Detecting and disrupting criminal networks
A data driven approach
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Chapter 6

Fluid connections within an old boys’ network? An empirical network study on tie-strength in organized crime

40 This chapter is based on a paper submitted as: P.A.C. Duijn, R. Quax, R.M.A. Sloot. 2016., Fluid connections within an old-boys’ network? An empirical study on tie-strength in organized crime.
**ABSTRACT**

*Background:* Criminal networks are essentially defined as sets of actors that are connected by one or more ties. While many empirical studies of criminal networks have focused on the properties of actors (i.e. key-players), less attention is paid to the importance of ties in terms of tie-strength and its influence on emerging criminal networks.

*Aim:* The aim of this study is to empirically study the associations between the structural, temporal and demographical dimensions of the strength of ties within organized criminal networks.

*Method:* We use a combination of social network-, statistical- and qualitative analysis to study the associations between three dimensions of tie-strength: the structural-, temporal- and demographical- dimension.

*Network-data:* A criminal meso-network consisting of N= 5178 actors.

*Results and conclusions:* Our findings suggest that weak ties are important for the exchange of information particularly at a meso-level, but not exclusively due to a small-world effect. The majority of these ties are fluid, instrumental in nature, and often based on trust in a third party instead of between actors at both ends. ‘Freelance’ co-operation emerges out of the fluid pools of potential co-offenders. The strong ties in the network rely heavily on kinship and attachment to local neighborhoods. Different clusters of strong ties are associated with an overarching ‘old-boys’ network’ that remains more durable over time and forms a sustainable pool of criminal cooperation within the overall fluid criminal network.
6.1 INTRODUCTION

The influence of embedding social networks on the structures and dynamics of organized crime networks has been widely acknowledged in academia and law enforcement. An important method to unravel the social embeddedness of organized crime is social network analysis (SNA). The starting point of SNA is that social life is mediated through relations and the patterns formed by these relations. Social networks are defined as sets of actors that are tied by one or more relationships, which are considered the smallest elements out of which complex criminal- and social networks emerge (Wasserman and Faust, 1994). Understanding the interactions between these individual units combine to produce the structure and behavior of the system as a whole is one of the main challenges in complex networks research (Newman, 2003; Quax et al., 2013). For law enforcement organizations such insights are essential to cope with the resilience of criminal networks against disruption (Chapter 4).

There are many empirical studies of criminal (and terrorist) networks that focus on the positioning and properties of the actors, for instance with regards to the identification of key players (e.g. Bright et al., 2014; Morselli and Petit, 2007; Xu and Chen, 2009). The uneven distribution of social- and human capital across actors in organized crime networks provides opportunities to detect and disrupt them efficiently and effectively at their weakest points.

In network theory the ties are evenly important as the nodes (Wasserman and Faust, 1994). The distinctive properties of ties do however not receive as much attention in criminal network research as that of actors. Many criminal network studies focus on binary representations of criminal connections, in which all ties are treated as of equal importance (Bright et al., 2015). Just a few studies take notice of tie-attributes when analyzing the structure of criminal networks, for instance by including edge-weight (Schwartz and Rouselle, 2009), level of trust and sharing sensitive information (Capana and Varese, 2011), the interplay between different types of ties (Papachristos and Smith; 2011), and the multiplexity of ties (Bright et al., 2015) to create a more nuanced understanding of criminal network structure. These studies emphasize that failing to incorporate the distinctive features of ties into the study of organized crime may result in an over simplistic interpretation of criminal network structures and behaviors (Carley et al., 2002; Robins, 2005; Hamil et al., Bright et al, 2015). Outside of the academic field, such insights are also particularly relevant in support of intelligence operations or investigations seeking the grasp the illicit network’s plans and activities (Strang, 2014). More empirical research is therefore needed on the influence on how multiple dimensions of ties affects the emergence and evolution of criminal networks as a whole.
Particularly neglected in the empirical study of criminal networks is the conceptualization of tie-strength and its impact on the emergence and evolution of criminal networks. Theoretically, an important distinction is made between strong and weak ties (Granovetter, 1974). Strong social relationships are considered the principle elements out of which criminal cooperation emerges. They provide the essential security and protection to survive in the unpredictable and unlawful criminal underworld. Internal secret information is assumed to travel easier along strong ties. Weak non-redundant ties are however important to expand from local activities to transnational illegal markets.

Some scholars have theorized how the distribution of strong and weak ties could help us understand the topological features of the overall network. Loosely knit criminal networks that constitute many weak ties are suggested to promote the dissemination of new information and resources amongst the different subgroups that populate the network. This is associated with high levels of adaptability to changing opportunities or external pressures, which makes them harder to detect (Van der Hulst, 2009). Dense cohesive criminal networks containing more strong ties are assumed to have more efficient internal communication, higher levels of group compliance, and are considered difficult to infiltrate (Xu et al., 2004). Criminal networks with a relatively balanced number of strong- and weak ties are expected to be most effective in achieving their goals, because they can easily adapt their strategy in accordance with continuously changing opportunities and external pressures (Everton and Robert, 2011).

Granovetter (1974) defined the strength of social ties as “the combination of the amount of time, the emotional intensity, the intimacy, and the reciprocal services which characterize the tie”. In his famous theoretical concept of ‘the strength of weak ties’, the structural positioning of ties in-between remote parts of the network is considered an indicator for weak ties, but at the same time this makes these ties important for introducing new phenomena and the proliferation of information and goods throughout the network. Actors on both sides of the weak ties benefit from reliance of others for exchanging information and resources between different sub-communities. Burt (1995) especially relies on structural positioning for his definition of ‘bridges’ fulfilling the structural holes between different parts of the network. Tie-strength is then defined not particularly as a function of the tie itself, but more as a function of the ties that surrounds them.

In addition to this structural positioning perspective, there is a line of research that focuses more on the attributes of the actual tie itself and its association with tie-strength (Marden and Cambell, 1984). This is particularly relevant when studying tie-strength in ego-networks for which data on the topology of the embedding network is not available. Moreover, since the structural positioning helps to identify strong and weak ties at both
ends of the scale, it does not distinguish between the ties that fall in-between. In this regard a distinction is made between indicators and predictors of tie-strength (Mathews, 1998; Marsden and Cambell, 2011). Indicators are considered the actual components of tie-strength (closeness, duration and frequency, reciprocity), whereas shared affiliations (shared activities, background, nationality) are predictors. Predictors are then associated with tie-strength but not the essential components of it. Kleemans and Van de Bunt (1999) elaborate on this perspective to qualitatively study strong ties in criminal networks by looking into overlapping layers of kinship and friendship. Weak ties on the other hand emerge from daily activities or are deliberately created and maintained. The strength of the tie is then more derived from the background of offenders (e.g. same country of origin), their daily activities (visiting same meeting places), and their geographical distance.

Differences in indicators for tie-strength are also related to different approaches to the study of organized crime: quantitative and qualitative. Although both methodologies would most likely lead to overlapping conclusions, the structural positioning of ties and the qualitative tie-attributes have rarely been studied in conjunction. The aim of this paper is to empirically study tie-strength from these two perspectives and reflect on its implications for identifying tie-strength in organized crime networks. Subsequently, this paper aims to compare these different measures to infer how organized crime networks emerge and evolve along these dimensions. Before we will explain the data and methodology in section 6.4, we will define the different indicators for identifying tie-strength (section 6.2) and define what we mean with organized crime networks (section 6.3).

6.2 CONCEPTUALIZING AND MEASURING TIE-STRENGTH

There are several indicators and predictors for measuring tie-strength, which also applies to criminal ties. These indicators can be divided into 3 dimensions:

1. Structural dimension
2. Temporal dimension
3. Demographical dimension

In this Section these indicators are further specified and explained according to theories and previous research on criminal networks.

The structural dimension

The structural dimension of tie-strength depends on and the topology of the overall network. Although there are more metrics available, the most important SNA-measure specifically aiming for the positioning of ties instead of nodes is edge-betweenness (Girvan and Newman, 2002; Marsden and Campbell, 2012). Other related measures to edge-
betweenness are dyadic redundancy and dyadic constraint that follow from structural holes analysis (Burt, 1995). The outcomes of these different measures are however redundant. In order to make the analysis for this paper not overly complex, we limit the indicators for structural positioning of ties to the measure of ‘edge-betweenness’.

**Edge-betweenness**

Edge-betweenness centrality measures the number of shortest paths between pairs of actors. If there is more than one shortest path between a pair of actors, each path is assigned equal weight such that the total weight of all of the paths is equal to unity (Girvan and Newman, 2002). According to Granovetter weak ties connect remote parts of the network. Within technical SNA this notion is represented by high scores on the measure edge-betweenness (Girvan and Newman, 2002).

Girvan and Newman (2002) used edge-betweenness as the basis for a procedure to identify sub-communities within large networks. The notion behind this procedure is that the network gets more dispersed that by structurally removing high edge-betweenness ties, which reveals the more densely clustered parts of the network. Edge-betweenness is therefore an important measure for identifying ties that form important elements of the networks topology. The distribution of edge-betweenness centrality across the network is therefore considered an indicator for distinguishing between Granovetter’s strong and weak ties within networks.

This results in research-question 1:

*To what extent is the structural positioning of ties in the overall network associated with tie-strength and the overall functionality of criminal networks?*

**The temporal dimension**

Another indicator of tie-strength is the duration and intensity of the relationship (Petróčzi et al., 2007). Because this involves the element of time, it is referred to in this chapter as the *temporal dimension*. In the study of criminal networks the duration and intensity of ties often follow from observations by law enforcement. An important goal of building strong ties in criminal networks is trust (Von Lampe and Johansson, 2004; Morselli, 2009). Trust reduces the risks and uncertainties involved in cooperating with potential accomplices to a level that reinforces the willingness to co-offend (Everton and Roberts, 2011). Strong trustworthy ties are therefore associated with long lasting, resilient and intense relationships (Granovetter, 1974; Mathews et al, 1998). This leads to two other important quantitative indictors for tie-strength are described below:
**Duration**

Strong ties are associated with a longer duration than weak ties (Granovetter, 1974; Mathews et al. 1998; Petróczi et al. 2007). Because strong social ties emerge early in life within settings of local neighborhoods, schools, or sport clubs, they can generally be identified by a longer duration than weak ties. Mentorship between established criminals and young recruits also emerges within these settings and may play an important role in the emergence of loyal ties that remain stable over longer periods of time (Morselli, 2006). Practically, the duration can simply be estimated by calculating the number of months between the first and last occasion that the tie was observed.

**Intensity (number of interactions)**

In general, the intensity of a relationship is considered an indicator for tie-strength (Mathews et al. 1998; Petróczi et al. 2007). Intensity of criminal ties is generally measured by counting the number of times two criminals are arrested together or reported under suspicious circumstances or by criminal informants. Whether this provides a good notion of strong and weak ties is however not without debate. Criminals are aware of their ‘outlaw status’ and may actively prevent detection by limiting their number of meetings or communications with accomplices to the ultimate minimum. This minimum however varies due to the overall nature and functionality of the overarching criminal network. In more sophisticated covert networks, interactions between key orchestrators in the network can deliberately be reduced to maintain security and prevent detection. The strongest ties may then consist of the most infrequent contacts (Strang, 2014).

This remark is particularly relevant in the case of espionage networks, of which the operations are most often strategically planned and designed on a drawing board. In criminal networks - with lots of opportunistic activity and high levels of self-organization - such security strategies are hard to maintain over time, especially in the inevitable times of uncertainty due to disputes or financial losses which are typical for day-to-day criminal entrepreneurship. Therefore, efficiency needs to be traded for security at times, increasing the probability of exposure (Erickson, 1985; Baker and Faulkner, 2003). Regardless of these considerations, the number of observations by law enforcement is considered a measure for intensity and therefore another indicator of tie-strength. Strong ties are considered have a higher number of observations by law enforcement agencies in this regard than weak ties.

This leads us to research question 2:

*To what extent are the duration and frequency of criminal ties associated with tie-strength and the overall functionality of criminal networks?*
The demographical dimension

The indicators described above are direct components of tie-strength. Besides these components that are indicators that represent the contextual enablers of tie-strength (Mathews et al. 1998; Petróczi et al. 2007). These indicators are related to the settings that predict tie-strength based on shared affiliations, such as described below:

**Homophily**

Similarity breeds connection. Strong ties are more easily found among groups of like-minded people, which is known as homophily (McPhearson et al., 2001). It represents the extent to which actors form ties with similar versus dissimilar others. Members of criminal networks are assumed to cluster around ethnic communities that provide them safety, concealment and a supply of ‘like-minded’ recruits (Bruinsma and Bernasco, 2003). Diaspora communities may therefore provide excellent safe heavens for criminal networks that spread across different countries, but share a similar cultural background (Kleemans and Van de Bunt, 1999; Williams, 2001).

Within transnational criminal networks cooperation does not always emerge from people with the same background. Especially if groups from different backgrounds rely on each other’s distribution networks, mixed-cultural groups are more frequently observed (Kleemans and Van de Bunt, 1999). Since trust between criminals is often established at a young age in countries, cities and neighborhoods where they up changes are higher of ending up with someone of the same cultural background. The alleged ethnic homophily found in criminal networks may therefore just also be a by-product of growing up within such a close geographical proximity instead of having a deliberate preference for cooperation with ethnically similar co-offenders. In criminal networks homophily can be identified through various parameters, such as similarity in gender, country of birth, nationality, age, or any other salient and similar characteristic of the actors on both ends of the tie. Strong ties are generally characterized by higher levels of homophily than weak ties.

**Multiplexity**

Another factor that fosters trust in criminal networks is multiplexity. This indicator refers to the number of relationship-types that are concentrated in one criminal tie, often represented by overlapping criminal, affective, friendship and kinship relationship-layers (Hanneman and Riddle, 2005). Because mutual trust if often the only guarantee for successful criminal cooperation, criminal networks often consist of many layers of social and instrumental connections (Malm et al., 2010). Strong ties in criminal networks are therefore often based on kinship or friendship. The trust that is found within family relationships has proven to be a strong foundation for a durable and structural criminal cooperation (McCarthy and Hagen, 2001; Von Lampe, 2009).
Multiplexity can also be observed within criminal cooperation itself. Two actors that share a connection in multiple criminal operations (i.e. value chains) are for instance considered to have stronger ties then criminal actors with less shared cooperation (Bruinsma and Bernasco, 2004; Malm et al, 2009; Bright et al. 2015). According to this notion the more criminal markets two individuals are involved in together the stronger is their relationship (see Toth et al., 2013).

This leads to research question 3:

*To what extent are multiplexity and homophily associated with tie-strength and the overall functionality of criminal networks?*

Figure 6.1 summarizes the identified dimensions and related indicators of tie-strength based on previous studies described above. The three circles on the left represent the three dimensions of tie-strength and the arrows at the right points the direction by which a score on these indicators increases or decreases in relation to tie-strength. As described in Section 6.1 the three dimensions of tie-strength have rarely been studied in conjunction, while a more holistic approach to the study of tie-strength is needed for understanding its complexity.

![Figure 6.1: Overview of the three dimensions and related indicators of tie-strength that forms the conceptual framework of the present study](image)

This leads to research question 4:

*To what extent are these three different dimensions associated to each other and what how does this interaction influence the way criminal networks emerge, operate and evolve?*

41 Visualization performed in Gephi
6.3 CONCEPTUALIZATION OF THE CRIMINAL MESO-Network

Although formal membership may exist in organized crime, several studies showed that participants are more likely to structure their criminal endeavors and operational networks on an *ad hoc* basis (Fijnaut et al., 1996; Kleemans and Van de Bunt, 1999; Klerks, 2000; Felson, 2006; Morselli, 2009; Spapens, 2010). Research shows that the majority of co-offending relationships lasts through the course of only one criminal event (Reiss and Farrington, 1991; Kleemans and Van de Bunt, 1999; Weerman, 2003; McGloin and Piquero, 2009). The strength of criminal ties therefore increases or decreases over time or may even been ‘switched off’ for a period of time or become reactivated when the opportunity arises. Time is therefore an important factor. This makes it particularly difficult to set a boundary to include or exclude network members when inferring criminal networks out of raw data. Many studies therefore only look into co-offending- instead of criminal networks, which also include ties that are manifest during a singular criminal endeavor (Weerman, 2003; McCarthy and Hagen, 2001).

Another more robust approach is to start from the premise that criminals who have successfully co-operated in the past will do so again in the future. In this regard three levels of criminal cooperation can be distinguished (Von Lampe, 2014):

1. **Manifest criminal ties**, consisting of connections between participants that are actively conspiring or cooperating within a criminal venture at a certain point in time;
2. **Criminally exploitable ties**, consisting of manifest and latent criminal ties that form the pools of reliable accomplices out of which operational cooperation continuously emerges. Latent ties based on previous (successful) criminal cooperation may become reinforced based on a new opportunity at a certain point in time.
3. **Potential ties**. These ties include indirect connections among criminals that are part of the same pool of potential accomplices and facilitators. As their social ego-networks expand during their criminal career, criminals sharing mutual social and criminal ties may become operationally connected over time. This is particularly relevant for the study of network resilience and adaptation after disruption.

These three types of ties correspond with the three levels of criminal networks described by Spapens (2010) in his research on synthetic drugs production networks in the Netherlands. First he distinguishes micro-networks, which are timely and may change during the course of one criminal operation. These micro-networks are part of an overarching macro-network, which is in principle a world-wide criminal network observed in transnational organized crime follow the major trafficking routes for illegal commodities and demonstrate

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42 Duijn et al. (2014) included the concept of potential criminal ties within their simulations of network adaptation as a result of different criminal network disruption strategies.
high levels of self-organization. In between these two extreme network-levels there are meso-networks, which are best described as the regional pools of criminally exploitable ties within the macro-network out of which new manifest criminal cooperation emerges (Spapens, 2010). These pools often have a local foundation in local infrastructures such as bars, brothels, and coffeehouses were criminally exploitable ties may become manifest when the opportunity arises also refered to as offender convergens settings (Felson, 2006).

A critique towards the application of SNA is that it is mainly applied to criminal networks inferred from manifest criminal ties, leading to static observations of a phenomenon that is in fact amorphous and unstable (Bossevain, 1974; Kleemans and Van de Bunt, 1999; Felson, 2006; Von Lampe, 2009; Spapens, 2010;). It is therefore emphasized that criminal network research should focus more on the overarching pools of criminally exploitable ties which remains more consistent and therefore better suitable for identification of the macro-scorpic changes over time (Spapens, 2010; Von Lampe, 2014). Network representations that also include potential ties are particularly relevant for simulating the effects of actor replacement following network disruption (e.g. Chapter 3) or for the nature of relationship between criminal groups instead of individuals (Malm et al., 2011). Potential ties are in fact hypothetical ties, which may predict future associations or replacement following disruption. The focus of this chapter is the empirical reality of tie formation and distribution by looking back at past criminal co-operation. Therefore, this chapter will focus on all manifest ties and latent ties that form a regional meso-network observed over a longer period of time.

6.4 DATA

A way to improve the validity and reliability of criminal network representations is to combine different sources of law enforcement data (see Berlusconi, 2013; Bright et al. 2015). This chapter relies on two different datasets: Human intelligence data (HUMINT) and street-patrol data. Both sets have been collected over a long period of time and contain many variables related to the indicators described above. The specific properties of these two datasets are described below.

The Human intelligence dataset

This dataset is the result of a human intelligence collection process in a specific police region in the Netherlands over a time period of 25 years (1991-2015). The data is collected by law enforcement specialists working for the criminal intelligence unit, which are responsible for collecting human intelligence from criminal informants and creating an intelligence picture of serious- and organized crime in the region. The initial law enforcement goal of this
intelligence collection process is to obtain all (potential) members of organized crime networks, their connections, and their activities. Such members could involve inhabitants of the police region itself or members outside of these regional boundaries, but with involvement in the organized crime activities in the region. Intelligence collected by other criminal intelligence units about the activities of the well-known criminals was also included in this dataset. Such intelligence is collected from criminal informants, who are often part of the criminal networks themselves. Criminal informants speak to undercover special agents (i.e. handlers) on a regular basis. In every conversation they provide information about criminals and their criminal offences and activities related to organized crime. In return they are paid for every piece of information that leads to a conviction. Most often these stories are based on the informant’s own experiences or information he or she achieves from other members of the criminal network.

Each piece of information collected from criminal informants is classified into three categories: 1) directly observed 2) directly heard from an observer 3) Indirectly heard from an observer. Every piece of information collected over time is stored in a secured relational database together with the date of collection and its classification. In this way it can be assessed on reliability and potential risk for revealing the identity of the informant, when shared outside the criminal intelligence unit or in court. Additionally, every person is represented by a unique entity where each piece of information is linked to the registration in the relational database as well as the locations, vehicles and companies. Over time new information related to persons already presented in the database is linked to the same unique entities, in order to prevent duplications. By aggregating these record-person data to ‘person – person’ relationship data, patterns of criminal networking start to emerge. For this study all aggregated data collected over the 25 years is made available and processed into an anonymous identifier for each node and edge. The result is a 1-mode matrix with all criminal relations following the database.

The street-patrol dataset

This dataset is collected from reports of police officers patrolling the streets of the main region around which the criminal network under study gravitates. These reports represent the observations during general law enforcement patrol work, involving suspicious incidents, observations during patrol or arrests following a criminal offence. After every patrol, police officers fill in their reports in a police database. In most cases links between these reports and the individual’s address and license plate registration number are also created as unique linked entities in the database. Over time this has resulted in a very large source of criminals’ cooperation, as seen through the eyes of the patrolling law enforcement officers.
These pieces of information are very valuable for completing the bigger picture on criminal networks. A random police check and registration of two persons in a car, may for instance confirm a unique criminal relationship between two well-established criminal entrepreneurs that was not observed by criminal intelligence specialists before. Every day multiple patrol officers and local police contribute to this collective image of criminal cooperation.

In the specific police region central to this chapter, police officers were equipped with smartphones directly connected to police organized crime databases. This allowed them to receive a pop-up on their smartphone informing them on the specific intelligence questions related to a particular suspect stopped or checked during the patrol. This endorses police officers to verify and report more observations of ties and provide context to what they observed. These data were also transformed from a 2-mode matrix (person-registration) into a 1-mode matrix (person-person).

However, street-patrol data also has its limitations. Due to the ad hoc nature of police work, not every observed incident is reported in the system (Ratcliff, 2016). Consequently, reports may fluctuate strongly in the level of detail and the completeness of links and entities. Missing data is therefore an unavoidable feature of this source of data. Since this data is collected over longer periods of time by hundreds of police officers during their daily duties, it provides a good estimate of criminal cooperation on a macro-level. Reliability of criminal links could for instance be improved by taking into account the number of times persons are observed together. Although the data is used for meta-analysis, access to the original report was always possible in case the nature of an established criminal relationship needed to be verified.

Both sources provide a different observation of the criminal network and the individual criminal ties out of which it emerges. However, it is not always clear to patrolling law enforcement officers if a reported individual is involved in organized crime or not. Within intelligence data this is much more straightforward. The patrol data is therefore used in this study as complementary to the intelligence data. In other words, actors are only included in the final dataset when they were reported in the intelligence database. Edges on the other hand can be identified from both datasets resulting in a criminal network operating in a region of the Netherlands and containing 16,933 edges and 8,225 actors (See Table 6.1).

**Table 6.1: Overview of network-data**

<table>
<thead>
<tr>
<th></th>
<th>Number of actors</th>
<th>Number of edges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human intelligence</td>
<td>8.225</td>
<td>15.199</td>
</tr>
<tr>
<td>Street patrol data</td>
<td>1.559</td>
<td>1.734</td>
</tr>
<tr>
<td><strong>Total network</strong></td>
<td><strong>8.225</strong></td>
<td><strong>16.933</strong></td>
</tr>
</tbody>
</table>
Inference of criminal network

The network data utilized for this study is collected over a longer period of time (1991 – 2015). However, due to changes in the use of software and in data-protection policies the data is not collected in the same way across this time-period. Until 2009 actors were only linked as database-entities to a report (also known as ‘registration’), but not to each other. The database therefore only contained a 2-mode network data structure.

From the beginning of January 2010, intelligence analysts also started to create actor-to-actor ties in the database and verified every relationship based on the content of the intelligence collected. When the content specifically mentioned that two actors were involved in the same criminal operation, a link between the two persons was established. Due to this extra validity check we assume that the data after 2009 is more valid and reliable than until 2009. The final network representation therefore only includes those ties that are at least observed one time after 2009. However, in order to maintain a optimal historical perspective on these relationships in relation to the temporal dimension of tie-strength, the assessment of the duration and the number of observations is based on the data before 2010 as well.

The two person-person matrixes were then merged into one relational database by matching the unique actors on their anonymized codenames. The data was then uploaded in UCINET 6 and Gephi for further analysis. For further inference of the criminal network a giant-component analysis is performed in UCINET. Through this algorithm a total of 686 component are identified of which the giant component contains 5178 actors and 12434 edges (see Figure 6.2). This giant component forms the final network representation for the present study.

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43 An important shift in data processing took place in January 2010, when analysts were first appointed to the criminal intelligence unit. This resulted in a more structured data-processing procedure for which more variables, such as a classification of criminal markets, were added to the database.
6.5 METHODS

The method for analyzing this network consists of three steps. The first step consists of the analysis of the general structure of the network (i.e. topology). The second step consists of the analysis of the three dimensions of tie-strength separately. The properties of the overall structure of the network will provide the necessary input for placing the outcome of step two in a wider context. The third step involves the relationship between these three dimensions.

The detailed operationalization of the indicators representing these three dimensions is presented in Table 6.2. How these indicators are interpreted in terms of tie-strenght is described below.
Table 6.2: Indicators for tie-strength and operationalization in the data

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Operationalization in the data</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Structural dimension</strong></td>
<td></td>
</tr>
<tr>
<td>Edge-betweenness</td>
<td>Output calculation edge-betweenness in UCINET</td>
</tr>
<tr>
<td><strong>Temporal dimension</strong></td>
<td></td>
</tr>
<tr>
<td>Duration</td>
<td>Last observation – First observation (in months)</td>
</tr>
<tr>
<td>Intensity</td>
<td>Total number of observations in both datasets</td>
</tr>
<tr>
<td><strong>Demographical dimension</strong></td>
<td></td>
</tr>
<tr>
<td>Homophily</td>
<td>Actors have same Country of birth (Yes/No)</td>
</tr>
<tr>
<td></td>
<td>Actors have same Nationality (Yes/No)</td>
</tr>
<tr>
<td>Multiplexity</td>
<td>Actors are active in same value chain network (Yes/No)</td>
</tr>
<tr>
<td></td>
<td>Actors have a kinship relationship (Yes/No)</td>
</tr>
<tr>
<td></td>
<td>Actors are members of same outlaw motorcycle club (Yes/No)</td>
</tr>
</tbody>
</table>

The operationalization of the structural- and temporal dimension is already described in Section 6.2.2. The demographical dimension of tie-strength is however more complicated. The operationalization of homophily and multiplexity is limited by the variables already available in the data.

The operationalization of homophily is based on two variables: similarity in nationality and country of birth. The underlying assumption is that actors from the same country of birth and/or the same nationality are generally considered more like-minded than actors from different backgrounds and therefore more likely to develop strong ties..

Multiplexity is defined by means of three variables. Kinship is the most obvious and is based on the previous research findings and assumptions described in Section 6.2.2. A shared involvement in more than one and different criminal operation, may lead to a shared interest and therefore stronger ties than criminal ties between actors who operate on different criminal markets. Weak ties consist in this regard between criminals who only know each other through shared visits to nightclubs, restaurants and pubs.

Finally, membership to the same outlaw motorcycle gang (OMG) is added as a variable of multiplexity, because it is a phenomenon that enforces loyalty between different criminals, particularly with reference to the Dutch organized crime situation. The number of OMGs in the Netherlands has grown significantly since the 2012 and the content of the data suggests that an increasing number of powerful and less powerful criminals are joining as prospect members or start their own OMG in response. It is assumed that the willingness to join an OMG is related to a violent reputation, protection, and access to an international criminal network of ‘brothers’. Shared membership to an OMG is therefore an indicator for stronger ties.
The outcomes of the second step will be input for comparison between these dimensions in the third step. This analysis relies on the Quadratic Assignment procedure (QAP) correlation analysis, as introduced in the study of criminal networks by Campana and Varese (2013). This procedure provides a solution to auto-correlation following the non-independence of observations in networked data (Krackhardt, 1987, 1988). The output of a QAP procedure is comparable with regular Pearson correlation analyses, but it differs in the way the significance test for coefficients is performed. By following the procedure, a number of randomly rearranged matrixes of the original one are created through random permutation, which is a form of bootstrapping. For assessing statistical significance of the correlation coefficient, the observed coefficient of the observed matrix is compared against the coefficients of the randomly permuted matrixes (Campana, 2015). If the observed coefficient is greater than 95% of the random coefficients this is considered to be statistically significant.

6.6 RESULTS

The topology of the network

In order to understand tie-strength a general perspective of the network’s topological properties is essential. Table 6.3 reveals that the network with 8225 actors and 12424 edges an average path length of 5.9 steps is relatively small, while the average clustering coefficient of 0.577 is relatively high. This suggests that the network resembles a small world network (Watts and Strogatz, 1998). In addition, the longest distance between two actors in the network is 15 steps (diameter), which for such a large network is relatively low and also points to a small world features. This is relevant to the study of tie-strength, because small world networks consist of many alternative pathways for information to flow from one side of the network to the other, making the network less reliant on weak ties for connecting its remote parts.

Table 6.3: properties of the observed network

<table>
<thead>
<tr>
<th>Network properties</th>
<th>Observed network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Degree</td>
<td>4.82</td>
</tr>
<tr>
<td>Max degree</td>
<td>224</td>
</tr>
<tr>
<td>Clustering coefficient</td>
<td>0.38</td>
</tr>
<tr>
<td>Average clustering coefficient</td>
<td>0.58</td>
</tr>
<tr>
<td>Density</td>
<td>0.001</td>
</tr>
<tr>
<td>Average path length</td>
<td>5.9</td>
</tr>
<tr>
<td>Diameter</td>
<td>15</td>
</tr>
</tbody>
</table>
At the same time, the low density score for this network suggests that there are a relatively high number of actors who score relatively high on degree centrality (see degree-distribution in Figure 6.3a). If the majority of actors is connected by just one connection to the rest of the network, the overall connectivity goes down. This means that some parts of the network outside of the dense core may be loosely connected (see Figure 6.1). Subsequently this means that the network could still rely on weak ties for connecting the periphery with its core.

![Figure 6.3: a) Degree distribution b) Log-log fits of the degree-distribution for Powerlaw, Truncated Powerlaw and Lognormal](image)

The degree distribution and the maximum degree of the network also point to the presence of hubs in the network (i.e. nodes with greatly higher than average degree) also visualized by the larger sized nodes in Figure 6.1. The presence of hubs suggests that the network’s topology has scale-free properties (Barabási et al., 1999). For scale-free networks the degree-distribution follows a power-law. Performing the Kolmogorov-Smirnov test using a Python package as described by Alstott, Bullmore and Plenz (2014), we compared the degree-distribution with different fits, including Powerlaw, Truncated Powerlaw and Lognormal distributions visualized in Figure 6.3b. We found that our degree-distribution differs from Powerlaw in the tail. By comparing these fits through a log likelihood ratio test the truncated Powerlaw best fits our degree distribution, although the differences with the other fits do not seem to be significant. A truncated powerlaw is common for degree distributions limited in resources and time, resulting in a lower number of nodes for the higher scores on degree centrality. In the context of criminal networks this makes sense, since the necessary trust for criminal cooperation described above is built over longer periods of time and cost investments in resources.

Although the network is not a purely scale-free network, the degree distribution reveals that it certainly has some scale-free properties. The presence of hubs in scale-free networks causes clustering into relatively separated communities. By performing modularity analysis as described in Blondel et al. (2008), we identified 13 communities in the network visual-
ized in Figure 6.4. The nodes in this visualization are sized according to their scores on degree-centrality and reveal that the network does not solely relies on the hubs for the flow of information between the different communities, because the direct periphery of the hubs provide many alternative pathways for information to flow in-between. Still, the visualization shows that connectivity is higher within communities than between communities, which does not diminish the importance of weak ties for the flow of information throughout the network completely.

Figure 6.4: Visualization of sub-communities identified in the network through modularity analysis. The size of the nodes represents degree centrality. The largest sized nodes represent the hubs in the network.

Modularity rate 0.765 with a resolution 3,0
**Structural dimension**

As explained above, weak ties are considered to be positioned in-between the different subcommunities within the network. We introduced three measures for identifying bridge positions: edge-betweenness, dyadic constraint and dyadic redundancy. This Section describes what these three measures say about the positioning of strong and weak ties in the network.

Figure 6.5 shows the distribution of score on edge-betweenness and suggests that just the a few ties score very high on potential ‘bridge’ positioning, while the majority of ties scores very low. Assessment of the top-20 scores on edge-betweenness further shows that they are positioned in-between different sub-communities based on modularity visualized in Figure 6.4. This suggests that the network relies on just a few weak ties for transferring non-redundant information between the different parts of the network. However, besides these high edge-betweenness ties, there are still many alternatives for connecting the different communities. What does this say about tie-strength? To answer this question, we need to evaluate the background information.

![Figure 6.5: distribution and top-10 of edge-betweenness scores](image)

An important aspect revealed by the background information is that the majority of ties with a edge-betweenness is strictly instrumental in nature, which can roughly be divided into three types. The first type refers to criminal ties that consist of a shared investment in a large shipment of illegal drugs. It is not uncommon within the transnational drugs market that multiple influential criminals from different criminal groups invest in a multi-ton shipment that is organized by a third-party criminal group. For most of these investors
the costs for security or risk of detection are low and the benefits are high. Guarantees 
that investments are returned to the investor are under these circumstances however never 
given. A powerful or violent reputation therefore often provides sufficient insurance for 
a return of investment in case the drugs get stolen, or seized by customs. Reputation is 
sometimes more important than trust within these deals. In one of these cases even rival 
criminals invested in the same shipment. In these settings criminal ties are therefore not 
necessarily strong and could just last during the time of investment in just one operation.

A second type of ‘weak ties’ identified through edge-betweenness involves the settlement 
of disputes. In several cases (e.g. N4418, N3641) the weak tie is related to one member of 
a criminal group accusing another of stealing his illegal merchandise, behaving disrespect - 
ful against one of his co-offenders, or leaking secret information. In some of these cases 
a representative of a third party criminal group is introduced as a mediator or enforcer.

A third type is more related to the specific role of one of the actors on both sides of the 
tie. The content of the intelligence data (i.e. N9253 and N9) suggests that weak ties are 
also related to the phenomenon of ‘information-broker’. This involves actors who actively 
obtain, sell and spread information to other criminals in the network. Their active informa-
tion brokerage role also explains the high scores on betweenness centrality, which suggests 
they provide many parts of the network with non-redundant information.

A fourth type is best defined as a symbiotic relationship. It involves the occasional co-
operation between friends, who are loyal to separate criminal groups in the network. For 
specific purposes they utilize each other’s ego-network if the occasion arises. For instance, 
one of these ties (N3068) involves a symbiotic relationship between a leader of a youth 
gang and a respected member of an outlaw motorcycle club. Through this tie two remote 
parts of the network become connected. The information suggests that the youth gang 
provides ‘rip deal’ services to the outlaw motorcycle gang in return for protection.45

At the other end of the spectrum low scores on edge-betweenness are associated with 
weak ties,. At the low end of the edge-betweenness distribution a total 497 ties have 
a lowest edge-betweenness score of 1. According to network theory these ties should 
represent the ‘strong ties’ in the network. Qualitative evaluation of the information con-
cerning these ties provides some evidence for this proposition, since 25% of these ties also 
involve a kinship relationship. Some dense clusters of these kinship ties show high levels 
of redundancy. These clusters consist of triangle relationships involving several infamous 
criminal families that populate the network. These families are known for high intensity

45 A rip deal is the robbery or theft of the stash of illegal drugs from another group.
co-offending on different criminal markets at the same time. Compared to other clusters in the overall network these clusters are strongly internally focused, with often one or two of the older brothers operating as the gatekeeper to the rest of the network. The younger brothers rely on the older brothers until they are old enough to achieve themselves a position within the overall criminal network. This provides an explanation why these ties are found amongst the lowest categories within the edge-betweenness distribution.

Following these findings, the scores on edge-betweenness appears to be an effective predictor for the identification of weak and strong ties. This is particularly relevant for law intelligence services and law enforcement agencies tasked with monitoring these networks over time. The weak ties provide a good indication for macro-cooperation between the remote parts of the network and for detecting on-going criminal disputes. The lower scores on the opposite end of the scale provide an indication for the presence of strong ties and potential clustering into groups. What lies in-between these two ends remain however open for speculation. In the next Section describes how the temporal dimension of tie-strength contributes to a further differentiation of tie-strength along the ties in the network.

**Temporal dimension**

The temporal dimension of tie-strength is measured through the duration and the number of observations. Figure 6.6 visualizes the relationship between number of observations and duration of all ties in the network. The duration is expressed in months and the intensity by the number of observations in-between the first and last observation in both intelligence and street patrol data.

To guide the analyses of this data six intelligence analysts who work within the criminal intelligence field within different police regions of the Netherlands were interviewed. They are tasked with analyzing similar intelligence data on a daily basis. They were asked how they would classify a strong or weak tie according to duration and number of observations. This led to a general agreement, that criminal ties could be defined as strong if they were observed 10 or more times and spanning at least 24 months based on their professional judgement. We utilize these thresholds and classify ties according to duration and number of observations into four distinctive categories (see Table 6.4). This categorization helps to interpretate the association between duration and number of observations with the other dichotomous indicators for multiplexity (kinship, same value chain, and same OMG) and homophily (same country of birth, same nationality) in the next step of the analysis.
Chapter 6: Fluid connections within an old boys’ network?

Figure 6.6: Scatterplot of the relation between number of observations and duration (in months) for all criminal ties in the network

Table 6.4: Typology of ties based on duration and number of observations

<table>
<thead>
<tr>
<th>Category</th>
<th>1-24 months</th>
<th>&gt;24 months</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-10 observations</td>
<td>8.913 (72%)</td>
<td>1.727 (14%)</td>
<td>10.640 (86%)</td>
</tr>
<tr>
<td>Fluid</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latent</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;10 observations</td>
<td>745 (6%)</td>
<td>1.049 (8%)</td>
<td>1.794 (14%)</td>
</tr>
<tr>
<td>Manifest</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Durable</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>9.658 (78%)</td>
<td>2.776 (22%)</td>
<td>12.434 (100%)</td>
</tr>
</tbody>
</table>

Table 6.4 shows that most ties in the network can be identified as fluid (72 %) as compared to 8% of the durable ties (See figure 6.6). This shows that the observed structure of the network as described in Section 6.1 is much more temporary as suggested by the analysis of the structural dimension alone. In-between these the fluid and durable ties, there are manifest (6%) and latent ties (14%).

The manifest ties represent short-term bursts of intensified co-operation between sets of criminals in the network, which may point towards the initiation of serious criminal
endeavors (e.g. setting up of a drugs trafficking route) or responses to imminent threats or situation that require intensified co-operation within a short period of time to cope with the consequences (e.g. in case of arrests or loss of criminal merchandize). These ties therefore represent short-term strong relationships.

Finally, there are latent ties that are characterized by varying periods of activity and inactivity (14%). Within organized crime this could refer to criminal ties that are only activated for specific purposes on particular occasions (e.g. exchange of specific skills or knowledge) or interactions between offenders following the settlement of conflicts within the network as described in paragraph 3.1. In terms of tie-strength this type could therefore be described as long-term weak ties. The next Section provides a deeper background description of these four types of ties for a deeper empirical understanding of these four types of ties.

**Fluid ties**

Fluid ties constitute many forms of short-term co-offending, which is best described as *freelance cooperation*. Criminal cooperation in this regard appear to provide a service to each other during one or two operations after which he moves on to the next ‘client’ or ‘co-creator’, similar to the legal freelance economy. The background information suggests that this ‘freelance’ phenomenon is more common for particular types of criminal activities then others, such as organized property crime. Within the overall network, ‘freelancing’ seems more common within subnetworks of offenders specialized in robberies, kidnappings and stealing drugs from violent criminals (i.e. ripdeals). Since this is a rather opportunistic type of criminal activity, co-offending also emerges when the occasion arises. Background information suggests that reputation is an an important factor for offenders to have a freedom of choice in picking co-offenders. Other offenders are more willing to join the criminal endeavours of high repected co-offenders. Changing the composition of co-offenders makes these particular subnetworks ‘lighter on their feet’ and may be part of a deliberate strategy to stay ahead of the police.

Another factor that influences the fluidity of these ties is related to gender. Although females represent a minority in the network (N=525, 10%), several fulfill central positions within the criminal meso-network (see Figure 6.7). The background information suggests that a few of them fulfill roles of ‘information-brokers’ within the criminal network (similar as described above). Their charm and appearance makes them welcome guests at exclusive VIP-rooms in nightclubs. These nightclubs also serve as popular networking places for respected criminals in the criminal network. Several intimate relationships that initiated in these settings, provided some of these females with unique access to important flows of

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46 Due to missing data on actor gender, this figure represents an estimation.
criminal information. This provides them with the opportunity to operate and exchange information in between different groups throughout the network. Whether this happens through natural dynamics on the network or as part of a deliberate strategy remains beyond the scope of this study.

A third significant category of fluid ties is associated with membership to outlaw motorcycle gangs (OMGs). A dispute and between different OMGs for power in 2012 prompted an expansion of OMG membership. New members where mainly recruited from organized crime networks. In this way OMGs wanted to establish protection and control within illegal markets. These new members managed their own drugs trafficking operations based on their own trusted accomplices outside of the OMG, but on the other hand they were becoming more and more restricted by the interests of the OMG. This resulted in internal disputes and many shifts of membership from one OMG to another. This multiplexity in combination with conflicting interests influenced many shifts within the general connectivity of the overall criminal network and the fluidity observed in the overall network.

Overall, the background information suggests that fluid ties exist as a result of a deliberate business model, which is characterized by many short-term coalitions instead of long-term criminal relationships. This business model is particularly observed in criminal markets in which success relies on improvisation and opportunistic behaviour. At the same time the background information also points to a more natural explanation for the fluidity observed in these ties. The fast changing circumstances and uncertainties that are associated with operating in an unregulated and unstable environment may just naturally select offenders that are able to flexibly cope with these conditions. From this perspective in fluid cooperation. Although potential co-offenders are preferably found within pools of like-minded accomplices, criminal cooperation remains incidental in nature. In accordance with previous studies of co-offending, these findings suggest that the majority of criminal co-operations emerge and terminate opportunisticly when the opportunity arises or ends.
**Manifest ties**

Manifest ties represent short intense cooperation between co-offenders during the course of one or two criminal endeavors. Analysis of the background information concerning the manifest ties suggests that they consist of very intense co-offending relationships between small collectives within the criminal network (2-3 actors). Visualization of the manifest ties (Figure 6.8) reveals the presence of many small co-offending networks and five larger clusters. The two biggest clusters are described next.

The largest cluster (purple, Figure 6.8) of manifest ties involves a multi-ethnic criminal group that is involved in running a heroin trafficking operation from Turkey to the Netherlands, from where it is further distributes to other EU countries. The operation gravitates around a heroin importer from Turkish nationality, who co-operates with a group of criminals from Dutch-Moroccan nationality specialized in the logistics of distribution of illegal drugs.

The actors (N=15) in this network all live in a particular neighborhood in a middle-size city in the Netherlands, where they own Turkish coffeehouses and shisha lounges located at a short distance from each other. The background information suggests that these social meeting places played an important role in the emergence of this coalition. The criminal operation ended after the distribution level operatives became arrested for drugs trafficking and as a result were sentenced to prison.

A second big cluster (dark yellow, Figure 6.8) involves a group of native Dutch criminals from a small city in the Netherlands who initiated a synthetic drugs production operation that lasted for at least a year. The synthetic drugs laboratories were set up in rural areas in farmhouses. This cluster worked intensively together with a clear division of tasks that were divided according to special skills, such as finding production location, setting up the hardware (i.e. equipement), or the actual preparation of the drugs.

**Figure 6.8:** visualization of the manifest ties identified in the overall network
These specialties were brought together through family and friendship connections. The co-operation fell apart after the arrest of the main chemists and driving forces behind the operation became arrested and after the unfortunate death of one of the members while working in one of the labs. A year after this coalition fell apart, a new coalition of a different composition emerged. The core of this former coalition remained the same, but some arrested actors were replaced by other member of the meso-network to initiate a new synthetic drugs operation.

These two examples represent the majority of manifest criminal cooperation observed in the data. Criminal cooperation that emerges within short periods of time between criminals from different backgrounds appears to be very unstable in nature and may therefore easily fall apart due to changes in its composition (e.g. arrest). This emphasizes once more that durable criminal cooperation demands a long lasting social investment resulting in enough trust amongst the individuals to withstand internal changes or external pressures.

**Latent ties**

The background information concerning the latent ties reveals that the majority consists of ties that are best described as external ‘old boys relationships’ that exist between local criminals and criminals who operate nationally.

As described above, the initial data-collection is restricted to activities that are related to a specific police region in the Netherlands. This regions gravitates around a large city, three small to middle-large cities, and a dozen of smaller towns in-between. This results in two types of actors: Those who originate from this same police region and those who originate from cities or countries outside of the police region, but operate within the regions boundaries. The later consists mainly of members of Dutch organized crime networks also known as the ‘Hollandse Netwerken’, who are infamous for managing criminal operations at a national- and transnational level. The background information suggests that most of the latent ties represent connection between these two types.

Within the overall meso-network these ties fulfill an important gatekeeper-function in connecting the regional criminal network and the transnational criminal macro-network as described in Section 6.3.. In this way regional activities become part on international criminal markets. Since the actors on both sides of these latent ties primarily rely on their own operations, the co-operation is selective in nature, with long period of inactivity followed by short exchanges of services, information or goods.. Subsequently, the background information suggests that most of these latent ties have a long history, often dating back to times spent together in prison. Latent ties can therefore be seen as long-term weak
ties, important for connecting the inner-core of the network with the outside criminal macro-network.

**Durable ties**

The durable ties represent the strongest relationships in the network, which are often retraceble to schools, local neighborhoods, or criminal youth groups. The following examples represent the overall nature of these strong ties found in the network.

The strongest tie in the network (based on temporal dimension) consists between two good friends from North-African origin who were close friends since they were very young and played in the same sports team. Since that time, they were also known to the police for being part of an infamous criminal youth group, mainly involved in burglaries and robberies. At the point where they shifted from stealing flat screen TV’s, to stealing stashes of cocaine or robbing illegal cannabis plantations from well-established drug lords, they became known to the criminal intelligence unit as well. This shift provided them with the money, status and reputation to boost their career in organized crime (e.g. extortion, drugs trafficking) and made them part of the most notorious criminals in the region. Tie N331 and Tie N10644 follow similar patterns, where N311 is even based on criminal ties between two brothers who, together with three other brothers, form an infamous criminal family who also worked their way up from a youth group to a respected criminal group in transnational cocaine and hashish trafficking.

Sometimes being part of the same local neighborhood community can enable trustworthy and durable criminal cooperation (Von Lampe and Ole Johansson 2016). For example, tie N3239 was observed more than 1000 times in almost 4 years and emerged between two native Dutch friends within a very internally focused neighborhood community. This neighborhood was constructed out of the inhabitants of a camp facility for arrested sympathizers of the Nazis at the end of World War II. The camp facility was later transformed into a neighborhood, in which most of the former camp inhabitants were provided housing and a fresh start. In this community, local self-rule, solidarity, and hostility towards the government fostered criminal behavior. Within this community these two actors grew up together and in the end became powerful co-offenders in the transnational illegal cannabis trade.

Tie N11373 has the longest duration that lasts for 10 years. It involves a criminal relationship that emerged out of a minority community of travellers. This community is known for their strong loyalty to family members and a general anti-establishment attitude. It is also a community with many connections across the world, providing the organized crime members amongst them with a very trustworthy international network to facilitate their organized crime activities. Most often these benefits provided them with important key-
player roles within the international illicit drugs trade. The trust and loyalty that is found within these communities may therefore often last for many years and form important backbones for the initiation of criminal activities within the criminal network.

These examples demonstrate how a social bond developed within the early stages of life could result in durable criminal co-operation later within the criminal career, forming ‘old boys’ networks’. Figure 6.9 visualizes the largest component within the identified population of durable ties and shows clustering into seven core sub-groups. Each of these subgroups gravitates around their own strong social foundation, represented by criminal youth groups, football hooligan groups, traveller communities, and local neighborhoods. The data suggests that as their criminal activities expand over longer periods of time within these local settings of redundant strong ties, non-redundant connections emerge with other strongly connected groups operating in the same time and space. This results in a core-network of subgroups consisting of durable strong ties, which remains relatively robust regardless of the fluctuating storm of fluidity within the criminal meso-network in which it is embedded.

**Demographical dimension**

Homophily and multiplexity are predictors of tie-strength, which relies on the assumption that like-minded individuals are more likely to co-offend. For analyzing to what extent homophily and multiplexity are associated with tie-strength, we assume that the more characteristics two actors have in common the stronger they are connected. We therefore create a cumulated score on the multiplexity and homophily attributes to allow for ranking all ties in the network based on the demographic dimension of tie-strength (see table 6.5).

---

47 Modularity: 0.816 with resolution: 2.71
Table 6.5 shows that a minority of ties (1%) has 4 or more attributes in common. Evaluation of the background information on these ties shows that 104 of the 127 (82%) represent kinship ties, which suggests it is a strong indicator for tie-strength.

Table 6.5: ranking of ties based on demographical dimension

<table>
<thead>
<tr>
<th># Indicators</th>
<th># Ties</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>1</td>
<td>0.008%</td>
</tr>
<tr>
<td>4</td>
<td>126</td>
<td>1.0%</td>
</tr>
<tr>
<td>3</td>
<td>1796</td>
<td>14.4%</td>
</tr>
<tr>
<td>2</td>
<td>4103</td>
<td>33.0%</td>
</tr>
<tr>
<td>1</td>
<td>1626</td>
<td>13.1%</td>
</tr>
<tr>
<td>0</td>
<td>4781</td>
<td>38.5%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>12434</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

We test the homophily-hypotheses by looking into clustering through common background within the overall network. As described above we focus on a criminal meso-network, which is bounded by a specific geographical region in the Netherlands. This resembles local pools of potential co-offenders out of which continuously new criminal coalitions are formed. The multiple ethnicities and cultures represented in the data, show that the network is very diverse in nature.

Figure 6.10 shows a projection the most common ‘countries of birth’ (99%) in the meso-network.48 It shows that from a meso-perspective, actors from similar background are positioned at a shorter distance than actors from different backgrounds. This suggests a level of clustering based on ethnicity and a preference for criminal groups to co-operate with other criminal groups from the same ethnic background on a meso-level.

In support of this hypotheses we find a significant correlation between modularity-classes representing sub communities in the network (Section 6.3) and ‘country of birth’ (Pearson r = 0.152, sig. 0.01). This suggests that actors from the same background are indeed more likely to cluster together within the meso-network.

Mixed-culture groups observed at a micro-level (e.g. Kleemans and Van de Bunt, 1999) can however not be excluded on the basis of this visualization on meso-level. Figure 6.11 illustrates a mixed network involved in cocaine trafficking from Colombia via the Dominical Republic to the Netherlands. It shows how criminals form similar and different backgrounds

48 The other 1% consists of 52 other ‘countries of birth’
come together to form networks that constitute various levels of intensity and duration of ties. It also symbolizes the complex interplay of durable, latent, manifest, fluid ties that occurs at a micro-level. The core exists of durable relationships between actors from common background (i.e. Moroccan), while the periphery of this network consists of fluid, latent and manifest connections between actors from different backgrounds. In the next Section we will elaborate further on this complex interaction by analyzing how the different dimensions for tie-strength are associated with each other.

Figure 6.10: Projection of ‘countries of birth’ for 99% of the actors in the network (N=5178).
Comparing the three dimensions of tie-strength

To assess how these four tie categories are associated with properties of multiplexity and homophily we use again the QAP correlation procedure as described by Hanneman and Riddle (2005).

Table 6.6 shows the QAP correlations between the four tie-categories and the indicators for homophily and multiplexity. Although the associations are not that strong, the QAP procedure reveals that all five properties are significantly correlated with all four categories. Kinship is expectedly correlated with durable ties. Somewhat contradictory to the strong ties theory is however the relatively strong associations between the weaker fluid ties and homophily as compared to the stronger durable ties. It suggests that fluid ties are most likely to emerge between similar actors then between actors from different backgrounds (i.e. same nationality and country of birth). How can this be explained?
Table 6.6: QAP correlation coefficients for comparison of temporal and the demographical dimension

<table>
<thead>
<tr>
<th>Multiplexity</th>
<th>Fluid</th>
<th>Manifest</th>
<th>Latent</th>
<th>Durable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kinship</td>
<td>.21**</td>
<td>.04**</td>
<td>.15**</td>
<td>.22**</td>
</tr>
<tr>
<td>Same Value Chain Network</td>
<td>.25**</td>
<td>.07**</td>
<td>.12**</td>
<td>.15**</td>
</tr>
<tr>
<td>Same Outlaw Motorcycle Gang</td>
<td>.12**</td>
<td>.05**</td>
<td>.04**</td>
<td>.08**</td>
</tr>
<tr>
<td>Homophily</td>
<td>.56**</td>
<td>.12**</td>
<td>.25**</td>
<td>.26**</td>
</tr>
<tr>
<td>Same Country of birth</td>
<td>.67**</td>
<td>.14**</td>
<td>.25**</td>
<td>.26**</td>
</tr>
</tbody>
</table>

Note ** significance at p ≤ 0,01

One explanation lies in the nature of the present criminal network. Within these regional settings options for finding non-redundant contacts are less available than within the transnational environment. The abundance of alternatives may therefore naturally lead to choosing accomplices from similar backgrounds, even when co-operation is fluid and temporary. Evidence for such ethical clustering at a meso-level is provided in the previous paragraph.

A second explanation lies in the nature of the indicators for homophily, which results in a potential underrepresentation of cultural and ethnic differences. Since it is not allowed in Dutch Law to register personal data on the basis of ethnicity, the only indicators available for a common cultural background is nationality and country of birth. This indicator shows that the majority of actors are born in the Netherlands (69%), but it does not reveal if their parents were born in other countries. This is especially relevant for the young generation of actors from Moroccan, Suriname, Turkish and Dutch Antilles origin, of which the majority is born in the Netherlands and also holds the Dutch Nationality. Similar bias influences homophily based on nationality. Hence, 22.3% of the actors in the dataset with a Dutch nationality originates from different countries. Similar nationality does therefore not exactly mean similar cultural background or ethnicity. This may result in underrepresentations in the data.

Another content related factor is concerns the phenomenon of ‘criminal mentorship’ as previously described by Morselli (2006). Several fluid ties represent the relationship between well-established criminal fathers or older brothers who fulfil a mentor role in relation to their ‘sons and siblings’. While the former has often already built a career in organized crime, the latter is still involved in street crime activities (e.g. robberies, burglaries). Background information suggests that as the sons and siblings gain experience and become older over time, they are naturally introduced to the serious crime activities of their mentors. By occasionally fulfilling small tasks they learn and improve their knowledge,
status and reputation through the process of differential association (Sutherland, 1947). In the early stages of this process the ties labelled as fluid, but they are essentially starting durables.

Table 6.7 shows the average difference in age between the actors on both sides of the observed ties in the network for each of the four tie categories described above... It shows that there is a significantly greater difference in age between actors connected by fluid ties than for the other tie-categories. The difference for fluid ties is 10.4 years, while for durable ties this is 7.5 years. Additionally, there is a stronger association between age-difference and the presence of kinship ties. On average kinship ties have an age difference of 12.3 as opposed to 9.6 years for non-kinship ties. This supports the notion that older actors (e.g. fathers and older brothers) are more commonly cooperating with younger actors (e.g. sons and siblings) when there is a kinship relationship that must be labeled as 'starting durables'.

Table 6.7: QAP correlation results for age-difference, kinship and tie-categories.

<table>
<thead>
<tr>
<th>Age-difference between two ends of a tie (actors)</th>
<th>Average number of years</th>
<th>Pearson r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Durable</td>
<td>7.5</td>
<td>.15**</td>
</tr>
<tr>
<td>Latent</td>
<td>8.9</td>
<td>.23**</td>
</tr>
<tr>
<td>Manifest</td>
<td>9.2</td>
<td>.33**</td>
</tr>
<tr>
<td>Fluid</td>
<td>10.4</td>
<td>.64**</td>
</tr>
<tr>
<td>Kinship</td>
<td>12.3</td>
<td>.33**</td>
</tr>
<tr>
<td>Non-Kinship</td>
<td>9.6</td>
<td>.33**</td>
</tr>
</tbody>
</table>

**Note = significance at p ≤ 0,01

The results of these QAP correlation analysis suggest that the temporal dimension is associated with demographical dimension. The next Section includes the third dimension of structural positioning into the comparative analysis. Figure 6.12a shows a 3D-scatterplot of the relationship between duration, the number of observations, and edge-betweenness with the four categories highlighted. It reveals that the fluid and latent ties mainly represent the high scores on edge-betweenness. This is also supported by Figure 6.12b, which shows that latent and fluid ties are more widely distributed across the overall network, and are therefore more likely to connect the different parts of the network as compared to the two other (and stronger) tie-categories.

Table 6.8 shows the association between the structural dimension with the temporal and the demographical dimension. It shows that all categories are associated with edge-betweenness, but the correlations are small. In accordance with the findings presented
above, the strongest correlation with edge-betweenees is found for fluid ties. It supports
the notion that weak ties identified through structural positioning in-between different
parts of the network (high score on edge-betweenness) are of a temporary and incidental
nature.

Figure 6.12a: Representation of the relation between tie-attributes and structural positioning based on edge-betweenness.
Table 6.8: QAP correlations for association structural with temporal and demographical dimension

<table>
<thead>
<tr>
<th>Edge-betweenness</th>
<th>Manifest</th>
<th>Durable</th>
<th>Latent</th>
<th>Fluid</th>
<th>Same Nationality</th>
<th>Same Country of birth</th>
<th>Kinship</th>
<th>Same OMG</th>
<th>Same value chain network</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.08**</td>
<td>0.13**</td>
<td>0.18**</td>
<td>0.35**</td>
<td>0.38**</td>
<td>−0.02**</td>
<td>−0.08**</td>
<td>0.04**</td>
<td>0.06**</td>
</tr>
</tbody>
</table>

Note ** significance at p ≤ 0.01

Table 6.5 also suggests that structurally positioned weak ties are not strongly associated with attributes of homophily and multiplexity. ‘Kinship’ and ‘same country of birth’ are even negatively correlated with edge-betweenness, but with little strength. Tie between actors of the ‘same Nationality’ are also associated with high scores on edge-betweenness. This is not inexplicable. Within regional settings, weak ties in organized crime do not only bridge the structural holes between networks operating in different countries but also between networks operating in different cities within the same country. It can therefore not be excluded that ties between criminal entrepreneurs of the same nationality fulfill important bridge positions between two or more criminal meso-networks in the same country.

Overall, these findings show that there is a less strong association between the demographical and structural dimension than between the temporal and structural dimensions of tie-strength.

6.7 DISCUSSION

Criminal networks can be defined -in essence- as sets of nodes and the ties between these nodes. Instead of focusing on the nodes, we focus on the properties of ties and their association with the structure and evolution of a large criminal meso-network, which accounts for a significant part of the organized crime activities within and outside of the Netherlands. In the present study we are particularly interested in to what extent the three dimensions of tie-strength (structural, temporal, and demographical) are related. We also study how these insights are associated with the emergent structures and evolution of criminal networks as a whole, through the qualitative assessment of available background
information. Before we elaborate on our main findings, we will emphasize the limitations of the present study.

**Limitations**

As in every study of criminal networks our data and methods are not without limitations. To limit the bias as a result of missing data, however, we combined different independent sources of law enforcement data (i.e. patrol data and human intelligence data) to infer the criminal meso-network unraveled in this chapter (See chapter 2 and 3).

An important part of this study relies on data collected through human intelligence (HUMINT). The way these data are collected provides some advantages in terms of data validity. First it is collected with almost the same purpose as our present study, namely obtaining a criminal network picture as valid and reliable as possible. HUMINT is collected with a much wider scope and aimed at uncovering what is unknown, as compared to data from criminal investigations aimed at collecting as much evidence as possible about a limited number of actors that are already known. Secondly, it is possible to direct the intelligence collection process towards these *intelligence gaps*, by recruiting new informants or asking them specific questions. Some requests for the collection about intelligence gaps were discussed with the responsible intelligence analysts. This contributed to directing the data-collection and processing in line with the aim of this study. Thirdly, HUMINT is collected over a longer period of time, making it possible to compare data over time and identify inconsistencies.

Unfortunately these same benefits could not be utilized for the collection of the patrol data. These data are more influenced by the nature of day-to-day police work. Observations therefore happen more by chance, which limits the reliability of the data-collection process. However, by combining this with HUMINT data, it is possible assess its validity and reliability. The combination of these data-sources therefore compensates to a certain extent for the unique limitations that are part of each of these two data-sets.

Nevertheless, it cannot be excluded that data misses from our final network representation. Rosatami and Mondami (2015) found different outcomes of surveillance data, co-offending data, HUMINT-data on the binary network representation and the ranking of nodes based on centrality. They recommend to rely more on co-offending data above the other types, since these are collected more ‘objectively’. However, the question what causes these different outcomes remains unanswered. A more qualitative comparison of the background of the data collection process and content of the quantitative outcomes is therefore needed (Duijn and Klerks, 2014). This may reveal that many influential actors operate in the background of criminal networks and are therefore less observed by patrolling officers than by criminal informants. Within co-offending networks such important
actors may remain undetected and do therefore not appear in arrest records on which co-offending data is based. Future research could therefore aim at evaluating such explanations for the differences found between criminal network representations based on different law enforcement data.

Another limitation of the present study is related to the boundary specification problem. The mandate of the intelligence unit responsible for our data-collection process is limited to a particular police region in the Netherlands. This limits the data-collection process to connections that consist mainly within these regional settings. Extensive historical data about extranal network members, such as actors originally operating from overseas countries (e.g. Colombia, Suriname), was most often not available. Nevertheless, for the purpose of the present study we expect that this does not affect the outcome of our analysis to a large extent, because our aim is on the networks at the meso- instead of the macro-level.

Another limitation is related to selection bias. The primary aim of the data-collection process is criminal ties within the criminal underworld. As a result between actors from organized crime and the mala fide upper world, consisting of facilitators of organized crime from legal professions such as lawyers, notaries and real-estate brokers. Previous research shows that such actors are particularly relevant for the evolution of criminal networks (Kleemans and De Poot, 2008). An extension of the present study with data from financial crime units is needed to provide insight into the weak and strong ties that exists between these two dimensions in organized crime.

Conclusions

There are a number of conclusions to be drawn from our results. First, the emergence and evolution of criminal meso-networks depends on the structural positioning, of ties the duration and intensity of ties, and the level of multiplexity and homophily represented by ties.

Analysis of the structural dimension reveals that weak ties enable flows of information to its more redundant and remote parts, but not exclusively as expected on the basis of the ‘strength of weak ties’ argument (Granovetter, 1973). There are many alternative connections between communities as a result of a small-world phenomenon. The strength of these weak ties is also not particularly derived from their structural positioning, but more from their regulatory nature related to the settlement of disputes and directing the most important flows of money into transnational criminal markets. Mediators, information-brokers and intermediary drugs-traffickers enable the emergence and evolution of these weak ties. Instead of relying on mutual trust, these ties are characterized by the absence
of trust. Mutual trust in these settings is often replaced by trust in common third party intermediary (Coleman, 1990, Von Lampe and Ole Johansson, 2004).

Analysis of the temporal dimension reveals that weak ties are often instrumental, fluid and temporary in nature. The majority of weak ties end once the purpose of its emergence is achieved (e.g. settlement of conflict). For the criminal meso-network we link this to a freelance-phenomenon, which is particularly visible amongst the younger-generation actors and within specific crime markets (e.g. specialization in violent raids on the stashes of other drugs criminals). New coalitions constantly emerge and end within the same pools of potential co-offenders, who on a meso-level are most likely to share a common cultural background or nationality (Bruinsma and Bernasco, 2004; Malm et al., 2011).

This contrasts with the perspective on weak ties as the long-term building blocks for increased mutual co-operation between different sub-communities, (e.g. Kleemans and De Poot, 2008). A reclassification of ties presented in this chapter, however, exposes a category of latent weak ties that can be characterized by various periods of activity and inactivity over a longer period of time. This concerns mainly symbiotic connections between (trans-) nationally operating criminals and regional level local heroes as also previously found in studies of Dutch organized crime networks by Kleemans et al., (2002), Kleemans and De Poot (2006), Klerks (2000), and Spapens (2006). The profile of the actors on both ends of these ties suggest, that ‘bridges’ and ‘criminal brokers’ (Burt, 1992) are rare but are not completely non-existent.

Analysis of the demographical dimension reveals that the phenomena of homophily and multiplexity are associated with the clustering found in pools of potential co-offenders at a meso-level. Within the unstable environment of mainly fluid criminal co-operation this may provide a minimum foundation of trust when time and resources to invest in social relations are not available. Such ethnic clustering in networks may also be explained by factors of social geography, such as policies to place migrants from the same ethnic background in the same neighborhoods. Co-operation is then not enabled by ethnic background per se, but more by growing up in a close proximity (Kleemans and Van de Bunt, 1999). Some examples presented in this chapter show that mixed ethnicity groups cannot be excluded based on these results.

Finally, by comparing these dimensions we saw that within the fluid criminal environment strong ties, grounded in durable old boys' networks and connected family groups, provide a secure foundation to fall back on in times of conflict, uncertainty or shortage of resources. The strong ties in the network provide its core foundation and correlate with multiplexity following kinship ties, as previously found by Campana and Varese (2011)
and Malm et al. (2010). The intergenerational transmission of criminal behavior also plays a significant role within these settings, as previously observed by Farrington et al. (2001; 2009) and Van de Rakt et al. (2008). Background information further reveals that some ties are related to ‘mentorship’ within criminal families. Protégés are slowly introduced into the organized crime arena by their older siblings or fathers until they are able to manage external ties themselves (Morselli et al., 2006).

Overall our results emphasize that organized crime remains an amorphous phenomenon in which the majority of ties are considered fluid (around 70%) regardless of the structural positioning of ties. Fluidity of ties exists in-between communities (weak ties) and also within more remote parts. This fluidity points at high levels of self-organization typical for complex network structures, which makes them particularly difficult to observe and control (Mei et al., 2015). Taking into account structural positioning and tie-attributes into the study of criminal networks contributes to creating such a deeper understanding beyond the binary network picture.

**Implications for law enforcement**

These results have a few implications for law enforcement practice. First this study show that for detecting criminal networks, law enforcement agencies should more carefully target their intelligence resources according to the robustness and fluidity of criminal ties. The classification of ties presented in this paper may provide intelligence analysts with some further guidance. Our results show that surveillance on especially latent and robust ties provides a more sustainable overall picture of the internal processes and outgoing information throughout the network. With regards to disruption, these ties may be utilized to influence networks from the outside within the ethical boundaries (Strang, 2014). Outside of the criminal network domain this may for instance be particularly relevant for disrupting Jihadist or radicalization networks in the process of recruiting new members through social media.

The results in this study show that describing and classifying criminal networks exclusively at a micro-level may result in an oversimplification of a complex criminal reality and may lead to false prioritization within targeting or surveillance. For intelligence purposes it is particularly relevant to observe change and variety in criminal cooperation at a meso-level. The fluidity and self-organizing nature of criminal networks makes every micro-description a snapshot in time. The pools of criminal co-operation (i.e. meso-networks) out of which these fluid co-operations emerge remain more stable in composition and structure and are therefore better suitable for building a sustainable information position on the targeted criminal networks over time (Chapter 7).
The fluidity that is inherent to these networks may provide better access points for criminal infiltration outside of the old boys’ networks. Since these networks rely less on social constructions of trust it may be possible to access these networks in a shorter period of time. However, since these fluid pools of co-operation are clustered towards certain cultural backgrounds it is important to invest in recruiting an equivalent representation of agents from multiple cultural backgrounds as well for these purposes.

**Implications for future Research**

There are a number of implications for future research that emerge from our findings. First, it is important to actually measure tie-strength in the empirical study of criminal networks, rather than just refer to it. Many studies of criminal networks use the concept of strong and weak ties to describe or explain the emerging structures of organized crime, but a limited number of studies actually defines and measures it. Our findings suggest it is important for this purpose to distinguish between the different dimensions of tie-strength separately and in conjunction. Especially to the study of the dynamics on criminal networks (e.g. the flow of information) it may be important to introduce a weight factor based on these three dimensions together, so structural positioning of nodes is not only based on network topology but also on the actual properties of the ties itself. More research is however needed to further specify these dimensions and their mutual associations and to further identify the parameters that form the input for such models.

Our findings also emphasize the importance of studying criminal networks by considering the interaction between the three network levels (micro, meso, and macro). System-level properties of criminal networks, such as a small-world effect, are particularly relevant for making sense of meso-level and micro-level processes. Our findings, for instance, show that weak ties identified at a meso-level loose importance when viewed from a macro-level perspective. Secondly, the clustering patterns associated with homophily observed at a meso-level, do not automatically imply homophily at a micro-level. Integrating these levels of analysis is therefore essential in uncovering the complexity and non-linear patterns in criminal networks. Furthermore, our findings show high fluidity and unpredictability in criminal co-operation at a micro-level. This supports previous arguments by Spapens (2010) and Von Lampe (2015) that the more consistent patterns of emergence and evolution in criminal networks are better observed at the meso-level. Future research should therefore aim at integrating these levels into data collection, analysis and modeling of criminal networks.

Although we looked at a criminal meso-networks observed over a period of 25 years, we did not include time as a variable of tie-strength in this study. The reason for this is that time can be biased by police efforts or priorities that change over time. At this
stage we were unable to correct for these uncertainties and biases. However, time could reveal dynamics within tie-strength, for instance the phenomenon of ‘burst-dynamics’ as observed in other complex networks such as neurological networks (Lee et al. 2010). This could lead to insights into the different dynamics between the different categories of ties and may have implications for the timing of surveillance operations by law enforcement. Future research should therefore look into variations in tie-strength as a function of time.

Most of all, this chapter shows that studying a multi-dimensional phenomenon such as complex criminal networks demands an equivalent multi-dimensional approach.

In this chapter we looked at the importance of the nature of ties in criminal networks and how their strength influences the emergence and structure of criminal networks. As in previous chapters we elaborated on what these findings imply for law enforcement practice. The next chapter binds all these insights together and provides an overview of the process from data to disruption.
REFERENCES


