As a rule of thumb, networks with modularity larger than .3 are considered to be subgroup structured (DellaPosta, 2017).

We also described the observed change in the network structure before and after disruption with two measures of similarity: Hamming distances and Jaccard's coefficients. *Hamming distance* is simply the amount of differences between network structure in one point and another, whereas *Jaccard's coefficient* is a ratio of ties being present at both time points relative to the number of ties present in at least one of them. Jaccard's coefficient is 1 if there is no observed change (the networks are identical) and 0 if no tie was preserved between the successive time points.

Statistical models

To answer our second research question about individual level mechanisms, we applied stochastic actor-oriented models (SAOMs; Snijders, 1996; Snijders et al., 2010; Steglich, Snijders, & Pearson, 2010) to model the tendencies of actors to interact with others in response to network disruption. SAOMs represent a class of statistical models for longitudinal data on social networks. If there are two observation times, as is the case here, the dependent

[36] We also used other algorithms suitable for our data (namely: Louvain, walktrap, and fast-greedy algorithm) and the changes in the values of modularity are in the same direction.

variable in these models is the network at the second time point, and the question is how this came about, given the network at the first time point. Changes in ties are assumed in the model to be results of a sequence of small incremental changes, so-called micro-steps, regarded as choices by actors. A change can be the creation of a new tie, or the dissolution of an existing tie; the latter will be interpreted as a choice against maintaining the tie, and the model will be formulated in terms of creating and maintaining ties. The relative frequency of opportunities for change by a given actor is represented by the *rate function*. How tie variables change may depend on endogenous network mechanisms (such as closure or preferential attachment), actor attributes (such as gender or age), and dyadic attributes (e.g., pre-existing ties). The so-called *objective function* determines the likelihood of specific tie changes, and contains parameters defining the importance of these mechanisms. The mechanisms of interest are captured by configurations, i.e., small subgraphs that operationalize the mechanism, such as triangles representing closure or a tie between two actors of the same type representing homophily. Parameter values indicate the contribution of a given type of change to the objective function, where positive values indicate that actors have preference for a given configuration, whereas negative values indicate a preference against it. Thus, SAOMs allow to disentangle the effect of different mechanisms. The objective function may contain *evaluation effects*, expressing the overall tendencies relating to creating and maintaining ties; and also *maintenance effects* and *creation effects*, differentiating between tendencies to maintain existing or create new ties respectively.

Stochastic actor oriented model specification

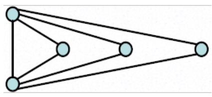
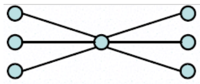
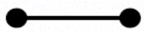
effect	visual representation	interpretation: tendency to…
degree (density)		create ties (model intercept)
GWESP		close open triads; closure
degree activity + popularity		concentrate ties around central actors; preferential attachment
dyadic covariate main effect: pre-existing ties		create ties based on presence of other ties; tie entrainment
dyadic covariate main effect: shared radical settings		create ties based on presence of other ties; tie entrainment
ego and alter effect: arrest		create ties to/from actors with given attribute; arrest deterrence
same ethnicity		of actors with given attribute to have similar alters; homophily

Table 6.1: Stochastic actor oriented model specification without control effects

Because the networks we study are undirected, we used the undirected variant of SAOM (Snijders & Pickup, 2017). We used the so-called forcing model[37] in which one actor during the simulations unilaterally imposes that a tie is created or dissolved. The number and variety of theoretically interesting effects is too large given the information available from the data, and therefore the analysis proceeded in two steps. We first estimated a model for general preferences of actors, containing only evaluation effects, without differentiating between the mechanisms favouring creation of new ties and those favouring maintenance of existing ties. Given the available data, it was impossible to estimate parameters for tie creation and tie maintenance separately. Therefore in a second step we tested the creation-maintenance distinction by so-called score-type tests (Ripley, Snijders, Boda, Vörös, & Preciado, 2019; Schweinberger, 2012). These allow testing parameters without estimating them. To assess goodness of fit of our models, we used a distribution of 1,000 simulations from our final

[37] We also estimated our models using the unilateral initiative and reciprocal confirmation model and the results did not differ substantially.

model and compared how well they re-create the observed data in terms of degree distribution, geodesic path lengths distribution, and triad census (counts of different configurations containing three nodes).

6.7. Results

Descriptive results

	Whole network measures			
	network 1 (n = 57)		network 2 (n = 26)	
statistic	wave 1	wave 2	wave 1	wave 2
density	0.16	0.05	0.11	0.24
centralization	0.51	0.27	0.17	0.40
transitivity	0.42	0.46	0.60	0.52
avg geodesic distance	2.25	2.03	2.82	1.78
diameter	5	4	6	3
avg degree	8.67	2.77	2.69	6.08
SD degree	7.34	4.21	2.22	4.71
isolates	0	27	7	3
core-periphery fit	0.62	0.77	0.59	0.79
modularity	0.12	0.18	0.5	0.01
Hamming distance	524		144	
Jaccard coefficient	0.11		0.23	

Table 6.2: Whole network measures of both networks at time point 1 and 2

Table 2 summarizes the description at the structural level[38]. Both networks underwent a considerable amount of change, which is captured by their Hamming distance and Jaccard coefficient. Only 11% of ties remained in network 1, whereas 23% of ties were preserved in network 2. This considerable change had two opposite results for some of the network indicators. The largest network 1 becomes substantially less dense and less centralized, the number of actors with no ties (isolates) increases sharply, and only transitivity slightly increases. In contrast, the smaller network 2 becomes more dense and more centralized, more actors become connected, and transitivity drops slightly. In both networks, distances among connected actors become shorter after the disruption, especially in network 2.

Both networks display a similar evolution considering the structural compositions of core/periphery and cell structure. Both networks may be considered as core-periphery

[38] It is common to visualize networks with sociograms. However, we are not allowed by the data provider to release any information that could identify specific actors and thus we are not visualising the network here.

structured. Prior to the disruption, both networks showed a correlation to ideal core/periphery structure around .6. The core/periphery fit of both networks increased considerably after the disruption (.77 and .79 respectively), suggesting a further solidification of the core-periphery structure. However, modularity as a measure of cell structure tells a bit different story. Network 1 did not have a cell structure, neither before nor after the disruption. Network 2 starts clearly cell-structured, showing high modularity (.5) with two subgroups. After the disruption, the cell structure disappears as the two subgroups merge and evolve into a core/periphery structured network.

Responding to research question 1, the descriptive results show that the cohesion of network 1 was strongly affected by the disruption. The only ties that remained relatively intact were those in densely interconnected regions of the network, as indicated by the increasing values of transitivity and core/periphery fit and by the fact that a substantial amount of ties were dissolved, whereas only a handful new ones created and no new actors joined. On the contrary, the disruption of network 2 seems to have strengthened its cohesion and further activated its remaining members, which is documented by the network measures. Furthermore, network 2 underwent a transition from a cell-structured network with two subgroups to a core/periphery structure, by the creation of several bridges between the previously rather separated subgroups. The core-periphery structure in both networks allowed substituting arrested actors with new ones in similar structural position, thus allowing the networks to continue functioning.

Model results

Stochastic actor oriented model results

	network 1 (n = 57)		network 2 (n = 26)	
effect	parameter	S.E.	parameter	S.E.
rate	**12.71**	**2.06**	**4.65**	**1.27**
degree (density)	**-3.87**	**0.63**	**-1.72**	**0.74**
GWESP (triadic closure)	**2.09**	**0.48**	**1.7**	**0.64**
degree activity + popularity	0.001	0.03	0.02	0.09
pre-existing ties	**2.51**	**0.55**	0.81	0.73
radical settings	0.08	0.19	0.32	0.26
same ethnicity	0.34	0.19	-0.1	0.35
arrested actor	-0.08	0.17	-	-
actor under attention	**-1.06**	**0.29**	**-0.99**	**0.33**
co-location	**0.95**	**0.2**	-0.09	0.32

Table 6.3: Stochastic actor oriented model results for evaluation effects in both networks. T-ratios for convergence are not listed, but they were all well below .1 in absolute value indicating good model convergence.

Table 3 summarizes the SAOM results. In network 1, apart from the control effects, two evaluation effects are statistically significant; GWESP and pre-existing ties. GWESP captures triadic closure and its value indicates that when two actors have ties to the same third actor(s), the chance they will also have a direct tie increases. Also, actors tend to create connections on the basis of their pre-existing ties. None of the remaining substantive effects (degree activity and popularity, radical settings, same ethnicity, and actor under arrest) are statistically significant. Therefore, the dynamics of network 1 shows no evidence for the mechanisms of preferential attachment, radical settings exposure, ethnic homophily, or arrest deterrence. The co-location control variable is positively significant in network 1 indicating that actors in this network who reside in the same municipality are more likely to cooperate.

In network 2, only the GWESP effect is significant and positive as in network 1, suggesting again that triadic closure influences tie formation in a disrupted network. Here, we did not find evidence for the translation of pre-existing ties. In terms of control variables, the ego and alter effect for police attention is significantly negative in both networks, suggesting that actors under initial law enforcement surveillance tend to have fewer ties than other actors, which is quite surprising as it is the opposite of the spotlight effect.

Score-type tests results - tie maintenance network 1 (n = 57)	
effect	z-score
GWESP (triadic closure)	**-5.4**
degree activity + popularity	**-2.11**
pre-existing ties	-1.7
radical settings	1.06
same ethnicity	-1.76
arrest ego and alter	1.43

Table 6.4: Score-type test results for endowment effects in network 1

Table 4 contains the results of score-type tests to investigate whether there is a difference for network 1 between the effects of creation of new ties and maintenance of existing ones. These tests are conducted assuming the model of Table 3. We found significant negative maintenance effects for GWESP and degree activity + popularity. This indicates that triadic closure and translation of pre-existing ties have significantly smaller effects for maintaining ties than for creating new ties, when controlling for the model of Table 3. For network 2, we did similar tests for tie maintenance as well as tie creation, but no significant effects were found.

Responding to research question 2, we can conclude that triadic closure was the driving force behind the change in both networks under disruption. Furthermore, we found support for the operation of translation of pre-existing ties into communication ties in network 1, but not for network 2. For the other mechanisms, no significant effects were found. The score-type tests revealed that triadic closure and preferential attachment in network 1 have a significantly larger effect on tie creation than on tie maintenance. For network 2, the score-type tests did not reveal such differences. Taken together, when actors face disruption of the network, they tend to act in accordance with trust-enhancing mechanisms by creating new collaboration ties especially with actors with whom they have pre-existing ties or common third parties. In contrast, for the risk-reducing mechanisms, we only found evidence in network 1 for the tendency of actors to drop ties proportionately to the number of ties they already have.

The results of the analysis of the whole network structure and the individual-level mechanisms can be combined and qualitatively reflected upon. The structure of network 1 changes as a result of the disruption – it is becoming less dense, decentralized, and the number of isolated nodes increases sharply, maintaining (and slightly strengthening) a core-periphery structure. The new core of the network includes several married couples, with two particularly active male actors. These two actors were among the initial actors in network 1. One vowed revenge after his arrest, the other was actively reaching out to others, organizing meetings and explaining the Jihadi narrative. In order to keep the network functioning, these actors were reaching to the pool of their pre-existing contacts and were fostering cooperation among their associates. This is supported by significant effects of triadic closure and pre-existing ties on tie formation. Interestingly, we find no statistical evidence for tendencies to accumulate ties (preferential attachment), despite the contextual information pointing out activities of particular individuals. By closely inspecting the degree of each actor before and after disruption, we can say that this is likely to be a result of highly central actors in the first time point dropping a lot of their ties (even becoming isolated), while other actors taking over the central role by creating a lot of ties in the second time point. These two changes might have evened each other out resulting in an insignificant preferential attachment effect, combined with a negative result of the score test for degree activity + popularity: this corresponds to some central actors losing many ties, while also some other central actors gain many ties.

In contrast, the structure of network 2 is becoming more cohesive after the disruption, with an increase in density and centralization, abandoning its cell structure in favour of a core-periphery structure. One of the couples involved became particularly active by organizing frequent meetings in their apartment, and teaching and sharing Jihadi material. After the disruption this couple seems to have taken over leadership from the actor who previously brokered between the two subgroups. Interestingly, the formation and maintenance of ties in this transition is also brought about by triadic closure. This suggests that triadic closure is an important mechanism when actors try to try to continue their activities both when they try to withstand the disruption as well as when they try to mobilize further. Again, triadic closure drives the evolution of the network despite 'qualitative' evidence pointing to activity of some visible individuals. It's not only the central actors being active, but also their contacts creating ties among themselves which makes the network denser and more core-periphery structured.

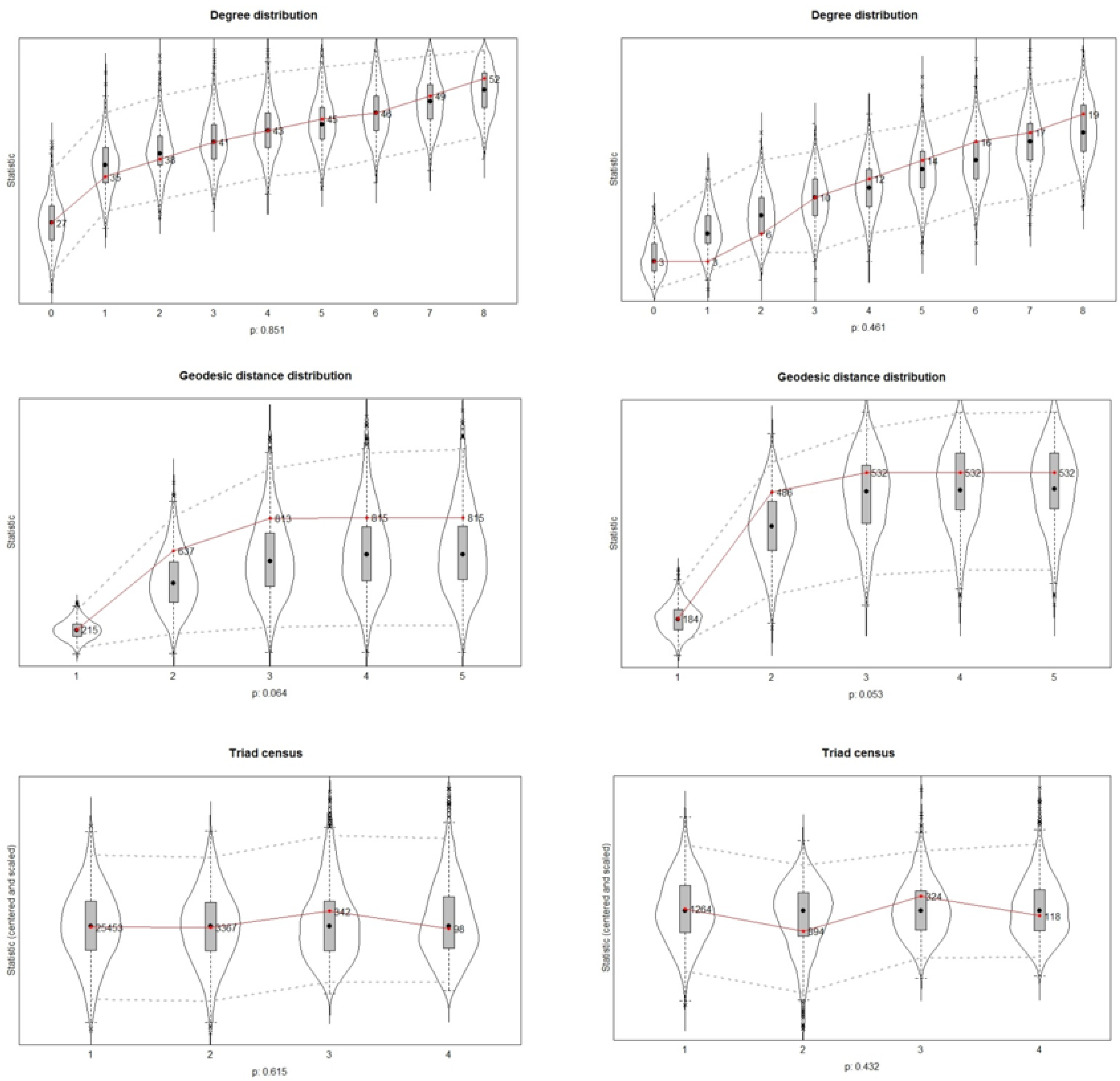


Figure 6.1: Goodness of fit results for degree distribution, geodesic distance distribution and triad census based on 1,000 simulations. Left-hand side corresponds to network 1, right hand side to network 2.

Figure 1 displays the goodness of fit results. The violin plots display how well our models re-create three macro-properties of our networks – degree distribution, geodesic path lengths distribution, and triad census. We conducted 1,000 simulations for each plot. Our data is represented by the red dot in each plot and as it can be seen, our data is central or close to being central (in the case of geodesic path lengths distribution) in each violin plot indicating acceptable fit of our models to the corresponding the data.

6.8. Discussion

In this study, we examined the dynamics of criminal networks over time in response to network disruption by law enforcement agencies. We argue that it is not only important to map changes in the structure as a whole, but also to analyse changes in actor tendencies, captured by relational mechanisms that either enhance trust or reduce risk. This is particularly salient when actors in criminal networks face disruption. Our analysis of two disrupted jihadi networks reveals that the structure of the first network becomes less cohesive and settles in a core-periphery structure, whereas the second network becomes more cohesive and turns from a cell-structure into a core-periphery structure. In terms of relational mechanisms, our statistical models show that in both disrupted networks, triadic closure is the main driver behind tie formation, accompanied by translation of pre-existing ties in the first network. Additional analyses reveal that in the first network, more ties are created but also more ties are dissolved for central actors. The model results thus complement available contextual information that highlights mostly highly active individual actors.

Some of our results line up with previous research on criminal networks. The important role of triadic closure confirms the ideas brought forward by other scholars that actors tend to rely on trusted contacts backed up by third parties (Coleman, 1988; Grund & Densley, 2014; Ouellet et al., 2017). Also the translation of pre-existing ties into operational ties has been theorized as another solidification of criminal ties (Diviák, Dijkstra, et al., 2019a; Erickson, 1981). However, for some other expected mechanisms we found no significant support with regard to responding to disruption. This includes the role of radical settings, which theoretically should provide focal points for radical activities (Wikström & Bouhana, 2017). When controlling for other mechanisms, there is no evidence for the effect of radical settings. One explanation is that the effect of radical settings is already captured by the triadic closure effect. Radical settings stimulate clustering of actors which is reflected by creating closed triangles, similarly to triadic closure. However, triadic closure also operates outside of radical settings, which in turn makes it a stronger explanation of network dynamics. Alternatively, actors might have avoided previous radical settings after disruption due to their fear of being arrested there. Future research may specifically focus on radical or convergence settings as a distinct set of nodes in a two-mode or multilevel network. In a two-mode network, actors in one mode and settings in the other would be connected by a tie representing affiliation or attendance. Such a representation of actors and settings not only allows to study the structural role of convergence settings more fully, but also to consider the attributes of settings.

It has been often proposed to use SNA to combat terrorist networks (Cunningham et al., 2016). However, some of the studies documenting effects of police disruption (Duijn et al., 2014; Morselli & Petit, 2007) as well as the present study show that such interventions may trigger contradictory unintended consequences, such as the radicalization and increased cohesion in network 2 in this study. There is a much wider palette of possible network intervention strategies, such as strategies focusing on groups of actors, or rewiring the ties in the network (Valente, 2012). First, interventions should not only focus on central actors, but also on the network structure as a whole. In a core-periphery network, one central actor may be substituted by another one from the core, whereas in cell-structured network, it may be much more important to target brokers interconnecting different cells. Second, potential unintended consequences triggered by a specific intervention strategy should be considered. A useful framework can be derived from Boudon (1982), who described several configurations of unintended consequences of social action. Such configurations consider the combination of intentions of a given action, the actors who are primarily aimed by a given action, and the actors for whom this action may bring unintended benefits or problems. The intention of law enforcement may be to target some or all the actors involved in given network. By doing so, it may trigger beneficial or detrimental unintended consequences for some (or all) actors. For example, law enforcement may target some of the most central actors in a core-periphery network with the intention to disintegrate the core and thus to damage the most vulnerable part of the network. However, if there are some core actors not targeted, it may incentivize them to foster their connections as they have already invested too much effort and time to abandon the network, while peripheral actors may be driven away from further participation. The remaining strengthened core may in turn radicalize even more and attempt to avenge their fellow collaborators.

As a method for disentangling the relational mechanisms bringing about the change in the dynamic network, we used Stochastic Actor-oriented Models, “SAOMs”. These models have been criticized by some researchers of covert networks particularly due to the assumption of stable node set, which was thought to be incompatible with real-world criminal network data (Stevenson & Crossley, 2014). Despite this fact, there have been recent applications of SAOMs in this research area (Bright et al., 2018; Cunningham, Everton, & Murphy, 2015) which together with the present study prove that the application of SAOMs can be fruitful for the study of criminal and terrorist networks. SAOMs have been developed and mostly applied in the context of classroom networks and subsequently in other overt networks such as inter- or intra-organizational networks. In such settings, the set of actors in the network under study usually does not change dramatically over time (i.e., only a few actors leave or join the network) and thus the data resemble a panel design. This is the most common, but not unique, data structure for the SAOM. Achieving a stable node set is considerably more difficult in criminal networks, because these networks usually have a fluctuating membership, and moreover the membership is hard to ascertain in the process of data collection. However, even in these cases, SAOMs can be meaningfully applied by using the change composition method (Huisman & Snijders, 2003), also known as 'joiners and leavers' method. This allows the researcher to specify which actors were present or absent in any given period and account for this in the modelling. This way, some turnover in the node set can be accommodated.

Even if the actor set is sufficiently stable, there may still be difficulties to fit a SAOM to a criminal network data due to another obstacle, most prominently too many changes in ties, indicated by high Hamming distances and low Jaccard indices. This was also the case for our data. This situation may be redeemed by using appropriate control variables.

Regarding the control variables, we also controlled for shared location and initial police attention. The initial police attention was supposed to control for the spotlight effect (Smith & Papachristos, 2016; Bright et al., 2018), denoting the tendency for actors to be focal points of the initial investigation and thus to have more ties due to more attention being paid to them. Unlike previous studies, we found no evidence of a positive spotlight effect. On the contrary, this effect is negative in both our networks, indicating that actors who came first under police surveillance were less likely to create and maintain ties. There may be three potential explanations for this result. The first potential explanation is a specific police surveillance strategy in which the initial set of actors under surveillance might have been used as an accessible gateway for getting more information on more prominent yet less accessible actors. The second explanation is that the initially monitored actors subsequently became primary targets of the disruption resulting in removal of them and their ties from the network, decreasing their likelihood of creating or maintaining ties. The last potential explanation may be that these actors might have become aware of the surveillance and responded to it by decreasing or hiding their activity in the network. These three explanations are not mutually exclusive and so the negative police attention effect may also be a result of some of their combination. Our contextual information indicates that a combination of the second and third argument seems most likely to at least partly explain the negative effect we found.

The fact that data on criminal networks are themselves produced by systematic activity of law enforcement makes it important to be able to account for distortions it may introduce into the results. Statistical models such as SAOM equip researchers with a powerful tool that can address these issues. From a methodological point of view, more frequent application of these models may in turn stimulate further development of models, which may be more applicable for specific issues pertaining to the area of criminal network studies. One aspect of this is the treatment of missing data in network analysis, an affliction of research of covert networks, about which there have been recent advances (Krause, Huisman, & Snijders, 2018), from which this field may profit in the future.

7. Key aspects of covert networks data collection: Problems, challenges, and opportunities [39]

7.1. Introduction

Covert networks[40] are defined by the aim of actors involved in them to avoid detection and to remain concealed (Morselli, 2009; Oliver et al., 2014). The fact that actors aim to avoid detection affects research on covert networks and also data collection in this area. Primary data collection is almost impossible under the assumption that actors aim to avoid detection, because reporting on fellow members of the network and activities shared with them would violate their secrecy. Thus, researchers have to rely on secondary data from sources such as phone wiretaps, police investigation documents, or even media, which bears its own issues and disadvantages.

The research on criminal networks has already brought revealing insights mainly by identifying central actors and describing network structures. As for central actors, previous research focused on their roles within the networks or on their individual attributes. Regarding covert network structures, previous research investigated their density, centralization, or segmentation into subgroups (for a comprehensive review, see Faust and Tita 2019; Bichler, Malm, and Cooper 2017). Our ability to generalize findings, point out contradictory results, and innovate research relies on our ability to be able to compare results across multiple studies. In order to do so, it is necessary to be able to assess to what extent results are comparable. Comparability is then dependent not only upon applied measures, but also on the data and the way it was processed prior to the analyses. However, the way data is collected, stored, and processed is frequently not treated systematically, which complicates not only the assessment of a single study, but also our ability to make cross-study comparisons and meta-analyses as a crucial step in advancing any field of inquiry (Cumming, 2012).

[39] This chapter is based on: Diviák, T. (2019). Key aspects of covert networks data collection: Problems, challenges, and opportunities. Social Networks, in press.

[40] As already mentioned in the second chapter, criminal networks are subtypes of covert networks and since most of the problems dicussed in this chapter pertain to not only to criminal networks, but to covert networks in general, I use the term covert networks instead of criminal networks unlike in preceding chapters.

In this chapter, I discuss the issues, decisions and complications of data collection on covert networks. I argue that being aware of these problems and being transparent about which decisions were taken during the process of data collection, coding, and analysis does not only add more clarity in the research, but may also contribute to research in this area in three important ways. First, it enables meta-analysis and comparison which is important to be able to derive more general conclusions. Second, there are various theoretical points and research questions that cannot be addressed without a clear delineation of some aspects in covert network data. For instance, it is impossible to study dynamics of covert networks without distinguishing different time periods in the data. Such efforts unlock new research questions and contribute to theory formation in the field, which is considered to be underdeveloped (Carrington, 2011; van der Hulst, 2011). Third, better data allows to use more advanced methods, such as statistical models for networks, and to combine social network analysis (SNA) with qualitative approaches (Bellotti, 2014; Domínguez & Hollstein, 2014; Robins, 2013; Snijders, 2011). The goal of this chapter is two-fold. The first goal is to review the main issues in the domain of data collection for covert networks together with good practices in dealing with them. The second goal is to argue for a more systematic approach towards data collection in order to increase transparency and comparability of research.

I start with identifying six key aspects of covert network data. Each of these aspects comes with a specific set of challenges and problems. Each aspect also comes with a specific set of theoretical opportunities, which may be addressed with better data. I demonstrate each of the identified problems using real data, which are all publicly available in the covert networks database maintained by the Mitchell Centre for Social Network Analysis at the University of Manchester (2019). For each aspect, I outline the problems first, then I show a fruitful approach towards it, and I also show which theoretical questions may be addressed. Furthermore, I discuss some considerations stemming from problems with secondary and missing data. I propose using biographies, checklists, and graph databases as more complex ways to systematically and transparently collect and store covert network data. Note that some problems discussed below also pertain to social network research in general. However, I will not go beyond the domain of covert network studies, as there are specifics in this area of inquiry that make the transition of tools and practices from or to the subdiscipline difficult or impossible in some cases.

7.2. Six aspects of covert networks data collection

1) Nodes

The problem with the definition of the node set is the problem of boundary specification (Laumann, Marsden, & Prensky, 1983). The boundary specification problem refers to the fact that when conducting a network analysis, researchers need to specify which nodes to include and which to exclude from the network representation. Two broad approaches can be distinguished. In the nominalist approach, the researcher imposes some external criteria on the network (e.g., nodes are included based on shared membership or because they were mentioned in a certain document). In the realist approach, the nodes themselves define the boundaries (e.g., respondents nominate other respondents). Because covert network data are usually secondary, this puts the researcher into the nominalist approach.

The question then is how to set the boundaries or what criterion to use for the inclusion/exclusion of nodes. This has far-reaching implications for calculations and the interpretation of results. One important decision needs to be made about including only directly involved actors or actors from the broader social context as well, which depends on the research question such as when investigating recruitment, support, or acceptance of covert activities by overt actors. Additionally, in some cases of criminal networks, it may be necessary to consider the inclusion of victims, such as in the case of women trafficking (Mancuso, 2014), which shows how victims interact with offenders and thus actively contribute to the organization of crime, or in the cases of fraud, in which the fraud diffuses across victims and thus it wouldn’t be possible to understand it fully without considering the victims (Nash et al., 2014). Similarly, in trafficking and illegal commodities distribution networks, this consideration needs to be made with regard to both the supply and the demand side, that is, producers and consumers. Lastly, especially important for terrorist groups, it needs to be clearly stated whether the studied network includes actors participating in one particular action (e.g., 9/11 hijackers) or whether the network represents the whole organization (e.g., Al-Qaeda).

Morselli (2009: 44-45) proposed what he calls criminal justice rings, which refer to different stages of criminal investigation. Criminal justice rings describe the increasing precision of information contained within criminal justice data sources. It is the least precise about actors who happen to be monitored in general criminal monitoring (the widest criminal justice ring) and it is the most detailed about those actors who are confirmed as guilty. Although not originally intended for this, the criminal justice rings can be used as a framework for boundary specification. Defining the boundary of the networks by a specific criminal justice ring provides a criterion, which can be compared to other definitions of boundaries, e.g., to other criminal justice rings, and subsequently subjected to sensitivity analysis. A similar approach was taken by Ouellet and Bouchard (2018) in their study on the Toronto 18 terrorist network. They found that considering only the 18 actors charged in the case captures predominantly the operational subpart of the network, whereas if 22 complementary non-charged actors are included, it also captures the ideological component of the network. In some cases, it may not be possible to draw a clear-cut boundary based on criminal justice rings, yet varying criteria may still be used to draw boundaries. As an example, consider Krebs' (2002) analysis of the 9/11 network. Krebs showed that with the inclusion of wider sets of actors the structure changed in some aspects (depicted in Figure 1): it shortened the distances among actors (diameter drops from 9 to 7) and also made the network denser (average degree increases from 2.8 to 4.8), whereas transitivity and centralization did not change markedly. In general, exploratory research may inspect several different network boundaries, whereas explanatory research should consider the boundaries corresponding to the research question, both types of research with regards to limitations of the data and its sources.

Figure 7.1: 9/11 perpetrators network with only those, who hijacked the planes (left), and with other associates (right, hijackers = blue nodes)

The definition of network boundaries in several, more or less fine-grained ways, opens opportunities to answer theoretical questions on the embeddedness of covert networks in overt settings by comparing boundaries based on substantively different criteria. This is important for the study of recruitment patterns, as for instance Sageman (2004) showed that the involvement in terrorist networks is a gradual process facilitated by expressive ties to those, who are already involved in radical and/or terrorist activities. Another theoretical problem, which may be addressed by using a more fine-grained distinction between different types of network boundaries, is the facilitation of organized crime in legitimate settings. Previous research showed that illegal activities are facilitated by connections to actors who are not directly involved in criminal activities, but have specific skills (e.g., lawyers or accountants, Morselli and Giguere 2006).

2) Ties

The problem with ties is how to define the content of ties, specifically how to treat substantively different types of relations, such as personal ties, criminal cooperation, or exchange of resources. It used to be quite common, perhaps due to paucity of available data, to aggregate different types of ties and interpret the results as if these ties represented cooperation. This potentially leads to misinterpreting ties such as kinship as if they automatically implied criminal cooperation. In the seminal study by Erikson (1981), she points out the crucial role of pre-existing ties for covert networks, which has since then been documented in many other cases (Diviák, Dijkstra, and Snijders 2018; Smith and Papachristos 2016). Conflating these relations would make it impossible to investigate the social embeddedness of criminal ties.

The challenge for researchers is how to distinguish different types of ties substantively as well as actually in the data. Some studies proposed a more general framework for multiplex covert or criminal networks. Smith and Papachristos (2016) distinguished three types of ties relevant for criminal networks: personal, legal, and criminal relationships. Bright and colleagues (2015) specifically aimed at mapping exchange of resources and classified multiple resources as tangible and intangible. Diviák and colleagues (2018) distinguish three types of ties based on the theoretical elements of corruption networks: collaboration, resource transfer, and pre-existing ties. The example in Figure 2 is taken from Diviák et al. (2018), which illustrates why it may be potentially misleading to aggregate different types of ties. The two depicted layers are collaboration and resource transfer. Although they overlap (in 22% of cases a tie in one layer is mirrored by a tie in the other), aggregating the two layers would yield a network in which a tie could be interpreted as transferring resources even though it might not be the case. Thus, conflating different types of ties may yield misleading results, which may further distort, for instance, centrality indices, as some actors may be specialists, limited to one type of tie, while others may have their ties spread more evenly across multiple relational dimensions. In a network with all ties aggregated, speacialists as well as multiplex actors may appear to have the same centrality, even though they are actually central in different ways. Given the heterogeneity in identified types of ties in the literature, it is not surprising that Gerdes (2015b) identified ten different classes in his review of different classifications of ties in covert networks. Although it is understandable that the coding will be different across studies as they will always depend on theory and available data, one generalization can be drawn from this – the choice between coding/classification scheme for ties needs to balance specificity and generality. On the one hand, a classification scheme that is too specific yields very narrow categories which may be difficult to code reliably, as the information in the data sources may not be precise enough. On the other hand, too general classification yields codes containing heterogeneous relations/interactions, which makes it difficult to interpret validly. Sometimes, the data source may not be specific enough about the content of ties, as some scientifically interesting information may not be considered essential by courts or police investigators. If that is the case, researchers may at least try to distinguish ties reflecting some sort of activity related to the case at hand (e.g., communication or collaboration) from ties representing some antecedents to the case or relational opportunities (e.g., pre-existing ties, similarities, or distances).

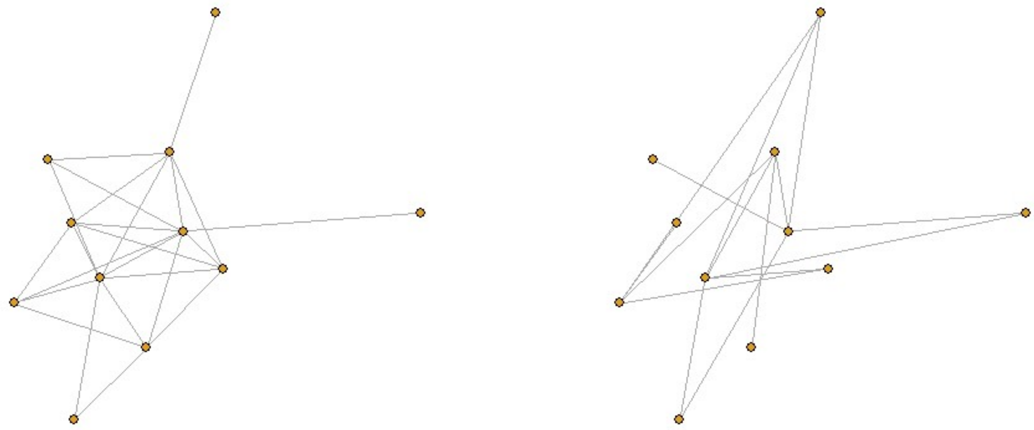


Figure 7.2: A corruption network with two types of ties: collaboration (left) and resource transfer (right). The position of nodes is the same in both sociograms.

Paying attention to different types of ties allows to clearly focus on a specific relation among actors in the network (e.g., focusing only on the flow of resources without confounding the results by pre-existing ties). Considering different types of ties jointly yields a great theoretical opportunity to study multiplexity in covert networks, referring to the fact that there may be multiple types of ties among the same set of actors. Treating covert networks as multiplex may help us understand some of their specific features. For instance, some authors argue that multiplexity compensates for the lack of legitimate institutions enforcing contracts in covert settings by anchoring criminal relationships in other types of relationships (Smith & Papachristos, 2016). Acknowledging the multiplex nature of covert networks also enables to study its underlying mechanisms. For instance, tie exchange, which denotes the tendency of actor to reciprocate a tie of one type with a tie of a different kind, such as in the case of exchange of different resources (Bright et al., 2015). Another mechanism worthy of attention is tie translation, that is, the tendency to create ties on the basis of already existing ties of different kind (Diviák, Dijkstra, and Snijders 2019), which may be one way how to operationalize the importance of pre-existing ties for creation operational criminal ties.

3) Attributes

Attributes come into play in covert network analysis in two ways. First, attributes capture substantively meaningful characteristics of actors, which create opportunities and constraints for individual behaviour including creation, maintenance, and dissolution of ties, or for reaching individual goals (Robins, 2009; Steglich et al., 2010). This is something which analysis of covert networks shares with the rest of SNA. However, due to specific circumstances with covert network data, the data collection may be focused on particular individuals creating what Smith and Papachristos (2016) call the 'spotlight effect'. Whereas descriptive measures (e.g., centrality measures) cannot really account for this, it is important for a correct interpretation to know who was in the spotlight. Models can include control nodal variables for each of these and thus correct for the effect of data collection which might otherwise distort the results (Bright et al., 2018; Smith & Papachristos, 2016). Thus, the second role played by attributes in the analysis of covert networks is that of variables helping to account for how the dataset was collected.

It is therefore important to know which variables we want to measure substantively and whether we need any control variables to account for the data collection. In terms of the substantive attributes, which attributes to analyse and how to define them depends heavily on theory. One parsimonious approach which may be helpful in systematically transposing theory to data collection is script analysis (cf. Morselli and Roy 2008). Script analysis decomposes the process of organizing illicit activities into a sequence of events. The idea is that in each part of the illicit script different types of activities need to be carried out by different actors with particular skills. For example, production and distribution of drugs requires someone first to actually create the product, then it is necessary to distribute it, and perhaps it is also necessary to protect the dealers. From this simplified script, three types of roles can be identified, which may be used as attribute(s) in the analysis – cooks, dealers, and thugs. With regard to attributes as controls, researchers may want to include an attribute referring to whether an actor was among the initial nodes under surveillance, as further observations are contingent upon being related to those under the initial surveillance. If the surveillance proceeds to further focus on those connected to the initial set of nodes, it starts to resemble a snowball or link-tracing sample and it may even be worthwhile to analyse the resulting network with appropriate methods for snowball and link-tracing samples (Heckathorn & Cameron, 2017; Pattison, Robins, Snijders, & Wang, 2013). An example of a control variable for the spotlight effect is Smith's and Papachristos' (2016) study on prohibition era Chicago criminal networks, where all the information revolved around Al

Capone and so authors created a dummy variable which had the value of 1 for Al Capone and 0 for the rest of actors.

Traditional quantitative criminology has focused on identifying important predictors of individual characteristics related to important criminological concepts such as delinquency, substance abuse, or commission of different types of crime. Network research may enrich the modelling of individual level outcomes with structural network effects (e.g., positions of actors within networks). This is arguably an important area of further research, as traditional individual profiling has been criticized for having a poor explanatory power (cf. Horgan 2008), but there are indications that structural network effects may be key to more profound explanation of phenomena such as involvement in terrorist activities (Sageman, 2004). This does not include only attributes in the role of substantively meaningful variables, but also in the role of control variables. Attributes as controls may be investigated as dependent variables providing the opportunity to reflect upon investigation and surveillance methods. On the one hand, it is possible that investigations overlook individuals with specific traits or network positions. On the other hand, they might predominantly focus on specifically positioned and predisposed actors.

4) Levels

Some covert network datasets have an intrinsic bipartite or even multilevel structure. For instance, Crossley and colleagues (2012) and Calderoni and colleagues (2017) studied networks of co-participation in arrests or in meetings, which are essentially bipartite networks with actors in the first mode and arrests/meetings in the second mode. Often, this is the only possibility to collect data on covert networks as exact information on interaction between actors is difficult to obtain. All network information then is derived from co-participation, co-appearance, or co-membership structures. However, it is important to note that affiliation does not necessarily mean interaction, it is only an opportunity to engage in it (Borgatti & Everett, 1997). This fundamentally limits what inferences we can draw from such data.

What researchers often do when they study co-participation structures in covert networks is that they either explicitly or implicitly work with a projection from two-mode data to one-mode. It is important to seriously consider the consequences of such data transformation, as it comes with the loss of information about the structure of the network. For example, 3-star and 6-cycle configurations in two-mode networks both yield a triangle in one-mode projection, albeit being initially very different structures. This illustrates that projection artificially introduces closure and clustering into the data. Therefore, care needs to be taken when interpreting these findings, as they may not be genuine tendencies of actors to form transitive ties, but rather a product of projection. For example, Figure 3 captures the initial bipartite network of N'dranghetta mafiosi and their meetings. The bipartite network's density is 0.06 and its transitivity (measured by bipartite clustering coefficient) is 0.46, whereas the actor-to-actor projection (where ties represent co-attendance in events) displays density of 0.13 and clustering coefficient of 0.58. But the loss of information also applies to information about the attributes of the second mode, that is, settings, places, affiliations, or groups. These may themselves be an important part of the explanation, which is completely disregarded when focusing solely on the actor-to-actor projection. It is a matter of the specific research question whether projection is a fruitful avenue for the study of a given network, or whether the loss of information hinders crucial parts of the explanation.

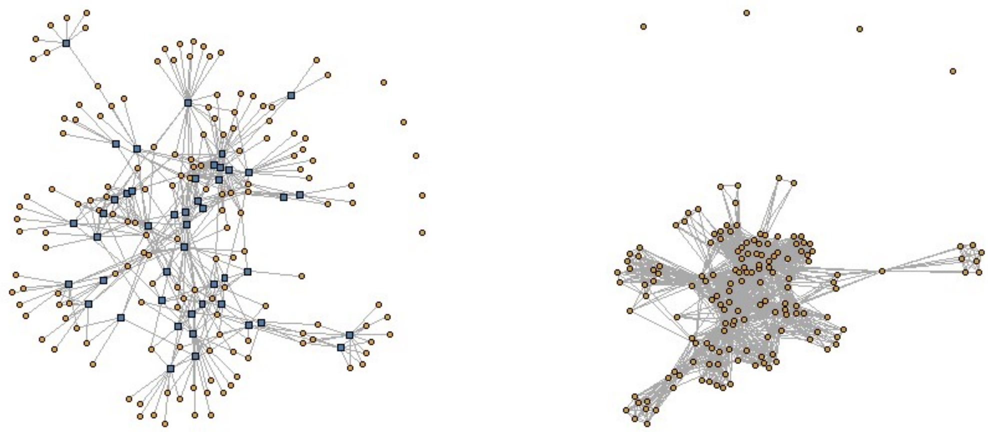


Figure 7.3: A bipartite network of mafiosi and their meetings (left; Mafiosi = yellow circles) and corresponding mafiosi-to-mafiosi projection (right)

What I propose is to carefully consider projecting the data, as the original bipartite structure not only contains full information, but might also be worthwhile to investigate in itself. Bipartite networks offer a way to study an important theoretical concept in criminology – convergence settings (Felson 2006; 2009). Convergence settings denote social or spatial settings that facilitate crime or cooperation of offenders, such as clubs, bars, restaurants or parks. This concept has also been used in the literature on extremist networks as radical settings (Wikström & Bouhana, 2017) facilitating radicalisation, diffusion of norms and ideas, providing an opportunity to pool resources for extremists such as clubs, shops, extremist party secretariats or radical temples for religiously motivated offenders. These settings can be operationalized as a mode in bipartite networks. This approach may in turn draw upon recent developments in the methodology for both descriptive analysis of bipartite networks (Everett & Borgatti, 2013) and for modelling of such network structures (Lazega & Snijders, 2016; Wang, Pattison, & Robins, 2013). The extension to multilevel network opens the possibility to analyse the relationship between cooperation among criminals (first level) and its facilitation by certain convergence settings (second level) or to jointly analyse ties among actors (e.g., gangsters), their affiliations to groups (such as gangs), and ties among the groups (such as territorial disputes).

5) Dynamics

It has been emphasized that covert networks are flexible, adaptive, and dynamic. Yet such claims have primarily remained metaphorical assumptions rather than empirically shown properties which has already been pointed out elsewhere (Bright et al., 2018; Campana, 2016). This may be due to lack of appropriate data to study the evolution of covert networks over time. However, there are pioneering studies aiming at unravelling the process of evolution of these networks and data are becoming increasingly available. Assessing covert network dynamics is a crucial task as it allows researchers to empirically test the concepts of flexibility and adaptability, and it also enables practitioners to improve monitoring of, and interventions in covert networks. For instance, without longitudinal data researchers cannot distinguish between the processes of selection and influence and therefore cannot assess whether a particular observed pattern is an outcome or a precondition (Steglich et al., 2010). For practitioners, cross-sectional data aggregated over time may yield a picture of a network which in this form actually never existed at any given time point (e.g., one actor might have died before another one joined). This may have serious implications for designing an intervention.

The first issue related to longitudinal covert network data collection is how to define the periods or waves for coding and/or observation of the network. Generally speaking, there are two possible ways to do this: time-based and event-based (Campana & Varese, 2012). A time-based definition requires to select specific time periods (e.g., weeks, months or years) and subsequently record the state of the network in each of these periods. An event-based definition demands to define specific events in the evolution of the network, which were theoretically important and/or interesting. Whereas the time-based definition may seem to be more clearly based on 'objective' time periods, testing certain hypotheses about development of structures in response to particular events (e.g., disruption attempts) or environmental conditions (e.g., abundance of opportunities for organized crime) may require more theoretically founded periodization. Related to this is the question of successful and failed covert networks, as one might argue that all the studied covert networks are failed cases, as they were uncovered after all (Morselli, 2009). Hence, these cases are supposed to provide a distorted picture of reality as the successful ones elude the attention of researchers and practitioners alike. A counterargument may be that success or failure is not a fixed binary state, but rather a status changing over time. Therefore, some networks may be considered successful (such as reaching their collective goal) at some point in time, but they may be uncovered and dismantled at another time point, considering them as failed at that point. This is demonstrated with an example of a drug trafficking network originally analysed by Morselli and Petit (2007). Figure 4 shows how the activity of actors in the network (measured by average degree) changed over time depending on how successful (for instance, at time points 4, 6, and 10) or unsuccessful (for instance, at time points 5 or 8) it was in terms of distribution of illegal drugs.

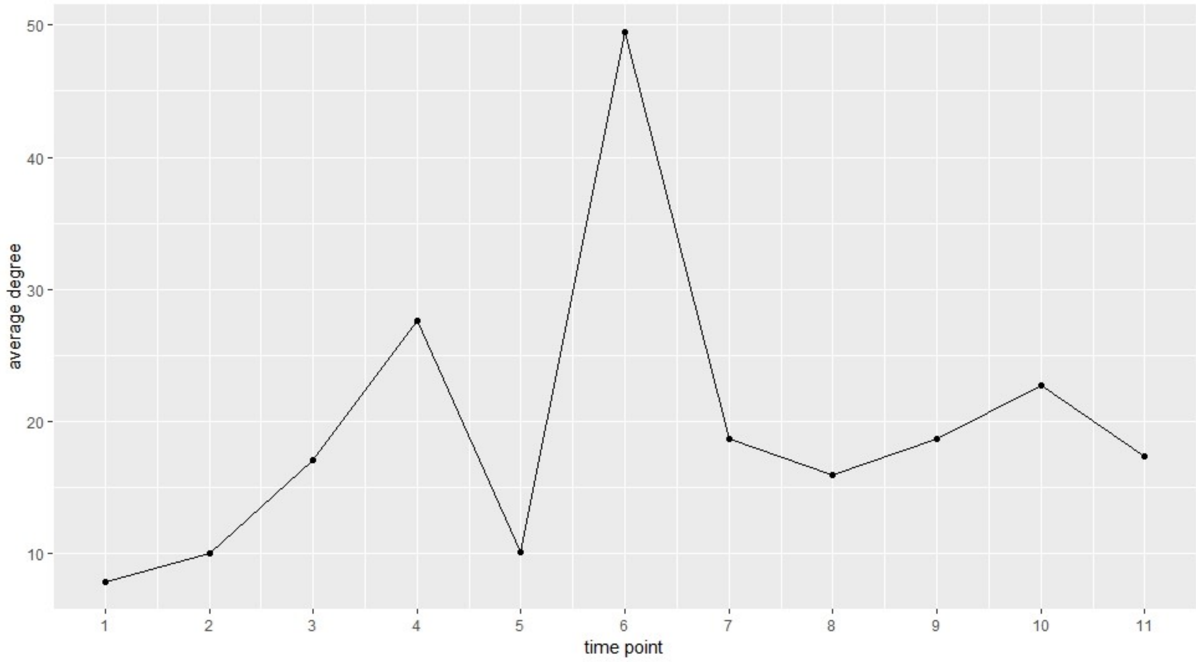


Figure 7.4: Average degree of actors involved in a drug trafficking over eleven time points.

Longitudinal data opens up the opportunity to assess the recovery and adaptation of covert networks after disruption. Research has shown performance and effectiveness of different disruption strategies, such as central node removal or random node removal (Bright, 2015). While simulation studies, for instance, consistently show that central node removal is a more efficient strategy for disruption than random node removal, they do not provide further evidence about the process of recovery from disruption. This is, however, crucial, as some observational studies show that attempts to disrupt covert networks may trigger unintended consequences and actually strengthen their structural cohesion (Duijn et al., 2014). Longitudinal data provides the opportunity to combine simulation and observational research and to realistically simulate not only the impact of disruption strategies, but also recovery from disruption. Vigorous development of models for network dynamics in recent years (cf. Snijders, van de Bunt, and Steglich 2010; Block et al. 2018) equips researchers with tools to address these issues and thus to move from metaphors to empirical evidence.

6) Context

The very definition of covert networks, covertness, is contingent upon the context of the network. Why is it covert? From whom? And how? It is assumed that covertness critically modifies the structure of networks and thus justifies the study of covert networks as distinct from overt networks (Morselli 2009). However, the information about context is frequently more qualitative and non-network, i.e., difficult to combine with network structure, as it goes beyond nodes and ties. At the present, the vast majority of studies incorporates these non-network aspects as a brief description in the section of case or context description, and subsequently some of the information is ad hoc evoked when interpreting results of network analysis. It is of course pivotal for a good study to situate the SNA results within the context to adequately interpret findings and draw valid conclusions from the results. However, the contextual information should be used systematically. The danger here is in confirmation bias – choosing only those bits of contextual information which confirm the theory rather than scrutinizing the network analytic results with confirming as well as rejecting contextual information.

In essence, this touches upon a broader recent methodological debate on how to combine qualitative methods with SNA (Bellotti, 2014; Domínguez & Hollstein, 2014). Almost all empirical studies of covert networks are case studies as they examine a particular network within a given context with respect to some aspects which are deemed as theoretically important. This may seem obvious and not very revealing, however the realisation that these studies are in fact case studies is crucial (Crossley & Edwards, 2016). There is now a growing body of methodological literature on systematic case study research from which the study of covert networks (or networks in general) may draw inspiration. Two promising methods are process-tracing (Beach & Pedersen, 2013) and qualitative comparative analysis (QCA; Rihoux and Ragin 2009). Process-tracing is a way to systematically use both network and qualitative evidence with regard to a given theoretical explanation of a case at hand. It provides a method to qualitatively test whether a certain condition is necessary or sufficient to explain given outcome. QCA offers a way to rigorously compare several cases, using set theory and Boolean algebra. Both network and non-network variables can be included in such analysis. The method can then distinguish different configurations of conditions to show which conditions and how they affect the outcome of interest (Fischer, 2014). This is in principle similar to using meta-analysis, although QCA may be especially useful in studies where non-network qualitative aspects are important for explanation, which may be difficult in traditional meta-analysis of network statistical models (cf. Lubbers and Snijders, 2007), and in cases where comparison of smaller number of cases is done (e.g., five to ten). For instance, one may be interested in successful commission of terrorist attacks (an outcome). It may hypothetically be argued that centralized network structure, short distances among actors, sufficient resources, and absence of law enforcement opposition explain the success of a terrorist attack. A researcher may collect data on several networks, some of which succeeded in committing an attack. QCA may then be used to assess which combinations of network (centralization and path length) as well as non-network factors (law enforcement and resources) are related to the outcome, and how.

The treatment of qualitative contexts opens up the opportunity to put the same weight on both network and non-network information in explaining studied cases. An important research issue is the individual perception and phenomenology of network structures and positions within them (Hollstein, 2014). For instance, the concept of strategic positioning has become frequently studied in criminal networks (Bright et al., 2015; Diviák et al., 2018; Morselli, 2010). Strategic positioning refers to tendency of some actors in covert network to seek out less visible positions (low degree) while retaining influence by being on top of many flows (high betweenness). From the point of view of the researcher, strategic positioning is usually explained as the attempt of actors to reduce their exposure while retaining some influence within the network. However, the intentions of these actors and their motivations for seeking (or avoiding) such positions may be very different, such as when actors are behaving "irrationally" in terms of their network positions. This happens, for instance, when actors proliferate their ties and thus expose themselves to detection, because they are strongly self-confident and believe they are invincible because of their elite membership status (e.g., politicians; Demiroz and Kapucu, 2012; Diviák et al., 2018).

7.3. Further considerations

In this section, I will discuss further considerations which typically arise in the research on covert networks. Note that these considerations are not a standalone aspect of data collection, but relate to all six aspects covered above.

Secondary data

As already stated above, research on covert networks usually draws upon secondary data, limiting researchers to whatever data that is available. This data may come from offender databases, transcripts of physical and/or electronic surveillance, summaries of police interrogation, transcripts of court proceedings, and on-line and print media (Bright, Hughes, and Chalmers, 2012). None of these types of sources is perfect in terms of validity or reliability. In terms of validity, a critical issue is that none of these sources is primarily collected for research purposes. Those who collect and process these data do so for very specific purposes, which critically determine the type of information available in the data source. So while researchers may, for instance, be interested in communication among a group of offenders, using data on phone calls among them does not capture their face to face communication. Similarly, some important piece of information may not be recorded, yielding invalid representation of the phenomenon in question. For example, police interrogation may not uncover certain features of the investigated criminal activities, which offenders themselves may be motivated to hide from police. Or some offenders may not yet be caught and thus they do not figure in the offender databases. In extreme cases, this may yield analytical results which are merely artefacts of the data collection. In order to assure that the data does not yield artificial results, clear and mutual information exchange between researchers and practitioners is necessary so that practitioners are familiar with up-to-date research methods and findings and researchers are well aware of potential blind spots in the data.

In terms of reliability, a key issue is that the procedures used to collect data are not always consistent across different researchers, practitioners, and/or organizations. This has obvious implications for potential comparability of results based on data from different sources. Sometimes, inconsistencies may occur even within organizations or teams of practitioners as their personnel fluctuates or as their rules and regulations change. Both researchers and practitioners may benefit from guidelines and cooperation with regard to data collection. The point here is not to mentor the practitioners but rather, to make their work easier by contributing to it with scientific knowledge and best practices on how to deal with difficulties they encounter in their daily work such as how to code different relations, define temporal periods or network boundaries. This could pay off to researchers with better data eventually as well as building better relations with practitioners, which may make the data more accessible, and it can improve the work of the organization in question.

Secondary data often entail another obstacle - accessibility. All data sources outlined by Bright and colleagues (2012), except for media sources, are in the possession of law enforcement agencies and have strict rules about the conditions of their use in scientific research. At present, very little is known about how different data sources compare on different criteria such as accuracy or analytical depth of information. There are only a few studies comparing results based on different data sources about the same covert group. For instance, Rostami and Mondani (2015) analysed a network of a Swedish gang based on criminal intelligence data, co-offending records, and police surveillance. They found substantial differences in terms of centrality measures between intelligence data and the other two sources. Another study was conducted by Berlusconi et al. (2016) on a network of Italian Mafiosi with the aim of inferring missing ties. This study used wiretap records, arrest warrants, and judicial documents, and showed that considering the same set of actors, the network of wiretap records is the densest. Media-based data are usually thought to be less valid than the remaining sources. However, such claims seem to be based solely on face validity, as no sound comparison of media-based data with other sources has been made. If there is enough evidence that media-based data consistently yield network data similar to other sources, it may encourage their more frequent usage considering that these data are also easier to access. However, this comparison may also provide substantiated evidence against using media-based, if they yield network representations incompatible with other sources. Alternatively, comparison of different data sources may point out systematic differences, which can in turn give us a hint how to use multiple data sources for triangulation.

Missing data

Missing data traditionally pose a problem for any quantitative method. In SNA, this problem maybe even more severe because of the interdependence inherent in the data. Results of some studies indicate that some network measures are quite robust even when dealing with networks containing a considerable amount of missing data (Borgatti, Carley, & Krackhardt, 2006; Smith & Moody, 2013; Smith, Moody, & Morgan, 2017). Yet, this robustness does not necessarily translate to the individual level and highly depends on the missing data mechanism (mechanism generating the missingness, Krause et al., 2018). Missing data present probably the most frequent objection to covert network data, which is due to the very nature of covert networks; they are covert, so it is likely that some piece of information will not be uncovered by researchers and/or practitioners.

Good practice in current research is to acknowledge this as a limitation. However, the problems with missing data should not only be acknowledged, but also tackled. In recent years, there has been a development of methods for handling missing data in networks (see e.g., Huisman & Steglich, 2008; Krause et al., 2018; Robins, Pattison, & Woolcock, 2004).

Although researchers may surely use these methods to their advantage, these methods are not automatically saving poorly collected datasets. The first thing researchers in covert networks have to realize is that there are different missing data mechanisms: missing completely at random (no relation to any observed or missing variable), missing at random (no relation to missing variable, but related to some observed variable), and missing not at random (whether some data point is missing itself depends on non-observed variables; Rubin, 1976). In covert networks, it likely that researchers will not only be dealing with data missing (completely) at random, but also with non-randomly missing data. The non-randomly missing information may stem from variety of reasons. Some highly prominent actors may have the tendency towards intentionally concealing themselves or some type of ties may be more likely to be missed due to its level of sophistication (i.e., encrypted messages). In order to at least alleviate correctly the problem of missingness, it is first necessary to identify the missing data mechanism. Then, appropriate imputation techniques can be applied.

However, before that it is important to know which information (which nodes or ties etc.) is actually missing. What researchers in this area are usually dealing with is an adjacency matrix with ones representing the existence of a tie and zeros representing the absence of a tie. The ones and zeros mask an important thing – both may be true or false. While the existence of ties is usually confirmed and thus the ones in the data are actually true ones, the absence of ties is usually not considered to require further confirmation. However, this is problematic. In order to be able to deal with missing ties, we need to be able to tell which ties are absent (i.e., it is known that there is no tie between a given pair of actors) and which are missing (i.e., we do not know whether the tie exists or not). One way to work around this problem is to use existing ways intelligence services use to classify the reliability of any given information, based on either cross validation by different sources or a measure of reliability of the original source. Sparrow (1991) mentions one such classification, where law enforcement investigators classify ties as 'strong' if their existence is confirmed from two independent sources, whereas 'weak' ties are those without an independent confirmation. A cautious analyst may want to work with weak ties as if they were missing ties and use some of the newly developed methods to impute them or they can analyse different variants of the network and see how the results differ. Of course, knowledge about which information is not confirmed may not always be available, but at least in the cases of working police investigation files or media databases (where some information is only "suspected" or “speculated”), this approach may be a way to incorporate the uncertainty in a covert network study.

7.4. Ways forward

The points I raised above beg the question whether there is some more general and complex framework for a more systematic approach to covert networks data collection. In this section, I discuss three such frameworks – biographies, graph databases, and checklists. These three frameworks can be used in data extraction, data storage, and in reporting how the data was processed. Since these three frameworks cover different areas of data collection and they are not mutually exclusive, they can be used together in one study, in selected pairs, or just individually depending on the study at hand.

The first stage of data collection that researchers are usually confronted with is extracting the data from a source material such as court files or transcripts of police surveillance. Some sort of content analysis is typically used to code relevant information from the data source and to turn it into network data. Such coding can be done simultaneously by different coders and the reliability of the coding can be subsequently checked. However, little is usually known about how to approach coding, i.e., what type of information to look for and how to store it. Constructing so-called biographies (van Nassau, Diviák, de Poot, & van Tubergen, 2019) can be useful for this task. Such a biography is a table whose rows represent nodes and whose columns represent time points. Each individual cell (node × time point) then stores all the available information about the given node at the given time point. Specification of the node set as well as definition of time points is dependent upon selected boundaries and definition of periods. The information stored in each cell should ideally correspond as much as possible to its counterpart in the data source, which it should refer to so that the information can be easily backtracked. For example, a cell for actor A and year N may state “had repeatedly been meeting B in setting S (court file F)”. Once all the available source information has been extracted into a biography, it may be coded and recoded as necessary, and so different types of ties may be distinguished, actor attributes assigned to actors, or multiple modes (such as settings) may be identified. Also, different node sets (e.g., affiliations) may be used as a starting point and periods may be recoded depending on the precision and depth of available information, as in practice, both the information about actors or time points may not necessarily be as fine-grained in some sources (typically in media or court files) as researchers would like it to be.

For storing collected data, the proposal of Gutfraind and Genkin (2017) to use graph databases may be useful. Graph databases store the information in a relational form of multimode and multilayered graphs, where pieces of information are represented as nodes and relations among them as edges instead of rows and columns. For instance, a transcript of surveillance describing a meeting between two actors in a bar can be represented in a graph database (visualized in Figure 5) as a three-mode network where the modes represent source of the data, actors, and location, connected by edges representing mentions (solid lines from the source file A), meeting (dashed line between actors B and C) and shared location (dotted lines to location C). Different networks may then be obtained from a graph database by using suitable projection techniques. Gutfraind and Genkin (2017) argue that this approach makes processing and transformation of data more transparent and easier to reproduce, adding to its generalizability and comparability of the findings. From the six aspects outlined above, graph databases can readily capture five of those in a transparent and unified manner – nodes, ties, attributes, levels, and dynamics. Actors can be represented as nodes in one of the modes in the graph database, ties can be represented as ties with the capacity to distinguish different types of ties. The bipartite or multilevel structure can be similarly included in the graph database as another mode and similarly for nodal attributes. Even network dynamics can be captured, for example by creating two separate graphs for two periods. The only aspect which may not have a clear representation in a graph database framework is the qualitative context, although there may be ways to incorporate this aspect (perhaps as yet another mode of nodes in the graph). Graph databases are an efficient way to use already collected data by merging, dividing or projecting the data to obtain a dataset feasible for answering a given research question. Moreover, such a way is principled, because it is possible to backtrack what was not included in the final analysis. Graph databases may seem considerably technically complicated, but even if researchers do not want to use them, they may consider using similarly constructed edgelists for their data collection and storage as a somewhat simplified variant. Such an edgelist should contain not only the information about which node is connected to which other node, but also about the types of ties, actor attributes, and all the available information on the remaining aspects of covert network data together with a reference to the data source (e.g., a specific court file), the exact citation on which each entry is based (e.g., “A and B were reported to be together…”) and a comment on some further contextual information (e.g., whether an actor is aware of being a part of a larger covert network).

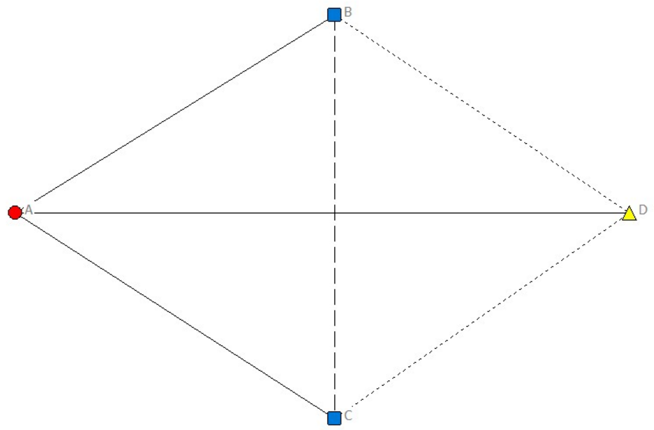


Figure 7.5: An example of simple graph database depicting a source file (node A), two actors (B and C), and a location (D) connected by ties representing mentions (solid line), meeting (dashed line), and shared location (dotted line).

There are no universal rules or algorithms prescribing exactly how to extract, store, and process covert network data. Arguably, this lack is understandable given how varied and differentiated network research is even if we consider only the subfield of covert networks research. Thus, what type of information will be coded in a biography or how a network will be derived from a graph database or a detailed edgelist depends on given research problem. In this area of research, research questions are not only delineated by theory, but also by practical limitations complicating all the supposedly ideal decisions. However, in order to facilitate comparability of findings and accumulation of knowledge, researchers need a common frame of reference. In such a frame of reference, researchers should be able to clarify both theoretical underpinnings and practical constraints of their data collection. Volk, Veenstra, and Espelage (2017) propose a simple checklist for researchers studying bullying, which is supposed to enhance validity and generalizability of studies in that area. Volk and colleagues' checklist contains five items considering mainly theoretical assumptions and clarifications. I propose a checklist based on the aspects and considerations discussed above pertaining to covert network data collection that could enhance transparent and systematic reporting of the way we handle our data:

1. What are the nodes and what were the criteria for their inclusion in the network?
2. What types of relations/interactions do the ties represent?
3. What are the theoretically relevant attributes of nodes and are there any variables mitigating the effect of the way the data were collected?
4. What are the modes distinguishable within the raw data and in what way is the final network representation obtained?
5. What is the temporal span of the network and if multiple periods were distinguished, how were they defined?
6. What are the theoretically relevant pieces of contextual information and what role do they have in the explanation?
7. What was/were the data source(s) used to obtain the information and in what way was the coding of information into network data conducted?
8. What is the nature of missing data and how was the missingness handled? If it was not possible to distinguish missing data from absent data, what impact may the hidden missing data have on the results?

7.5. Conclusion

In the present paper, I discussed different issues, challenges, considerations, and opportunities researchers of covert networks face. I identified six aspects of data collection on covert networks (nodes, ties, attributes, levels, dynamics, and context), all of which contain unique problems as well as opportunities for researchers. All these six aspects are affected by the secondary nature of the data and the problem of missing information. There are fruitful approaches for data collection on each aspect. Besides, I brought up three potentially more general ways which may serve as a common frame of reference, namely biographies, graph databases, and checklists. While all these recommendations and good practices may be useful first steps towards making research more transparent, replicable, and comparable, they are by no means definite solutions to the problems arising in the study of covert networks. However, I hope that this chapter will stimulate discussion about what to improve and how to push the research on covert networks further as a whole.

One matter which kept reoccurring in this study was the usefulness of statistical models for network data. There has been a rapid development of statistical models for network data (cf. Snijders, 2011; Robins, 2013), but the research on covert networks is still predominantly driven by descriptive measures (Campana, 2016). There is quite a steep learning curve from basic descriptive measures to advanced statistical models in SNA, but researchers in this field could benefit from investing time and effort into adopting statistical models, as with good data, these models provide powerful and flexible tools for testing a variety of (sometimes even mutually competing) hypotheses. Specific problems arising in the context of covert networks may in turn stimulate further development of network models.

Similarly to statistical modelling, another avenue for future development in the research of covert networks consists of link-tracing and other network sampling methods (Heckathorn & Cameron, 2017). I have touched upon this issue in relation to individual attributes as variables controlling for data collection induced effects. Due to difficulty (or even impossibility) to map the entire network in covert settings, link-tracing and network sampling methods have been considered to be particularly useful for collecting the data on hidden populations (Frank, 2005). At present, very little is known about specific procedures used by police or intelligence services to collect the data, e.g., how they build offenders databases, how they choose whom to surveil, or which phones to wiretap. Mapping these techniques may critically improve the data quality and open the way for using appropriate estimation methods.

Since science is not only a system of knowledge production but also a matter of social relations and communication, researchers should communicate more with one another and share their knowledge, experience, and data. In short, we as a community of researchers should continue networking. Initiatives such as the Illicit Networks Workshop or organized sessions in both general network or general criminological conferences are productive platforms in this regard. However, this communication and cooperation should not be restricted to the community of covert network researchers. We critically rely on practitioners such as law enforcement agencies, courts, and media and it is necessary to further cultivate our relations with them. Researchers should keep working with practitioners, try to use their data, and warn them about potential pitfalls pertaining to data collection and storage. However, this should not be a one-way street – we should reciprocate and show what SNA, and science in general, has to offer for practitioners and how we can help them understand covert phenomena or make their day-to-day routines easier with tools and methods for data collection and analysis. This is especially important given that most of the recommendations outlined above are only available if researchers have access to the data – if not, the practical and logistical constraints prevail over scientific guidelines. Helping practitioners may in turn relax some of the constraints and therefore make our research easier.

8. Conclusion

In this chapter, I will first briefly summarize the results of preceding chapters. Subsequently, I reflect upon the recurring findings found throughout the studies. Finally, I sketch some of the potential directions for future research in terms of substantive research, theoretical development, and methodological development and issues.

8.1. Summary of the research

Social network analysis is a promising approach for the study of organized crime. It allows researchers to empirically study the structure of organized criminal groups with no other assumption than that organized crime is built from relations and interactions among a group of actors. Provided that researchers have access to data, they may use a wide range of theoretical concepts and methodological tools to uncover important actors, characterize the properties of networks, and identify mechanisms operating behind these structures and their dynamics.

Chapter 2 provides an introduction to the basic terminology of social network analysis together with the most frequently used measures and models. The use of all the introduced measures and models is reviewed with regard to their applications in criminology. This chapter concludes with identifying three main challenges in research on criminal networks – theory building, the use of appropriate methods, and data collection. The following chapters in this dissertation face these challenges in different ways.

Chapter 3 is a study of a Czech political corruption network known as the Rath affair. In this case, political actors were collaborating with businesspeople on manipulating public contracts and abusing European Union subsidies. The network is defined as a network of ties that have the content of collaboratin and/or resource transfer. The results indicate that the network exhibits a perfect core-periphery structure. In such a structure the actor set is divided into a core and a periphery; the density of ties within the core and between core and periphery is very high, while the density within the periphery is very low. Within this structure for the Rath affair network, the collaboration ties are evenly split between core and core-periphery blocks, whereas the resource transfer ties are mostly located in the core-periphery block with pre-existing ties sparsely underlying a few of the collaboration or resource transfer ties.

Collaboration and resource transfer ties rarely were overlapping. Actors are either clearly central or clearly marginal in the network, corresponding with the core-periphery structure. The majority of actors have their ties evenly spread across multiple types of ties and none of them occupies a strategic position (i.e., having low amount of ties, but brokering a lot).

Chapter 4 is a study of a network of counterfeit alcohol distribution from the Czech Republic known as the methanol affair. Actors involved in this network manufactured and distributed poisonous alcohol beverages leading to tens of cases of death or permanent injuries. This network consisted of two components connected by a bridging tie. The two actors who were manufacturing the poisonous beverages did not have the shortest possible distance to other actors, suggesting that the dangerous beverages could have been distributed even more efficiently in network terms. Furthermore, results indicate that the structure of the network was brought about by triadic closure, translation of pre-existing ties into operational ties, and aversion against preferential attachment (i.e., the tendency against accumulating numerous ties). Other mechanisms are not found to be systematically operating in this network.

Chapter 5 tests a frequently cited and influential theory called the efficiency/security trade-off. The theory predicts that profit-driven and ideology-driven networks should differ structurally. Specifically, profit-driven networks are assumed to be inclined towards efficiency reflected by the proliferation of ties, whereas ideology-driven networks are thought to be inclined towards security reflected by the avoidance of redundant ties. This theory is tested on a sample of all available networks, in which ties refer to communication or cooperation: eleven profit- and nine ideology-driven networks. The testing is conducted by comparing the two types of networks in terms of four structural properties: density, centralization, closure, and brokerage. These tests find either no differences between the two types of networks, or differences that are opposite to the theoretical predictions. Furthermore, the implications of the theory for actor-level mechanisms are explored by using exponential random graph models. This is done because the intentions of actors (profit or security) may not necessarily translate to the network level, sometimes even triggering contradictory unintended consequences. No differences are found between the mechanisms that determine the structure of profit- and ideology-driven networks. Actually, there are considerable differences within rather than between these types of criminal networks.

Chapter 6 investigates the dynamics of two Dutch jihadi radical networks, in which some actors committed terrorist acts, which prompted law enforcement agents to disrupt this network. This study analyses the effect of law enforcement disruption on both network structure and individual tendencies. Disruption attempts are usually aimed at weakening or dismantling network structure, but actors may respond to the disruption, which might in turn strengthen the network. For this reason, the dynamics of the two networks are studied both at the level of networks and actors. The network-level analysis shows that after the disruption, the first network of Dutch jihadi became less cohesive and remained a core-periphery structure, whereas the second network becomes more cohesive and changes from a cell-structured network into a core-periphery structured one. The analysis of relational mechanisms with stochastic-actor oriented models reveals that triadic closure was the main driving force behind the dynamics of both networks, together with translation of pre-existing ties into communication ties in the first network. Additional analyses reveal that actors with numerous ties are more likely to dissolve them in the first network, and some other actors become more central. All these findings contradict the information from the police and judicial documents which emphasizes the activity of highly central individuals as the main driver behind the network evolution.

Finally, chapter 7 reflects upon one of the most challenging issues in the research of covert and criminal networks - data collection. This study identifies six aspects of network data collection, namely nodes, ties, attributes, levels, dynamics, and context. Addressing these aspects presents challenges, but also opens theoretical opportunities. Furthermore, specific issues arise in this research context, stemming from the use of secondary data and the problem of missing data. While each of the issues and challenges has some specific solution in the literature on organized crime and social networks, the main argument of this chapter is that researchers should try and follow a more systematic and general solution to deal with these issues. To this end, three potentially synergistic and combinable techniques for data collection are proposed for each stage of data collection – biographies for data extraction, graph databases for data storage, and checklists for data reporting.

8.2. Recurring findings

Several findings were recurring throughout the studies in this dissertation. First, this concerned the role of pre-existing ties. These ties are usually defined as non-criminal relations among criminal actors established before the criminal activity in a given criminal network took place (Erickson, 1981; Morselli & Roy, 2008). Chapters 4 and 6 provide evidence for the mechanism in which pre-existing ties translate into operational ties, that is, when pre-existing ties become a basis for the interactions within the criminal activity itself. Chapter 3 shows that pre-existing ties in a corruption network were not numerous, but they were always underlying other ties. None of these findings is surprising considering the fact that criminal networks are not isolated from the broader social context. Rather, criminal networks are embedded within broader social and institutional contexts (van de Bunt, Siegel, & Zaitch, 2014). Pre-existing ties are among the most important channels through which criminal relations are embedded in legitimate social settings. As such, they serve two roles in criminal networks. First, they provide a pool of potential co-offenders and pathways for recruitment. This is supported by evidence in chapter 4 when actors distributing poisonous alcoholic beverages were reaching out to their legitimate business partners or employees to advance the distribution network. Further evidence for pre-existing ties being recruitment pathways is in chapter 6, where some of the actors were initially drawn into the network by their friends or neighbours and radicalized afterwards.

The second role of pre-existing is in enhancing trust among co-operators in criminal settings. Although this argument is theoretically sound as there are no legal ways of enforcing contracts in criminal settings (Papachristos & Smith, 2014) and choosing to cooperate with untrustworthy partners may have even fatal consequences, there is empirical evidence that trust may not be a necessary condition of criminal collaboration. Criminal actors sometimes have no reasonable alternatives to untrustworthy partners or they may even find it exciting and entertaining to run risks (von Lampe & Ole Johansen, 2004). Thus while it may be assumed that pre-existing ties fulfilled a trust-enhancing role in the cases studied in chapters 3, 4, and 6, there is no empirical way how to reliably ascertain trust among actors from these data and thus there is also no incontestable evidence that pre-existing ties had the function of building trust among actors.

Triadic closure is another mechanism that has been shown to be important in the studies in this dissertation. Triadic closure is a relational mechanism denoting the tendency of actors to close open triads (Coleman, 1988; Rivera, Soderstrom, & Uzzi, 2010; Snijders, 2013). Statistical models controlling for other mechanisms revealed the effect of triadic closure in chapters 4, 5, and 6, supporting the existence of triadic closure in cross-sectional as well as longitudinal network data. Moreover, chapter 5 provides evidence for triadic closure on a larger sample of networks regardless of their collective goal (profit or ideology). Closure in criminal networks is usually explained by its effect on building trust (Coleman, 1988; Grund & Densley, 2014; Ouellet, Bouchard, & Hart, 2017). The fact that two collaborators share a common third partner is supposed to provide someone to oversee the interaction and someone who enables to overcome uncertainty in initializing the interaction. Similarly to the trust-enhancing role of pre-existing ties, closure enhancing trust may seem theoretically plausible, yet not necessary for criminal cooperation. There is no empirical evidence on trust in the data in chapters 4, 5, and 6, and so the effect of triadic closure on enhancing trust can only be assumed as it currently stands. However, triadic closure is a general mechanism operating in human social networks across different empirical contexts where the content of ties is positive (Newman & Park, 2003; Rivera et al., 2010; Snijders, 2013) – from friendship networks in classrooms to cooperation networks in organizations. Before criminal networks analysts attribute a special function to closure in criminal settings, it should be clarified and empirically supported that the effect of closure is not just carried over from the general human propensity to interact in closed microstructures, which may even be "hardwired" on neural level in human brains (Zerubavel, Hoffman, Reich, Ochsner, & Bearman, 2018).

With regard to structural properties of networks, a core-periphery structure is found in chapters 3 and 6. A core/periphery network consists of two types of nodes – core and peripheral. In an ideal case, core nodes have ties to one another and some ties to the periphery, whereas peripheral nodes have ties only to the core (Borgatti & Everett, 1999). In the corruption network study, the core/periphery model had a perfect fit with the network structure. In the study of two dynamic jihadi networks, the first one maintained a core/periphery structure after the disruption whereas the other transitioned into this structure after the disruption. The emergence of core/periphery structures may seem unexpected in criminal networks from the point of view of network theory as a core/periphery network is centralized with a dense core. Consequently, these properties contribute to increased visibility – something actors in criminal networks should try to avoid. However, core/periphery structure allows the core actors to directly control much of the network while enabling quick replaceability of actors who leave the network. Also, the peripheral actors may be engaged only ad hoc for specific tasks or occasions, therefore do not necessarily risk prolonged involvement in criminal activities. From the actors' point of view, actors in possession of power (e.g., knowledge of public contracts in corruption or religious knowledge in religious extremism) may be inclined to densely connect to others with a similar status, thus forming a core. These high-status actors may prevent excess involvement of lower status actors by interacting with them only ad hoc, thus forming a periphery. The fact that structures emerging from these tendencies may have some undesirable qualities is something actors may not inherently perceive, as it would require them to be able to oversee the network structure. However, it is more realistic to assume that actors act based on properties of the network they can perceive (i.e., what they are able to "see", such as direct control) instead of properties which they can't realistically perceive or understand (i.e., structure of the whole network) and this may be the reason why core/periphery structures are regularly observed despite their vulnerability to detection.

One of the most prominent concepts in criminal network analysis is centrality of actors (cf. Bichler, Malm, & Cooper, 2017; Faust & Tita, 2019). I investigated centrality of actors in chapters 3 and 4 in this dissertation. In chapter 3, the analysis of actors' centrality is combined with multiplexity of their ties. None of the actors is found to hold a strategic position (high betweenness and low degree) and all of them had their ties evenly spread across the types of ties under study. Interestingly enough, even though the whole corruption network was called the Rath affair after one of the actors who was supposedly the main actor, the centrality analysis does not find him to be the most central. In chapter 4, actors' centrality is analysed in conjunction with their network distance from the actors who mixed the poisonous beverages. The analysis reveals that the manufacturers relied on distributors to get the batches of counterfeit alcoholic beverages across the network, which made the distributors the most central and also increased network distances to manufacturers. Thus there were two distinct types of important actors; those with a crucial skill (manufacturers) and those with a critical network positions (highly central distributors). On the one hand, these results show that even basic descriptive measures in SNA can provide non-trivial and unique information that would not be gained by simply reading through contextual or qualitative description of the case. On the other hand, even though clearly central actors were found in all the studies here, whenever results were accompanied by a statistical model, the model did not provide any evidence that this centralization was brought about by some endogenous centralizing mechanism such as preferential attachment (cf. Barabási & Albert, 1999). What this shows is that it is not only beneficial to complement qualitative accounts with centrality measures, but that it is also necessary to accompany centrality measures with statistical models controlling for other mechanisms. This prevents from making erroneous inferences about how the network structure emerged – although the network may be highly centralized, it might have not emerged by gradual concentration of ties around central actors but other mechanisms (e.g., related to actors' attributes) might have been at play. An example of this is qualitative evidence highlighting the activity of central actors in the two jihadi networks in chapter 6, which was in contrast with model results that provided no evidence for operation of preferential attachment (the mechanism of accumulation of ties). Instead, triadic closure and translation of pre-existing ties into communication ties were found to be operating instead.

8.3. Directions for future research

The recurring findings in this dissertation open up pathways for future research. In this section, I discuss some of the directions for future research that could extend studies in this dissertation in terms of substantive research, theoretical, or methodological development.

Substantive research

The case study of a corruption network in chapter 3 is one among only a small number of studies using network approach to analyse political corruption. As chapter 3 demonstrates, corruption at this scale bears resemblance to organized crime and thus it can be analysed with SNA (cf. Campana, 2016; McIlwain, 1999). Network analysis has so far been mostly applied to terrorist, gangs, or profit-oriented criminal groups (e.g., drug trafficking, human trafficking etc.; cf. Cunningham, Everton, & Murphy, 2016; Morselli, 2014). It is understandable that SNA has been applied by researchers predominantly from Western countries given that terrorism, gangs, mafias, and trafficking networks present a considerable threat to security in these countries. However, in other parts of the world, such as post-communist countries or Latin America, political corruption may be as threating as gangs or terrorism, because of its far-reaching implications for development and welfare therein (Uslaner, 2008). The multiplex approach presented in chapter 3 may be just one possibility how to study corruption networks. Further aspects, such as studying the dynamics of corruption networks over time or the attributes or volumes of resources at stake, may be incorporated in future research.

Convergence or radical settings were touched upon in chapter 4 and explicitly studied in chapter 6. Recall that convergence settings denote spatial or social settings that provide criminal actors opportunities to meet and gain information and resources, which facilitate collaboration among them (Felson, 2006, 2009). In terrorism and radical movements, this concept has been reiterated as radical settings, that is, settings facilitating dissemination of radical ideas and resources (Wikström & Bouhana, 2017). As I propose in chapter 7, bipartite or two-mode networks may be used to empirically test the effect of convergence settings and their attributes on network structure. In this case, two-mode networks capture actors in one mode and settings as another mode with ties representing co-attendance or co-affiliation of actors to the settings. Operationalizing convergence settings as a distinct mode in a two-mode network allows to specifically address how these settings facilitate criminal collaboration or how different types of settings (e.g., public or private settings) differ in the structure of the network. Deeper understanding of the role played by convergence settings in criminal networks may be not only scientifically important, but it may also have substantial practical implications. Unlike actors, settings cannot run or hide and thus they are easier to target for law enforcement surveillance. Knowing their structural importance may in turn help to uncover important actors or ties among them.

The last substantive area I want to discuss here is the study of individual attributes in criminal networks. Chapters 4 and 6 have explicitly looked at some of the individual characteristics (such as experience with entrepreneurship) and how they affect the structure of criminal networks with the underlying reasoning that attributes like these represent preconditions and predispositions towards acting in certain way (Robins, 2009). However, individual attributes do not only affect network structure, they are also affected by the structure (see the discussion about selection and influence; Steglich, Snijders, & Pearson, 2010). For instance, there is some research on leadership in criminal networks showing how leaders in criminal networks minimize risk (Calderoni & Superchi, 2019; Hofmann & Gallupe, 2015). This research can be fruitfully extended by theorizing not only how leaders shape the networks, but also how networks shape the leaders, or even how network structure and leadership co-evolve. Similarly, research on terrorism has attempted to explain how actors become involved in terrorism or how they come to commit acts of terror (Horgan, 2008; Sageman, 2004, 2014). As these researchers point out, relying solely on individual factors to explain these phenomena falls short. Including network structure and network positions of actors among potential explanations and, subsequently, testing these explanations with proper models on empirical data may be a way forward here.

Theoretical development

As I mentioned throughout this dissertation, the lack of theoretical development in criminal network analysis has been criticized by some researchers as a serious problem for development of the field (Bright et al., 2012; Carrington, 2011; van der Hulst, 2011). The efficiency/security trade-off theory (Morselli, Giguère, & Petit, 2007) has assumed a position of a widely accepted theory about the structure of criminal networks. This theory posits that profit-driven networks are structured for efficiency allowing their members to make profit on regular basis, whereas ideology-driven networks operate in longer time frames, planning towards high-impact actions (e.g., bombings or kidnappings). This implies that while profit-driven networks should exhibit proliferation of ties, their ideology-driven counterparts should instead be geared towards reduction of redundant ties. However, recent research (de Bie et al., 2017; Ünal, 2019) together with the study in chapter 5 found evidence against some of the hypotheses deduced from this theory, specifically that there are either no structural differences between networks driven by profit and networks driven by ideology or these differences are even opposite to what the theory would imply.

Nevertheless, as both chapter 4 and 6 demonstrate, the efficiency/security trade-off may still be a good starting point for formulating a theory of criminal networks. However, instead of deriving wide network-level implications from the efficiency/security trade-off, it may be used in line with the approach of analytical sociology (Hedström, 2005; Hedström & Bearman, 2011; Manzo, 2014a) as a basis for a theory of action which deduces how and why actors would act (i.e., form ties in networks) in specific cases under more general expectations. The role of a theory of action in analytically oriented criminal network research would be to formulate hypotheses and subsequently confront them with available data instead of post-hoc explain observed results. The theory of action could be used to explain why actors in criminal networks would be motivated for or against forming ties in certain ways which are captured by relational mechanisms (Rivera et al., 2010). I attempted to proceed this way in chapters 4, 5, and 6. There is a great benefit to such an approach in that it may borrow explanations and findings from other network research subdisciplines, which helps building theory and also allows to contribute back to the study of networks in general. The efficiency/security trade-off does not have to be the only theory of action; network modifications of other theories, such as Hedström's (2005) desires-beliefs-opportunities theory or Lindenberg's (2008) goal-framing theory, may be used instead. Multiple theories of action can even be tested against each other, helping us to formulate hypotheses and explanations and to eliminate those with little or no empirical support.

All empirical studies in this dissertation (chapters 3, 4, 5, and 6) distinguish between the analytical levels of individual actors and whole networks. Having a plausible and testable theory of action is just one part of the explanatory puzzle of how network structures arise. If we admit that network structures arise as a consequence of overlap and accumulation of individual ties (Robins, Pattison, & Woolcock, 2005; Snijders & Steglich, 2015), we also need to specify how exactly these ties overlap and accumulate to give rise to a network structure. In other words, it is necessary to specify the micro-macro link (cf. Coleman, 1990). To this end, specification of relevant relational mechanisms together with their empirical testing using appropriate models should provide a solid basis for disentangling the network structure into its constituent micro-level elements. In order to advance our understanding of emergent network level properties, more theorizing about consequences of different relational mechanisms should be done and these consequences should be subsequently investigated in simulation studies (akin to Robins et al., 2005; Snijders & Steglich, 2015). A specific example is the mechanism of brokerage. There has been a lot of emphasis on the importance of brokers in criminal networks suggesting that brokerage provides brokers with profit while allowing them to not expose themselves and that it helps to interconnect different regions of the network (Bright, Koskinen, & Malm, 2018; Morselli, 2010; Morselli & Roy, 2008; Robins, 2009). However, the conceptualization of brokerage is not entirely clear from the extant literature, as on the one hand, it may be viewed as a tendency of actors for maintaining structural holes among their partners (Burt, 1992, 2005), while on the other hand, brokerage may be viewed as a tendency of actors to assume positions bridging between different regions of the network (DellaPosta, 2017; Morselli, 2010; Morselli & Roy, 2008). These two dimensions of brokerage may also yield different structural outcomes, as the one emphasises neighbouring actors whereas the other considers the network as whole. Only more theorizing about their similarities, differences, preconditions, and outcomes together with empirical research may shed light on which one is more prevalent, in what circumstances they occur, and which structural outcomes they yield.

Methodological development

Even though the research on criminal networks is still largely descriptive (Campana, 2016; Stys et al., 2019), criminologists are starting to adopt statistical models for networks. These models are methodological cornerstones of chapters 4, 5, and 6. Descriptive analysis in SNA can go a long way to uncover structure and central actors in criminal networks. However, descriptive analysis cannot be used to draw inferences about mechanisms and processes that brought about observed outcomes. For instance, claiming that a network was brought about by a process of gradual tie accumulation akin to cumulative advantage or preferential attachment, just because it is descriptively highly centralized, is potentially erroneous as descriptive analysis does not account in any way for other potential mechanisms that might have played a part in formation of a given network. Statistical models are designed to separate effects of multiple competing mechanisms, which is one of the reasons why they have become so popular in all domains where network approach is used. Nevertheless, the context of criminal networks is specific enough that straightforward adoption of these models from other areas may not be without problems.

One of the promising types of models for criminal networks are autologistic actor attribute models. Autologistic actor attribute models (ALAAM; Daraganova & Robins, 2013; Robins, Pattison, & Elliott, 2001) are in principle similar to exponential random graph models (ERGM; Lusher, Koskinen, & Robins, 2013) – they also use configurations as explanatory variables and simulate distributions of outcomes, but the outcome in this case are individual attributes (unlike tie variables in ERGMs). These models have not been used nearly as much as ERGMs – one of the few studies is Kashima and colleagues' (2013) study on adoption of norms and there is only one example in criminal networks comparing the structural position of men and women in organized criminal networks (Diviák, Coutinho, & Stivala, 2019). Other potential uses for ALAAM includes explaining the structural and individual factors behind leadership in criminal networks.

In a similar vein to modelling categorical individual attributes, a model-based approach to centrality measures would greatly aid the research on criminal networks. As I argued in the section on future substantive research, this is central to the development of the whole subfield of criminal network analysis, in which huge attention is paid to identifying central actors. Formulating a model for centrality of actors would contribute not only to identifying central actors, but also to explaining what makes them central and quantifying the uncertainty of the results. For instance, is centrality of actors in a terrorist network affected by a specific skill (an individual attribute), the centrality of their neighbours (a network predictor), or by the amount of pre-existing ties they have (a dyadic predictor)? Having a model that could answer these questions without relying on violated assumptions (e.g., independence of observations) would increase our understanding of central actors in criminal networks and would also give us a more powerful tool in designing interventions against criminal networks.

Another avenue for extending existing models for specificities in criminal networks research is constituted by models for network dynamics. As discussed in chapter 6, one of the key differences of criminal networks from their overt counterparts is that the node set (‘population’) is usually not stable. New actors join and previously active actors drop out or are removed from the network. This makes modelling dynamics of these networks challenging, as stochastic actor-oriented models (SAOM; Snijders, 1996; Snijders, van de Bunt, & Steglich, 2010) assume a stable node set. Even though some change can be accommodated using the change composition method (Huisman & Snijders, 2003), actors joining or leaving the network are not just a nuisance. The change in composition of the node set may be due to theoretically important reasons such as constraints or opportunities for criminal cooperation. In other words, criminal network analysis could use models that can account for actors joining or leaving the network, and for the way they create or drop ties. Two possible steps towards such models may be models for network growth (cf. Bell et al., 2017; Fellows, 2018) or models for relational events (Butts, 2008; Stadtfeld & Block, 2017; Stadtfeld, Hollway, & Block, 2017), although both these types of models are currently restrained by some assumptions that limits some of the criminologically interesting applications. For network growth models, some of them build on the assumption that nodes and ties can only be added (Fellows, 2018), but criminologists may be equally or even more interested in deletion of nodes and ties as chapter 6 demonstrated. The models for relational events currently only consider dyadic events (Stadtfeld et al., 2017), yet for criminologically interesting applications, triadic events (such as three actors together robbing a bank) may be crucial. Overcoming these limitations may help not only the study of criminal networks, but network science as a whole.

Successful application and further development of statistical models suited for criminal network data is predicated upon availability of valid data. The issues related to data in criminal networks can be considered an Achilles heel of the whole subdiscipline (Berlusconi et al., 2016; Gutfraind & Genkin, 2017; Rostami & Mondani, 2015). In this dissertation, I used data from media sources, court files, data combining court files with police investigation and surveillance, and data collected by other researchers. All these sources have different advantages and disadvantages, which sometimes makes research of some aspects of criminal networks (such as dynamics or multiplexity) impossible due to information not being available in the given source. As chapter 7 suggests, the situation is not hopeless and there are many things that may be done in order to improve the accessibility, validity, and reliability of the data in criminal network analysis. There are two fundamental directions which seem especially important for further development of the field as a whole.

The first direction is development of data collection techniques. In chapter 7, I propose to use biographies, graph databases, and checklists as tools for systematic data collection from data extraction, through data storage, to data reporting. In theory, using these tools should increase transparency and also validity and reliability of data in the context of criminal network studies. This needs to be tested by using these tools in practice. However, we should also increase our knowledge about the procedures and techniques used by practitioners (e.g., law enforcement or media) in order to adequately capture how the secondary data we work with are primarily created. In other words, we should use our contacts with the practitioners and specifically study the ways they use to collect the information for primary data sources. If we know the data generating process, we can then employ corresponding methods for analysing the data or at least introduce appropriate controls to distinguish genuine properties of criminal networks from artefacts induced by data collection. Thus, it may be important to systematically study the way law enforcement agents collect the data. For instance, the way police surveillance generates the pool of individuals to observe may closely resemble snowball sampling, where new individuals are included based on their contact with those already under surveillance. If we have enough evidence that snowball sampling is a good approximation of the process generating given dataset, suitable measures and models for snowball samples may be used to analyse such data (Heckathorn & Cameron, 2017; Pattison et al., 2013; Spreen, 1992).

The second direction for future research regarding data about criminal networks is the ubiquitous problem of missing data. More research needs to be done on how missing data affect criminal networks and how to deal with it. In terms of the effect of missing data on criminal networks, future studies should investigate how different missing data mechanisms (such as missing completely at random and missing not at random; Rubin, 1976) affect network structure, i.e., where these ties are located in the structure (e.g., bridging ties) or which actors are incidental to them (e.g., leaders). In a similar vein, different approaches towards imputing the data may be examined and their performance compared, such as by comparing model based imputation (Krause et al., 2018; Robins et al., 2004), with imputation based on classification of reliability of information (e.g., confirmed versus unconfirmed ties, Sparrow, 1991), and with imputation based on combining different data sources (Berlusconi et al., 2016).

As it is apparent, there is still a lot to be done in terms of theoretical as well as methodological work in the research on criminal networks. Analytical sociology, statistical models for network data, and systematic approaches to data collection have much to offer in this regard. The studies in this dissertation may be seen as small contributions from these positions to our knowledge of criminal networks, uncovering positions of actors in criminal networks, mechanisms through which they relate to other actors, and how these mechanisms translate into network structures. This dissertation thus provides a few more pieces into the mosaic of our understanding of the fascinating, yet dangerous phenomenon of organized crime.

9. Samenvatting

Sociale netwerkanalyse is een veelbelovende discipline die veel kansen biedt voor de studie van georganiseerde misdaad. Haar methoden maken het mogelijk om de structuur van criminele netwerken te bestuderen, vanuit het gezichtspunt dat deze tot stand komt door de keuzes van, en interacties tussen individuele actoren. Onderzoekers hebben beschikking over een breed scala aan theoretische concepten en methodologische tools om invloedrijke personen te identificeren, netwerkkenmerken te kwantificeren, en mechanismen bloot te leggen, die verantwoordelijk zijn voor de totstandkoming en de ontwikkeling van criminele netwerken.

In hoofdstuk twee van dit proefschrift wordt de basisterminologie, en de meest gebruikte meetinstrumenten en statistische modellen van sociale netwerkanalyse geïntroduceerd. Daarnaast geeft dit hoofdstuk enkele voorbeelden van toepassingen van deze meetinstrumenten en modellen binnen de criminologie. Het hoofdstuk wordt afgesloten met het aanwijzen van de drie belangrijkste problemen binnen het onderzoek naar criminele netwerken: theorievorming, keuze van analysemethoden, en dataverzameling. De hierop volgende hoofdstukken gaan hier elk op hun eigen manier op in.

Hoofdstuk drie betreft het netwerk rondom de zogeheten "Rath affaire" – een politiek corruptieschandaal in Tsjechië. In deze affaire misbruikten enkele politici hun macht bij de gunning van overheidsopdrachten en werkten ze samen met zakenmensen om onder valse voorwendselen Europese subsidies te bemachtigen. De analyse toont dat het netwerk een perfecte kern-periferie structuur laat zien. In een dergelijke structuur is de groep actoren verdeeld in een kern en een periferie. Relaties binnen de kern evenals tussen kern en periferie zijn heel dicht, terwijl relaties tussen actoren in de periferie vrijwel niet voorkomen. De overdracht van hulpbronnen vindt vooral plaats binnen de kern en tussen de kern en periferie. Relaties die samenwerking tussen actoren aangeven overlappen slechts zelden met relaties voor de overdracht van hulpbronnen. De scheiding tussen kern en periferie is heel duidelijk. Voor de meerderheid van de actoren zijn hun relaties evenredig verdeeld over verschillende typen, en geen van de actoren neemt een uitgesproken strategische positie in (d.w.z. een positie met weinig relaties, maar waarvan de bestaande relaties belangrijk zijn om andere actoren met elkaar te verbinden).

Hoofdstuk vier is een studie naar een netwerk van personen betrokken bij de verspreiding van namaak alcohol, in Tsjechië bekend als de "methanol affaire". Dit netwerk produceerde en verspreidde giftige alcoholische dranken, met tientallen doden en ernstig gewonden tot gevolg. Het netwerk bestond uit twee groepen actoren, verbonden door slechts één relatie, een zogenaamde ‘brug’. De twee actoren die verantwoordelijk waren voor productie van de alcohol stonden relatief ver weg van de andere actoren in het netwerk, wat suggereert dat met een andere netwerkstructuur alcohol efficiënter verdeeld had kunnen worden (met minder tussenpersonen). Verder gaven de resultaten aan dat de structuur van het netwerk kan worden verklaard door een combinatie van het sluiten van triaden, het omzetten van reeds bestaande relaties naar operationele verbanden, en het vermijden van centralisatie. Andere mechanismen, waarvan we weten dat ze in veel gevallen de netwerkstructuur bepalen, bleken niet een rol te spelen bij de totstandkoming van dit netwerk.

Hoofdstuk vijf test de vaak geciteerde en invloedrijke “efficiëntie/veiligheid trade-off theorie”. Deze theorie voorspelt dat door winst gedreven en ideologisch gedreven netwerken structureel van elkaar zouden verschillen omdat ze tot stand komen met een ander doel voor ogen. Winst-gedreven netwerken zouden geneigd zijn tot efficiëntie, weerspiegeld in een groot aantal relaties in het netwerk. Ideologie-gedreven netwerken zouden sterker gericht zijn op individuele veiligheid en het voorkomen van de ontdekking van het netwerk door buitenstaanders, wat tot uiting komt in het vermijden van relaties die niet strikt noodzakelijk zijn. Deze theorie is getoetst met een steekproef van alle mogelijk beschikbare en vergelijkbare netwerken: elf door winst gedreven, en negen ideologisch gedreven netwerken. De beide typen netwerken zijn vergeleken op basis van vier structurele eigenschappen: dichtheid, centralisatie, transitiviteit (gesloten triaden), en ‘brokerage’, de mate waarin veel actoren een verbindende positie innemen. Al deze vergelijkingen vonden echter ofwel geen verschil tussen de twee typen netwerken, of een verschil dat omgekeerd was ten opzichte van de theoretische verwachting. Daarnaast werden de implicaties van de theorie voor mechanismen op het niveau van individuele actoren verkend, middels het gebruik van exponentiele willekeurige grafen-modellen. Hiermee is onderzocht hoe de waargenomen structuur van een netwerk kan worden verklaard door lokale mechanismen op het niveau van individuele actoren (mechanismen die uitdrukking geven aan het winst- of veiligheids-oogmerk van het netwerk). Hieruit bleken geen verschillen tussen de mechanismen die ten grondslag liggen aan de door winst gedreven en de ideologie-gedreven netwerken. Er werden zelfs aanmerkelijke verschillen gevonden binnen, in plaats van tussen de twee netwerktypen.

Hoofdstuk zes onderzoekt de dynamiek binnen twee jihadistisch terrorisme netwerken in Nederland. Een aantal leden van deze netwerken pleegden een terroristische daad, waarna politie en justitie ingrepen om de netwerken te verzwakken. Deze studie analyseert het effect van deze ingrepen op zowel veranderingen in de netwerkstructuur, als op het gedrag van de actoren. Doorgaans zijn pogingen om criminele netwerken aan te bestrijden gericht op het verzwakken of ontmantelen van de netwerkstructuur, maar soms lukt het actoren het netwerk te herstellen of zelfs te versterken. Om deze reden worden de dynamieken van de twee netwerken bestudeerd op het niveau van het netwerk, én van de actoren. De analyse laat zien dat na de verstoring, het eerste netwerk van Nederlandse jihadisten minder cohesief werd en zijn kern-periferie structuur behield. Het tweede netwerk werd echter juist hechter en veranderde van een netwerk met een celstructuur, naar een netwerk met een kern-periferie structuur. De analyse van relationele mechanismen, met behulp van stochastisch actor-georiënteerde modellen, laat zien dat het ontstaan van gesloten triaden de belangrijkste drijvende kracht is achter de veranderingen in beide netwerken, in het eerste netwerk samen met het omzetten van eerder bestaande relaties naar communicatierelaties. Uit aanvullende analyses bleek dat actoren in het eerste netwerk die veel relaties hebben veel hiervan hebben verbroken, terwijl andere actoren meer centraal werden. Deze bevindingen zijn in tegenspraak met informatie van de politie en justitie, die de blijvende activiteit van zeer centrale personen juist zagen als de belangrijkste drijfveer achter de ontwikkeling van dit type netwerken.

Ten slotte wordt in hoofdstuk zeven gereflecteerd op een van de lastigste kwesties in het onderzoek naar geheime en criminele netwerken: het verzamelen van data. Er worden zes aspecten van de verzameling van netwerkgegevens benoemd, die elk gepaard gaan met hun eigen uitdagingen, problemen en kansen, namelijk: actoren, verbanden, eigenschappen, niveaus, dynamiek en context. Bovendien doen zich in deze bijzondere onderzoekscontext nog specifieke problemen voor die voortvloeien uit het gebruik van secundaire, en vaak incomplete gegevens. Hoewel er voor elk van deze problemen al een aantal specifieke oplossingen bestaat, zou het nuttig zijn om een systematisch te hanteren en algemene oplossing te presenteren. Om dat te bewerkstelligen worden drie potentieel synergetische en combineerbare technieken voor gegevensverzameling voorgesteld voor elke fase van gegevensverzameling, namelijk: beschrijving van gegevensextractie, grafen-databanken voor gegevensopslag, en checklists voor gegevensrapportage.

In dit proefschrift komen een aantal bevindingen komen terug in meerdere hoofdstukken. Ten eerste, het belang van reeds bestaande relaties voor de ontwikkeling van relaties binnen criminele netwerken komt naar voren in zowel hoofdstuk vier als zes. Hier is ondersteuning gevonden voor het mechanisme dat reeds eerder bestaande banden – niet-criminele relaties die reeds vóór de criminele activiteit bestonden – de basis vormen voor interacties binnen het criminele netwerk. Ten tweede blijkt het sluiten van triaden (transitiviteit) een belangrijk mechanisme in de studies binnen dit proefschrift. Dit mechanisme is de neiging van individuen tot het sluiten van indirecte relaties ("de vriend van mijn vriend is mijn vriend"). In elk van de hoofdstukken vier, vijf en zes wordt ondersteuning gevonden voor dit mechanisme. Daarmee is bewijs geleverd voor dit mechanisme in zowel cross-sectionele – als longitudinale netwerkdata. Ten slotte is er in dit proefschrift op diverse plaatsen aandacht voor de kern-periferie structuur van netwerken. In een dergelijk netwerk, hierboven beschreven, is een duidelijk onderscheid tussen twee soorten actoren: kern- en periferie actoren. Deze structuur is gevonden in zowel hoofdstuk drie als zes.

Tezamen toont dit proefschrift het belang van netwerkmechanismen voor de positie van individuele actoren binnen criminele netwerken, en de structuur en ontwikkeling van criminele netwerken.

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