CRIMINAL NETWORK DISRUPTION

A SIMULATION STUDY ON THE EFFECTIVENESS OF LAW ENFORCEMENT INTERVENTION STRATEGIES

- Master thesis -

H.I. Dietzenbacher
S2935651
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Supervisor: Dr. G. Stulp
Second Reader: Dr. G.E. Huitsing
MSc Sociology of Crime & Safety and
Sociology of the Network Society
University of Groningen

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ABSTRACT

This research deals with effectiveness of disruptive and dismantling law enforcement interventions. Unique Dutch Police data were applied to the crime setting of synthetic drug production and trafficking, to assess the effectiveness of five law enforcement interventions. Three interventions targeted actors with high social capital (i.e., degree, betweenness, and closeness centrality targeting) and two interventions targeted actors that possessed high social and human capital – or network capital (i.e., information and skills/knowledge targeting). By means of social network simulations – in which network adaptation had (or had not been) included – these five intervention strategies were tested, removing actors from the network accordingly. The effectiveness of each intervention was subsequently evaluated, using multiple outcome measures for disruption on a network-level (i.e., number of steps until the network was disrupted, fragmentation, and efficiency) and extensive analyses on actor-level. The results showed that targeting actors based on betweenness centrality – and thus actors with high social capital – was the most effective law enforcement intervention strategy, as it: (1) dismantled the network consistently in the least number of steps, (2) produced the fastest fragmentation of the network, and (3) showed the steepest decrease in the ability of the network to operate efficiently. Furthermore, the actor-level analyses showed that the shifts that can occur in the network-structure in the aftermath of disruptive interventions have to be taken into consideration throughout the entire law enforcement operation. Actors that might initially seem unimportant, could become key players in the continuation of the organisational process following such interventions. Research findings were discussed in the context of restricted data availability that law enforcement faces. With the rise of intelligence-led policing, this study has formed an important step in dynamic and realistic interventions for combatting organised synthetic drug crime.

Keywords

Criminal networks; synthetic drug production and trafficking; social network analysis; crime script analysis; computer simulations; law enforcement interventions

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1. INTRODUCTION

Serious and organised crime has been globally marked as one of the largest threats to modern day society as it undermines the rule of law (Europol, 2021a; Tops & Tromp, 2017). Criminal organisations interfere with all societal spheres: they try to infiltrate local and national governments to enhance corruption, emerge in (il)legal businesses to launder money, and interfere with daily life – for example, by persuading underprivileged into taking care of cannabis plants to earn extra money or getting involved in local sports clubs to recruit new members (Duijn, Kashirin & Sloot, 2014; Europol, 2021a; de Graaf & Wiertz, 2019; LIEC, 2019; Tops & Tromp, 2017). Moreover, economic development is vigorously affected, as parallel underground economies divest governmental budgets from contributing to public services – such as education, infrastructure, and health care – hence directly and negatively impacting citizens' quality of life (Europol, 2021a; Tops & Tromp, 2017). Furthermore, the use of demonstrative and excessive violence appears to be an increasing trend in serious and organised crime networks and thereby poses a threat to the safety of society (Europol, 2021a; Peeters & Boutellier, 2020). As a consequence, serious and organised crime is worldwide considered one of the most important topics on the political agenda (Europol, 2021a; LIEC, 2019).

In Europe, serious and organised crime is dominated by the trade or production of illegal drugs, as 38 percent of the reported criminal networks appear to be involved in this criminal market (Europol, 2021a). On a global scale, the European producers of synthetic drugs, which are mainly based in the Netherlands and Belgium, are among the most profitable criminal organisations and are still increasing their capacities for synthetic drug production and trafficking (EMCDDA, 2021; Europol, 2021a; UNODC, 2021). Following these developments, over the past decades there has been a growing societal and scientific interest in criminal (synthetic) drug networks and expanding our understanding of how these illicit networks operate is crucial to composing effective policy and crime disruption strategies (Bichler, Malm & Cooper, 2017; Diviák, 2019; LIEC, 2019). While there have been internationally successful attempts to disrupt criminal organisations (e.g., Operation Trojan Shield (Europol, 2021b)), the disruption of organised crime is a long-term strategy: criminal networks have shown to be resilient and evolve and adapt to these law enforcement attacks, to both exploit new opportunities as well as elude law enforcement attention (Bichler, et al., 2017; Europol, 2021b).

One of the few theories in sociology that can be applied at multiple levels of analysis, ranging from small groups to international organisations, and also to criminal organisations, is social network theory (SNT) (Kadushin, 2012). This theory implies that people – or 'actors', in SNT – are embedded within a larger network, in which the role of their social relationships is pivotal in affecting their accessibility to information, and consequently to power and influence (Kadushin, 2012). For example, criminal actors that have a large number social relationships, often also have access to critical information, are well trusted, and have great prestige. In sociology, social network analysis (SNA) is commonly used to unveil these social structures, and in criminology to gain insight in the relations and organisational processes of criminal networks, which can be summarized and described in so-called *crime scripts* (Morselli & Roy, 2008). This research builds upon the existing knowledge of the organisational processes of synthetic drug production and trafficking networks, but adds a new aspect to this criminal value-chain as well: the use of violence and weapons. While the use of violence and weapons in criminal networks appears to be increasing, this trend is not reflected in research on criminal (synthetic) drug networks (Europol, 2021a; UNODC, 2020). By acknowledging the use of violence and weapons as an essential part of the criminal value-chain, this research distinguishes itself from others studies, in an attempt to approximate the social reality of criminal networks as accurately as possible.

Even though the accessibility of data on criminality can be an issue, SNA can be useful to give insight in these covert illicit networks (Diviák, 2019). In the past, researchers have used SNA to – amongst other things – characterize criminal networks and highlight key actors within networks (Bright & Whelan, 2020). Furthermore, SNA can be used beyond descriptive purposes, to provide insights into the effectiveness of law enforcement intervention strategies, that intend to disrupt and dismantle the organisational processes of criminal networks (Bright, et al., 2017; Duijn, Kashirin & Sloot, 2014; Valente, 2012). In practice, such interventions often come down to removing, or arresting, one (or several) actor(s) from the network (Bright, et al., 2017; Duijn, et al., 2014). While there already is a rich body of existing knowledge regarding criminal network disruption, consensus on which – if any – law enforcement intervention strategy is most effective in achieving these aims is currently lacking (Bichler, et al., 2017; Bright, et al., 2017; Duijn, et al., 2014). That is to say, researchers have used different methods, such as computer modelling and social network simulations, and different outcome measures, such as network efficiency and density, to assess the impact of law enforcement interventions and only few have incorporated the concept of network resilience against these interventions (Bright & Whelan, 2020).

In this study, social network simulations will be performed, using unique data on criminal registrations of a synthetic drug production and trafficking network, that is derived from the Dutch Police, Research and Analysis department, unit Northern Netherlands (Dutch Police, 2020). This study builds on previous research on law enforcement intervention strategies by adapting and expanding the use of social network simulations and crime scripts that underlie the simulation, and applying them to the crime setting of synthetic drug production and trafficking. Previously tested law enforcement intervention strategies (e.g., targeting degree centrality) will be tested through these simulations, as well as novel intervention strategies (e.g., targeting closeness centrality). Moreover, multiple outcome measures, that have been used previous research to assess the effectiveness of the interventions on a network-level in– such as network density and degree centralization – are combined to provide an extensive and unified interpretation of the effectiveness of the law enforcement interventions. Furthermore, actor-level analyses of the simulations are performed in this research in order to give concrete starting points for future intervention strategies, thus distinguishing itself from other studies in the field, that have predominately focused on network-level outcomes (Bichler, et al., 2017). In this way, this study attempts to answer the following research question:

> "*Which law enforcement intervention strategy is most effective in disrupting and dismantling criminal networks, according to social network simulations?"*

Below, a theoretical framework is proposed, that underlies the social network simulations. This section thus elaborates on crime as a network problem, the concept of crime scripting, approaches for network interventions, evaluating interventions through social network simulations, and simulating network resilience. Subsequently, the method section describes specifications of the network data, the social network simulation, operationalizations of network adaptation, the law enforcement interventions, and the outcome measures. Hereafter, the research results are presented and discussed on both a network- and actor-level. Finally, the limitations of this research, suggestions for future research, and implications for policy will be elaborated on.

2. THEORETICAL FRAMEWORK

2.1. EFFICIENCY VERSUS SECURITY

While the use of SNA can be applied to describe or analyse any type of social group, criminal networks are considered to be different, because they operate in a covert setting (Bichler, et al., 2017; Bright, et al., 2019). The hostile and covert environment requires for specific relational characteristics and interactions within and outside of the network (Diviák, 2019; Morselli, Giguère & Petit, 2007). Using SNT is helpful to unveil these specific relations and their characteristics. In legitimate organisations, business processes are organised such that the *efficiency* of the operations are maximized; whereas criminal organisations are obliged to work in *secrecy* (Bichler, et al., 2017; Morselli, et al., 2007). To sustain operations, criminal organisations therefore constantly have to balance an efficiency/security trade-off: carrying out illegal activities and maintaining their market position, whilst remaining concealed and avoiding law enforcement (Bichler, et al., 2017; Duxbury & Haynie, 2019; Morselli, et al., 2007).

The weight that is imposed on either the efficiency or security varies significantly in accordance with the objectives of the criminal organisation and the limitations that are associated with the concerned crime type (Morselli, et al., 2007). In (synthetic) drug production and trafficking networks, which can be regarded as profit-driven organisations (i.e., as opposed to ideological-driven organisations, such as terrorist networks), efficiency is conventionally favoured over security (Bichler, et al., 2017; Duxbury & Haynie, 2019; Morselli, et al., 2007). As a result, (synthetic) drug production and trafficking networks tend to be relatively visible – in terms of the number of relations and communication between its actors – and efficient (Bichler, et al., 2017; Bright & Delaney, 2013; Morselli, et al., 2007). The understanding of these criminal network dynamics is pivotal to the development of disruption strategies, as law enforcement interventions have shown to affect the efficiency/security trade-off (Morselli & Petit, 2007). When seizures and criminal targeting are enforced, the network generally tends to become more secure and efficiency is (temporarily) disfavoured (Morselli & Petit, 2007). However, previous studies have also shown that law enforcement interventions can have a counter-productive impact as criminal networks became more efficient after such an intervention (Bichler, et al., 2017; Duijn, et al., 2014). In order to assess the effectiveness of the law enforcement intervention strategies, it is therefore of importance to include outcome measures that reflect the extent to which either efficiency or security is favoured in the network.

2.2. THE CONCEPT OF CRIME SCRIPTING

Criminal networks are complex organisations, where multiple actors can have several roles and can be involved in multiple stages and phases of the organisational process (Chiu, Leclerc & Townsley, 2011; Duijn, et al., 2014; Malm & Bichler, 2011; Morselli & Roy, 2008). These roles, stages, and phases are different for each type of criminal organisation, or each criminal market. For example, in a synthetic drug production and trafficking network, an important phase is the production of the drugs, while recruitment is of importance for human trafficking networks (UNODC, 2021). These roles, stages, and phases can be schematically summarized and visualized in a crime script, to gain insight in the criminal value chain (Morselli & Roy, 2008). Because these criminal value chains are different for each criminal market and there is often overlap between several markets within a network (e.g., synthetic drug trafficking and trafficking in firearms), the current crime script is adjusted to the network under study (Europol, 2021a; Malm & Bichler, 2011; Spapens, 2017). Composing a crime script is of essential value to this study, as it used as a starting point for the social network simulation model: in order for the network to continue the organisational processes, it must have access to all resources of the synthetic drug production and trafficking value chain (Bright, et al., 2017; Chiu, et al., 2011). Additionally, the crime script is used as a tool to help determining which roles are pivotal for the functioning of the network and therefore for developing effective network disruption strategies (Bright, Koskinen & Malm, 2019; Duijn, et al., 2014).

In current research on synthetic drug production and trafficking networks, six stages are typically distinguished in the crime script: the financing, the coordination/organisation, the acquiring of locations, the acquiring of resources (i.e., equipment and precursor chemicals), the drug production, and the distribution of the drugs (Chiu, et al., 2011; Bright & Delaney, 2013; LIEC, 2019; Tops, Valkenhoef, van der Torre & van Spijk, 2018). Even though the first three stages are not always explicitly described, they are nevertheless important for the functioning of the network: the organisers are, for example, involved in the coordination of multiple elements of the value chain and are therefore often referred to as multi-stage facilitators (Chiu, et al., 2011). Each of the aforementioned stages corresponds to a specific set of skills and/or resources, that can be regarded as the essential attributes an actor operating in that stage should possess (Morselli & Roy, 2008). The eight corresponding resources that are typically distinguished for synthetic drug networks are: money, information, premises, equipment, precursors, skills/knowledge, labour, and drugs. The stages and resources that are described, and are essential for the continuation of the criminal value chain of synthetic drug production and trafficking, are schematically depicted in Figure 1.

An important aspect of the criminal value chain, that is currently neglected in research on (synthetic) drug production and trafficking networks, is the use of violence and weapons (UNODC, 2020). At the same time, the use of violence – both in terms of severity and frequency – as well as the seizures of firearms, nonetheless appear to be increasing, especially in relation to drug trafficking networks (Europol, 2021a; UNODC, 2020). The use of violence and weapons within criminal networks has multiple reasons. Within the network – or between its members – violence is predominantly used to ensure security (e.g., punishing whistle-blowers or intimidating members, or their families, so that information remains concealed), to settle conflicts, to ensure discipline, and as punishment (e.g., for violations of the rules that are in force within the criminal organisation, or unsuccessful operations) (Europol, 2021a; Harding, 2020; Spapens, 2017). Outside the network – or against others – violence is mostly used to protect itself from and to compete with other criminal groups, which can culminate in rip deals or liquidations (Europol, 2021a; Harding, 2020; Spapens, 2017). As criminal networks become more professionalized, the use of violence and weapons is more routinely employed as a part of their criminal value chain and increasingly offered as a stand-alone service (Europol, 2021a; Harding, 2020). Therefore, the use of violence and/or weapons, as a show of power and way to ensure control, is added as a separate stage and resource in the crime script, to provide for a realistic representation of criminal network behaviour.

In accordance with the crime script, specific stages and/or resources that are crucial for the continuation of the criminal value chain can be identified (Morselli & Roy, 2008). Regarding the technical chain-like system of the synthetic drug production and trafficking market, the '*coordination/organisation*' stage is essential for the efficiency and security of the network, as it controls every other stage of the value chain and keeps all of its actors together (LIEC, 2019; Tops, et al., 2018). Furthermore, the coordinators are crucial for the flow of essential information and operate as brokers between (groups of) criminal actors to bring together other pivotal roles at the right time and place (Chiu, et al., 2011; Duijn, et al., 2014; Morselli & Roy, 2008; Tops, et al., 2018). For example, the coordinator ensures that the right precursors are delivered at the right location. Regarding the substantive aspect of the criminal value chain, specialist actors can be identified that are essential to the continuation of the synthetic drug production and trafficking value chain because of their specific skills and/or knowledge (Bichler, et al., 2017; Bright, et al., 2017; Duijn, et al., 2014). Within this crime script, this stage involves the '*drug production*', as explicit chemical knowledge is required for the manufacturing of the drugs (LIEC, 2019; Tops, et al., 2018). An example of an actor that is involved in the drug production-stage and possesses specific knowledge, is a laboratory technician, that transforms the precursors into MDMA or Amphetamine. As a result, law enforcement could focus their interventions on targeting actors that either possess the resource *Information* and/or *Skills/Knowledge*.

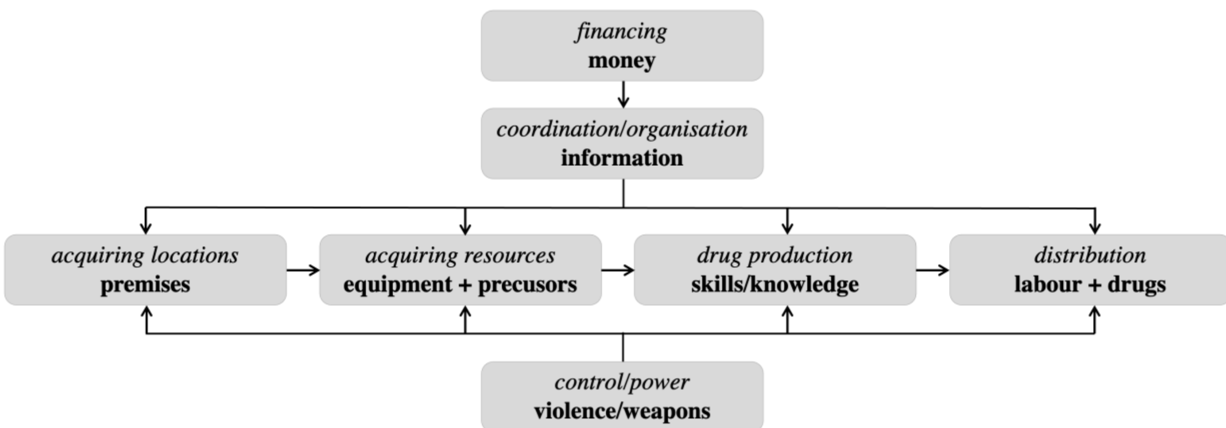

Figure 1. Crime script for synthetic drug production and trafficking, showing the seven value chain *stages* and the nine corresponding **resources**.

2.3. APPROACHES FOR CRIMINAL NETWORK INTERVENTIONS

Network interventions, which can be defined as deliberate attempts to change the behaviour of actors within a network, are important to achieve behavioural change (Valente, 2012). Traditionally, the cooperation of actors is needed in network interventions in order to establish this change. Since cooperation to change behaviour cannot be expected from criminal organisations, network interventions in the field of criminology often aim for actor removal instead (Bright, et al., 2017; Duijn, et al., 2014). In practice, such an intervention would come down to arresting one (or several) actor(s) by law enforcers. In current research on criminal networks, two approaches for disrupting and dismantling these networks can be distinguished that are used to identify the relevant actor(s): the social capital approach and the human capital approach (Bichler, et al., 2017; Bright, et al., 2017; Duijn, et al., 2014).

The social capital approach focuses on the relationships between the actors within a network – which are in SNA terms referred to as 'ties' – in order to determine which actors are most influential. These ties represent the social connections of an actor, by which knowledge, resources, and/or information can be exchanged (Bright, et al., 2017; Duijn, et al., 2014). The social capital approach thus attributes the *position* of actors within the network in terms of network structure. Consequently, interventions based on the social capital approach target actors who possess key positions and should therefore be removed from the network. In criminological, social network research two types of *key positions* are commonly distinguished (Bright, et al., 2017; Duijn, et al., 2014).

The first position identifies actors that have many direct connections, or ties, to other actors and are often referred to as key-players (Valente, 2012). Because these actors are highly connected, they are assumed to have an influential position within the (criminal) network (Bright, et al., 2017; Duijn, et al., 2014; Valente, 2012). In social network research, key-players are identified by means of the metric degree centrality (Borgatti, et al., 2013). An example of a key-player within a criminal network could be the leader of an outlaw motor gang or the actors that regulate the distribution of the drugs, because they are both assumed to have many connections to others. Consequently, law enforcement interventions often intend to target key-players (Bichler, et al., 2017; Bright & Whelan, 2020). The second position identifies actors that form bridges between different subgroups of actors, which are in SNA terms referred to as clusters, and are often defined as so-called brokers (Bright, et al., 2017; Duijn, et al., 2014; Valente, 2012). By looking at actors that are in-between clusters, the indirect connections of that actor are taken into account as well. Because of their strategic position in the network, brokers are assumed to be essential in the exchange of information, resources, and knowledge (Bright, et al., 2017; Duijn, et al., 2014). In social network research, brokers are identified using the metric betweenness centrality (Borgatti, et al., 2013). An example of a broker could be an organiser of organised crime, as they manage different stages of the criminal value chain and thus connect different subgroups within the network (e.g., assuring that the right precursors are delivered at the right location). Therefore, brokers are often targeted in law enforcement interventions (Bichler, et al., 2017; Bright & Whelan, 2020).

While criminological research on criminal networks has mainly focused on the aforementioned two key positions, SNA research distinguishes a third important position in terms of social capital, which can be defined by the metric closeness centrality (Borgatti, et al., 2013). In this respect, the structural network position is examined regarding how close a specific actor is to other actors, or how many intermediaries an actor on average needs to reach all other actors within the network (Borgatti, et al., 2013). Actors that are relatively close to others are assumed to be in a favourable position to control and acquire vital information and resources within the network (Borgatti, et al., 2013). It could therefore be relevant to test whether targeting actors that are relatively close to others is an effective law enforcement intervention, as it is of importance for the advancement of current knowledge to test novel interventions (Bright, et al., 2017).

The human capital approach looks beyond the position of actors in the network and is used to identify actors that possess a *key role*. Thus, the personal characteristics, knowledge, and competences of actors are taken into account, in order to determine which actors are important for the functioning of the network (Duijn, et al., 2014; Bright, et al., 2017). In other words, the human capital approach examines which actors are essential links in the (criminal) business process, or value chain (Morselli & Roy, 2008). Consequently, a potential law enforcement intervention strategy could be to target actors with high human capital. Deduced from Figure 1, in the synthetic drug production and trafficking value chain, the actors operating in the stages '*coordination/organisation*' and '*drug production*' can be identified as the actors that possess the most human capital, as specific information or skills/knowledge are required (Chiu, et al., 2011; Duijn, et al., 2014; LIEC, 2019; Morselli & Roy, 2008; Tops, et al., 2018).

2.4. EVALUATING INTERVENTIONS THROUGH SOCIAL NETWORK SIMULATIONS

SNA has been used as a tool to determine intervention strategies of which the impact has been tested by means of computer modelled social network simulations (Bichler, et al., 2017; Bright & Whelan, 2020). This method is regularly used in criminological research, as data on criminal networks – and especially on actual interventions that have been used to disrupt these networks – is particularly difficult to retrieve (Diviák, 2019). By simulating these networks and their evolution in the aftermath of an intervention, an attempt is made to determine the potential effectiveness of the disruption strategies. Different types of criminal organisations have been subjected to law enforcement intervention strategies, such as terrorist networks and drug trafficking networks (Morselli, et al., 2007). As the focus of this research is on synthetic drug production and trafficking, however, only simulation studies that examined such networks are discussed in the section below.

Early studies that have analysed the effectiveness of law enforcement interventions, have used the social capital approach to target actors in the simulations (i.e., actors with key positions, using centrality scores). Their results have shown that removing actors that operated as brokers and connected different subgroups of actors was the most effective targeting strategy, compared to random actor removal and targeting actors with many direct connections (Bichler, et al., 2017; Bright & Whelan, 2020, Morselli &

Petit, 2007). When both strategies that targeted actors using the social capital and human capital approach (i.e., actors with both key positions and roles) were tested, the combination of these targeting strategies appeared to be more effective than either of them alone (Bright & Whelan, 2020). This suggests that removing actors, using a network capital targeting strategy (i.e., combining social and human capital) is the most effective approach to achieve network disruption.

Resilience to law enforcement interventions

Even though there is a general consensus on the importance of law enforcement interventions and the significance of SNA research in battling crime, there is controversy on the overall effectiveness of these interventions (Bright, et al., 2017; Duijn, et al., 2014). In this scientific debate the concept of network adaptation is of importance, because network interventions can cause unintended and unexpected effects, such as the strengthening of the network and increasing its efficiency (Duijn, et al., 2014; Morselli & Petit, 2007). That is, if the network is able to continue the criminal value chain, despite the fact that an actor has been removed due to a law enforcement intervention, its actors do not have to find a replacement. This could mean that actors that actually turned out to be redundant were removed, allowing the network to operate more efficiently and thus undermining the effect of the intervention (Duijn, et al., 2014). In other words, in that case, the network appears to be resilient. Therefore, the resilience of criminal networks should be taken into account when law enforcement interventions are studied (Europol, 2021a).

Studies in which network adaptation was included in the social network simulation, showed that the overall impact of the interventions varied (Bright & Whelan, 2020). While the article of Bright, et al., 2017, showed that the network became less centralized and less efficient, the article of Duijn, et al., 2014, showed that the network – at first – became more efficient and denser. Nevertheless, targeting actors that operated as brokers and based on specific roles or attributes (i.e., human capital), were in general the most effective law enforcement intervention strategies (Bright & Whelan, 2020). Therefore, removing actors that possess a specific role or resource or operate as brokers, are expected to be the most effective targeting strategies in disrupting and dismantling synthetic drug production and trafficking networks. By including adaptation in the social network simulations, realistic criminal network behaviour is better mimicked as these organisations have shown to be resilient to law enforcement interventions (Bichler, et al., 2017; Bright & Whelan, 2020).

2.5. SIMULATING NETWORK RESILIENCE

In current research, there are different approaches on how network recovery, and therefore resilience, can be achieved (Bright, et al., 2017; Duijn, et al., 2014). In the article of Duijn et al., 2014 – who examined law enforcement interventions on a cannabis cultivation and trade network, by using social network simulations – it is assumed that, when the criminal value chain is disrupted by law enforcement interventions and an actor is removed, replacement for that actor can be found within as well as outside of the network. However, as Bright et al., 2017 – who examined law enforcement interventions on a methamphetamine production and trade network, also by using social network simulations – argue, criminal organisations have to make a trade-off between network efficiency and security; in order to operate efficiently compromises have to be made regarding the security (Duxbury & Haynie, 2019; Morselli & Petit, 2007). Especially when an actor from the network has been arrested, and the organisational process has been momentarily disrupted, security will become increasingly important, so no other actors are arrested (Morselli & Petit, 2007). Therefore, the actors would first seek to re-connect with actors within the original network, rather than seek replacement from the outside world (Bright, et al., 2017).

3. METHODOLOGY

3.1. DATA

The data that were used in this study were provided by the Dutch Police, Research and Analysis department, unit Northern Netherlands, and were constructed out of Basic Enforcement (BE)-registrations (i.e., *Basisvoorziening Handhaving (BVH)* in Dutch), that the police use for basic police services (Police Academy, 2020; Dutch Police, 2020). The basic police services comprise activities such as supervision, enforcement, recording of declarations, providing emergency assistance, and the first reception of victims and witnesses. The data were processed under article 8 of the Police Data Act (*Wet Politiegegevens* in Dutch) in the period 2018-2020. Due to reasons of confidentiality, privacy, and investigation interests, only anonymized data were included in this study.[1] In the data, there was information on 11781 individuals, which together represented 28216 BE-registrations. This implied that one individual could be registered for multiple criminal offences, and therefore could have had several roles on several criminal markets. The information known about the offender in the data consisted of the following elements: a unique identifier for the offender, on which of the 29 criminal markets the offence has taken place (e.g., synthetic drugs, weapons, etc.), which role the offender had in the offence (e.g., laboratory technician, burglar, etc.), the age of the offender, the country of birth, and the nationality.

For the construction of the social networks, ties were considered to be present when two or more actors were jointly registered in one BE-registration. Because no access was granted to the actual BE-

[1] The data that was obtained for this study, had already been anonymized by the Dutch Police and no access was granted to the actual Basic Enforcement registrations. For other articles that have used similar data see Hiemstra, Huitsing & Dijkstra, 2021 and Wolters, Oosterhuis & Dijkstra, 2017.

registrations, the exact nature of the connections between actors or the offences were unknown in this study and the ties were therefore undirected and unweighted. By examining the connections between actors, networks could be identified. In this dataset there were 4307 individual connected networks, which are here referred to as components (i.e., “separated regions with no ties between them” (Robins, 2015, p.26)). For the purpose of the social network simulation, the largest component was selected from this dataset, for which comprehensive information on actor-level roles was available and that mainly involved BE-registrations on synthetic drug production and trafficking (for further elaboration on the component selection, see Appendix A). The selected component consisted of a total number of 70 network actors that were predominantly active in – what was assumed to be – a (synthetic) drug production and trafficking network and is hereafter referred to as “the (overall/full) network”.

3.2. RESEARCH DESIGN

Criminal networks are complex organisations, where multiple actors could have several roles and be involved in various stages and phases of the organisational process (Bright, et al., 2017; Morselli & Roy, 2008). These roles, stages, and phases are different for each type of organisation, or each organised crime type, and can be schematically summarized and visualized in a crime script to gain insight in the criminal value chain (Morselli & Roy, 2008). Because these criminal value chains are different for each type of organised crime, the crime script should be adjusted to the network under study. Therefore, the first step of this research was to establish a crime script, using literature on synthetic drug production and trafficking networks, to help determine which roles, stages, and phases were most important for the functioning of the network (see Figure 1). Consequently, it was assumed that the production and trafficking of synthetic drugs requires nine different resources: money, information, premises, equipment, precursors, skills/knowledge, labour, drugs, and violence/weapons. Based on the roles that were assigned to the network actors by the law enforcement officers, resources were attributed to all 70 actors. For example, for the role ‘laboratory technician/cook’ the resources *Skills/Knowledge* and *Drugs* were attributed and for the role ‘victim’ no resources were attributed (for further elaborations on the data transformation, see Appendix A). Thus, it was possible for actors to possess no, one, or more than one resources. The distributions of these resources are shown in Table 1 below.

Table 1. Overview of the resources and the number of actors (*N*=70) that possess each of these resources.

Resources	Number of actors
Drugs	30
Money	24
Labour	20
Violence/Weapons	19
Information	14
Skills/Knowledge	10
Precursors	4
Premises	4
Equipment	2
None*	20

*Actors that did not possess any resources were not eligible as a replacement node.

Subsequently, social network simulations were performed in an attempt to determine which law enforcement intervention proved most effective in disrupting and dismantling a synthetic drug network.[2] Each law enforcement intervention strategy translated into a targeting method, aiming to disrupt the full network of 70 actors. To simulate the interventions, and following the method used in Bright, et al., 2017, in each step within the simulation one actor – or node – was removed from the network, according to the specific targeting method being tested. Components that subsequently became inactive – that is, lacked access to one or more of the nine required resources – were (or were not) given the opportunity to adapt (as described in the section below). When a component was (and remained) inactive, all actors from that component were removed from the overall network. The simulation stopped when no active components remained (see Appendix B for the simulation flow diagram).

To assess the effectiveness of the interventions on a network-level, five outcome measures were computed in each step within the simulation: the total number of (active) components; the size of the largest active component; the total network degree centralization; the density of the full network; and the efficiency within the full network.[3] By combining multiple outcome measures, an extensive and unified interpretation

[2] The *R*-scripts that were used to perform this research can be viewed without request via OSF.
[3] The first three outcome measures were derived from the article of Bright, et al., 2017, and the latter two from Duijn, et al., 2014. By means of the total number of (active) components and the maximal component size, the effectiveness of the interventions in terms of fragmentation of the network could be assessed. In criminological research, the metrics degree centralization, density, and efficiency are commonly applied to reflect the efficiency/security trade-off and can be used to determine how efficiently a network can execute its criminal operations (Bichler, et al., 2017). Higher network density – which usually coincides with a more centralized network structure – positively effects the network's efficiency, as resources can take direct paths through the network, but negatively effects the network's security, as its actors become highly visible (Bichler, et al., 2017). Therefore, the network structure in profit-driven networks, such as drug trafficking networks, appears to be relatively centralized and dense – compared to ideologically based networks, such as terrorist organisations – because efficiency is generally favoured over security (Bichler, et al., 2017; Morselli, et al., 2007). As degree centralization, density, and efficiency all have pre-built functions within the *R igraph*-package, no further operationalizations are provided here (Csardi & Nepusz, 2006). For (mathematical) definitions, see for example Borgatti, et al., 2013.

could be given of the effectiveness of the intervention strategies. For each targeting method, 100 runs – or repetitions – of each simulation were executed, after which the outcome measures were averaged over those 100 runs to produce plots of the average values over time. Finally, in-depth actor-level analyses of the simulations were performed, by examining the targeted actors that were removed within each step of the simulation, to provide a concrete starting point for policy implications.

3.3. MODELLING NETWORK ADAPTATION

Because criminal networks are resilient organisations, it was assumed that they would quickly recover from potential setbacks, such as the arrest of an actor within the network (Bright, et al., 2017; Duijn, et al., 2014). Therefore, network adaptation was modelled and included in the social network simulation. Thus, the differential effectiveness of the law enforcement intervention strategies on network disruption could be examined. Network adaptation was modelled by giving the network the opportunity to replace the actor that had been removed (in correspondence with the method that was used by Bright, et al., 2017). In each step within the simulation, it was initially determined for each component whether it was missing the presence of one or more of the nine resources, that were required in the criminal value chain. If a component was lacking one or more of these resources, it was considered inactive and was subsequently given the chance to find a replacement within the remaining overall network – or to adapt (for an overview of the adaptation process, see Appendix B).

The first step of the adaptation process (Figure 2) was to ascertain which of the nine resources were missing in the component. Consequently, a set of actors was identified that possessed at least those resources that were missing from that component. From this set of actors, a replacement actor was then chosen by means of the shortest path distance: actors that were closest to the removed actor (i.e., had the shortest path to that actor) were eligible as replacement actors. When there were multiple actors with the same shortest path distance (i.e., actors were equally close), one of these actors was chosen randomly. After an actor was chosen, all neighbours of the removed actor were given the opportunity to connect to the replacement actor with a probability of 0.5.[4] This process meant to reflect the efficiency/security trade-off and the network's behaviour in the aftermath of the intervention accordingly. In terms of efficiency, only neighbours were given the opportunity to connect to the replacement actor, as they were most likely to require one or more of the resources that had been supplied by that actor. In regards to the security of the

[4] In order to compare the results in this research with those from Bright, et al., 2017, as many simulation properties as possible remained unchanged and a probability of .5 was chosen accordingly. Future research, however, could explore varying this probability or – for example – only allowing neighbours from the inactive component to form new ties to the replacement actor, rather than all direct neighbours from the actor that was removed according to the targeting strategy.

network, it was unlikely that all actors would directly seek for replacement, which was reflected by the 0.5 probability of a new tie.

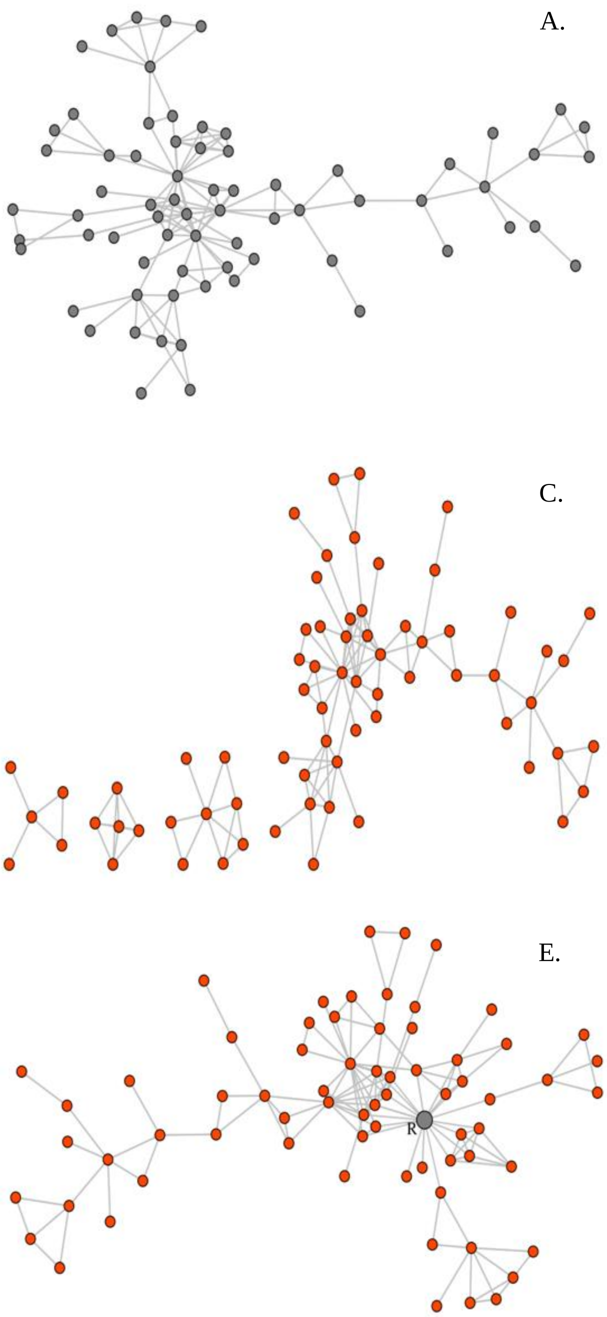

Figure 2. Visualization of the network adaptation process in the simulation, using the betweenness targeting strategy as an example: (**A.**) from the overall network (**B.**) a target (T) was chosen – in accordance to the intervention strategy – that would be removed from the network. (**C.**) Subsequently, the target was removed from the network and (**D.**) a replacement node (R) was chosen that possessed at least all resources that were missing from that component. Finally, (**E.**) the neighbours from the target were allowed to form new ties to the replacement node, resulting in (**F.**) a new, adapted network.

3.4. LAW ENFORCEMENT INTERVENTION STRATEGIES

In the simulation, six law enforcement interventions have been tested, in accordance with the criminal network approaches, the crime script, and the objectives of law enforcement agencies to dismantle and disrupt criminal organisations. The six law enforcement interventions that have been tested, were divided into random targeting, social capital targeting, and network capital targeting (i.e., a combination of both social and human capital).

The first intervention tested was the random targeting method, in which no strategy was applied at all and actors were targeted randomly for removal. In practice, such interventions could, for example, include stop and search operations (e.g., vehicle checks). This intervention was used as a baseline, to see whether the strategies that were tested, were more effective than a non-strategic law enforcement intervention.

(1) Random targeting. In each step within the simulation, an actor was selected randomly to be removed from the network.

Second, interventions were tested that targeted social capital only. By using this strategy, actors with high degree centrality (i.e., many relations), high betweenness centrality (i.e., brokers between components), and high closeness centrality (i.e., close to other actors) were removed from the network.

(2) Degree centrality targeting. In each step within the simulation, an actor was selected to be removed from the network, in order of decreasing degree centrality. If there was more than one actor with a maximal degree centrality value, one of these actors was selected randomly.

(3) Betweenness centrality targeting. In each step within the simulation, an actor was selected to be removed from the network, in order of decreasing betweenness centrality. If there was more than one actor with a maximal betweenness centrality value, one of these actors was selected randomly.

(4) Closeness centrality targeting. In each step within the simulation, an actor was selected to be removed from the network, in order of decreasing closeness centrality. If there was more than one actor with a maximal closeness centrality value, one of these actors was selected randomly.

Finally, using the network capital targeting strategy, two intervention strategies that targeted actors that have high social capital as well as human capital, were tested. The strategies were established using the crime script analysis, and targeted actors that possessed resources that were crucial in the criminal value chain for the functioning of the network. Therefore, targeting the resources *Information* and *Skills/Knowledge* were selected as intervention strategies.

(5) Information targeting. In each step within the simulation, an actor that possessed the resource *Information* was selected to be removed from the network, in order of decreasing degree centrality. If there was more than one actor with a maximal degree centrality value, one of these actors was selected randomly.

(6) Skills/Knowledge targeting. In each step within the simulation, an actor that possessed the resource *Skills/Knowledge* was selected to be removed from the network, in order of decreasing degree centrality. If there was more than one actor with a maximal degree centrality value, one of these actors was selected randomly.

4. RESULTS

4.1. DESCRIPTION OF THE NETWORK

In this section basic descriptive statistics of the network are presented, in order to provide a framework for understanding its structure (Bichler, et al., 2017; Robins, 2015).[5] Therefore, in Figure 3 the overall network is visualized and in Table 2 the network descriptive statistics are shown. Furthermore, an in-depth analysis of the actors is provided to see how the resources are distributed across the network and examine which actors are most likely to be targeted by the law enforcement interventions. Therefore, in Figure 4-9 the network actors' centrality scores, and resource distributions are visualized.

Network descriptive statistics

The overall network consists of a total number 70 nodes – or actors – that are connected through a total number 270 links – or ties – resulting in a network density of 0.112 (Table 2). This is relatively low for a profit-driven network, as it is suggested to negatively affect the efficiency of the network (Bichler, et al., 2017). However, with an overall degree centralization of 0.410 and efficiency of 0.309, it can be concluded that efficiency is not substantially affected by this relatively low network density score, as both degree centralization and efficiency scores are comparatively high (Bichler, et al., 2017). The large number of

[5] Due to the novelty of using SNA (and specifically simulations) in criminological research, Bichler, et al. (2017) suggest in their systematic review that researchers in the field should incorporate reporting standards and methods. This way, cross-case comparison, replication, and meta-analyses can be facilitated.

subgroups within the network (8) [6] and high network transitivity (0.473) [7] rather imply that an efficient and highly centralized network is not achieved at the expense of security, but security seems to be optimized through high-trust relations (Bright, et al., 2019). From these results, and by looking at the network visualization (Figure 3), can be deduced that the network structure can be described as a core-periphery structure, which results in both a secure and efficient network. Here, subgroup number seven can be defined as the core of the network, with highly centralized actors, and the other subgroups consist of somewhat peripheral actors, that are less centralized. The average shortest path between the actors within the network is 4.366, meaning that – on average – information or resources need to travel through four ties to reach its target. With an average nodal degree of 7.714, the detection of one member would typically lead to the discovery of eight other members within the criminal network (e.g., wiretapping one actor's phone, could reveal eight other criminal contacts).

Table 2. Overview of network descriptive statistics.

Network characteristic	
Number of nodes	70
Number of links	270
Density	0.112
Degree centralization	0.410
Efficiency	0.309
Number of subgroups	8
Transitivity	0.473
Average shortest path	4.366
Average nodal degree	7.714

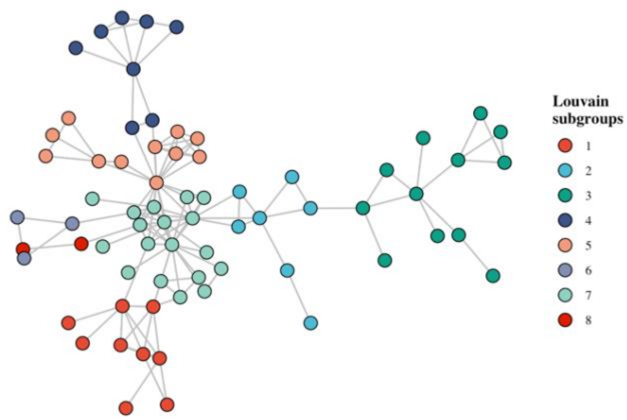

Figure 3. Visualization of the subgroups within network.

Actor-level analysis of the network

In the figures below the centrality scores (Figures 5-7) and resource distributions (Figures 4, 8 & 9) of the actors within the network are visualized in order to establish which actors are most likely to be targeted by the law enforcement interventions (for visualizations of the network per resource, see Figure C.1., Appendix C). For the figures in which a centrality score (i.e., degree, betweenness or closeness centrality) is included,

[6] To determine the number of subgroups within the network, the Louvain algorithm – that is implemented in the *R igraph*-package – was used (Blondel, Guillaume, Lambiotte & Lefebvre, 2008). This algorithm groups nodes into communities based on modularity optimization and results in high quality subgroups, where boundaries are more clear than other community detection algorithms.

[7] Transitivity refers to the occurrence of triadic closure (i.e., sets of three actors that are all interconnected) in a network (Robins, 2015). In criminological research, triadic closure is regarded to indicate trust in illicit networks, as closed triangles provide an environment in which (un)trustworthy behaviour of its actors can be observed and reinforce a collective commitment and responsibility to their criminal operations (Bright, et al., 2019). Thus, while a higher number of subgroups (indicated by transitivity) poses a risk to the network's security – as visibility to law enforcement increases – the nature of the ties between its actors also enhances security.

nodes are highlighted and ID-numbers are shown for actors that have a centrality score higher than 0.35. This value was chosen, because it revealed the two or three actors with the highest centrality scores for each centrality type.

In total, there are three actors that are remarkably vulnerable to the interventions, according to their positions and resources within the network. Actor *5107* in particular, can be defined as an actor with both a key position and -role, and is therefore considered a key target for the law enforcement interventions. Closer inspection of the BE-registration data corroborates this view and shows that this actor was registered as – amongst other things – organiser/investor/financer, laboratory technician/cook, and supplier/acquisitor of chemicals (see Table C.1., Appendix C). Another important target, in terms of both key positions and -roles, that emerges from the visualizations is actor *10807*. BE-registrations reveal that this actor was registered as executor debt collection, principal of property crimes and had multiple registrations regarding violence/threat/abduction of which the exact role was unclear. While this information – and specifically the role of principal – suggests that this actor has both a key position and -role, no robust assertions can be made about the presence or absence of its role, as it remains uncertain whether these roles are pivotal to the continuation of the synthetic drug production and trafficking value chain. Finally, actor *4436* can be defined as an actor with a key position in the network, based on its scores on both betweenness and closeness centrality.

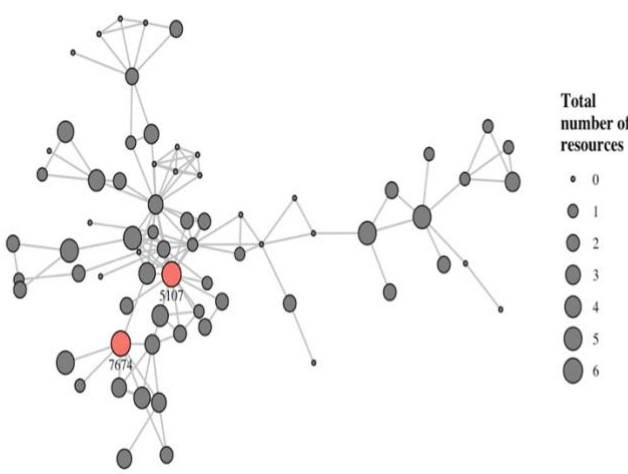

Figure 4. Total number of resources.

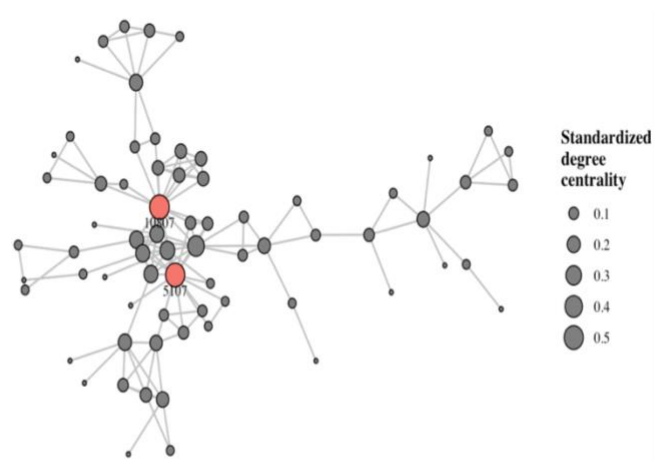

Figure 5. Standardized degree centrality.

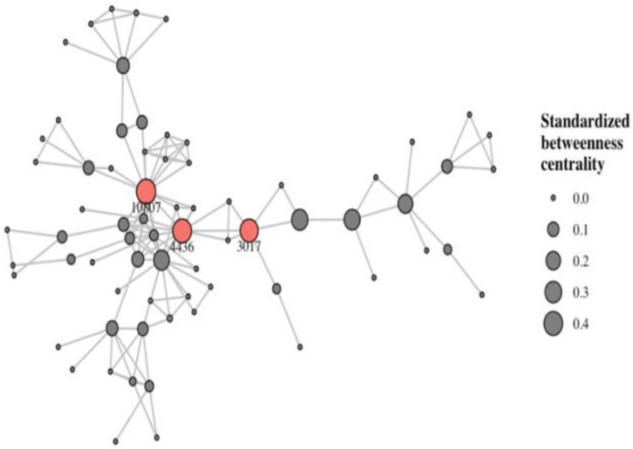

Figure 6. Standardized betweenness centrality.

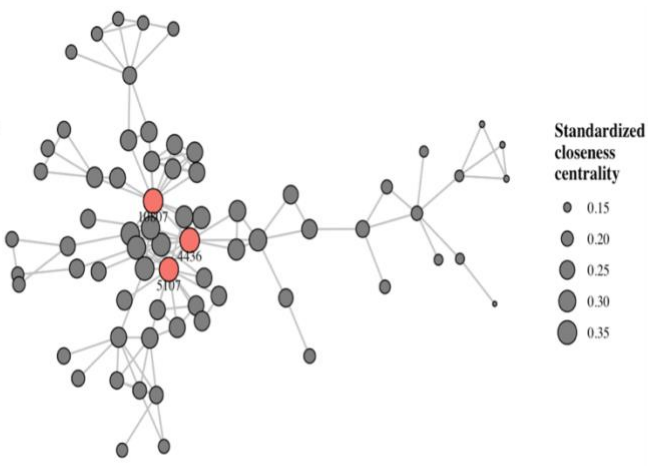

Figure 7. Standardized closeness centrality.

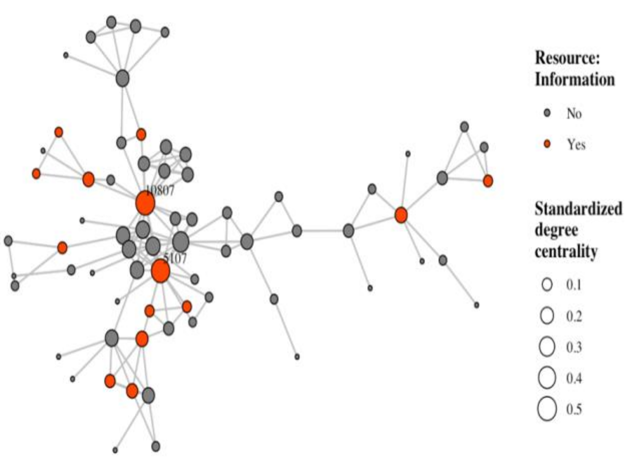

Figure 8. *Information* and degree centrality.

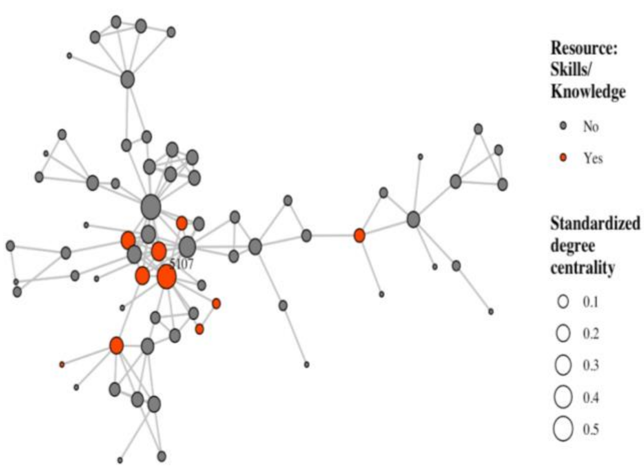

Figure 9. *Skills/Knowledge* and degree centrality.

4.2. LAW ENFORCEMENT INTERVENTION SIMULATIONS

In the section below the results from social network simulations are discussed. First the network-level outcomes are presented, using Table 3 and 4 and Figures 10-14. Subsequently, an extended analysis is provided of the actors that were removed according to each intervention strategy, using Figure 15 (for supplementary results, see Appendix C).

4.2.1. NETWORK-LEVEL OUTCOMES

Simulations without network adaptation

Table 3 displays the results of the six law enforcement intervention strategies, that were tested using a social network simulation without adaptation, and includes the outcome measures: mean, standard deviation, median, minimum, and maximum numbers of steps until the network was disrupted and no active components were remaining (i.e., when all components lacked access to at least one of the nine required resources of the synthetic drug production and trafficking value chain). As expected, the results show that the random targeting strategy is clearly the least effective, disrupting the network fully in a median of 19 steps. With a median of 4 steps, skills/knowledge targeting appears to be the most effective strategy to disrupt the network, followed by the three social capital targeting strategies (i.e., degree, betweenness, and closeness centrality), and information targeting.

Table 3. Outcomes for the number of steps required until there are no active components remaining for all interventions without adaptation.

Targeting strategy	Mean	Standard deviation	Median	Minimum	Maximum
Random	20.0	8.7	19	2	38
Degree	5.0	0	5	5	5
Betweenness	5.0	0	5	5	5
Closeness	5.0	0	5	5	5
Skills/Knowledge	4.0	0	4	4	4
Information	8.0	0	8	8	8

Simulation with network adaptation

Table 4 displays the results of the same law enforcement intervention strategies, this time including network adaptation in the social network simulation to better resemble realistic criminal network behaviour. In most interventions, a greater number of steps is needed to disrupt the network fully. Random targeting remains the least effective strategy with a median of 34 steps (i.e., 15 additional steps). The effectiveness of betweenness, closeness and skills/knowledge targeting are not strongly influenced by including network adaptation in the simulation, as the median number of steps remains the same for those strategies. For degree targeting one additional step, and for the information targeting strategy two additional steps are required to disrupt the network. While skills/knowledge targeting appears to be the most effective strategy according to the median, it also takes one step more to disrupt the network according to the mean (5.6), than the betweenness targeting strategy (4.6) and results in the highest standard deviation (2.1). Thus, the skills/knowledge targeting strategy is not a very reliable one. Taken all together, betweenness targeting is the most reliably effective intervention, as this strategy shows the lowest mean (4.6) and standard deviation (0.6) of all strategies and never seems to require more than six steps to fully disrupt the network. Thus, targeting actors with the highest betweenness centrality scores – or actors that bridge between different subgroups within in the network and therefore operate as brokers – is the most effective intervention strategy, according to the number of steps in the simulation with adaptation.

Table 4. Outcomes for the number of steps required until there are no active components remaining for all interventions with adaptation.

Targeting strategy	Mean	Standard deviation	Median	Minimum	Maximum
Random	32.9	9.6	34	8	55
Degree	6.7	1.9	6	6	16
Betweenness	4.6	0.6	5	4	6
Closeness	6.0	1.6	5	4	12
Skills/Knowledge	5.6	2.1	4	4	9
Information	10.3	0.7	10	9	11

Differential effectiveness of the interventions

In order to compare the results across the law enforcement intervention strategies (excluding random targeting), the five outcome measures that are measured in each step within the simulation, are plotted in five separate graphs: total number of components (Figure 10)[8], maximal component size (Figure 11), network degree centralization (Figure 12), network density (Figure 13), and network efficiency (Figure 14). For all graphs, the lines – reflecting the mean outcomes of the 100 simulation runs for all five targeting strategies – are returned to zero when the maximum number of steps to disrupt the network (i.e., until no active components remained) is reached, as the network can then no longer recover from the interventions.

Figure 10 shows that, while the strongest fragmentation is caused by degree targeting (i.e., a maximum of almost six components by the sixth step), betweenness targeting is the fastest and most consistent strategy to achieve fragmentation of the network, with a maximum of two and half components by the fourth step, as opposed to almost two components for skills/knowledge targeting and no fragmentation for the other three targeting strategies at that step. An interesting observation that can be deduced from this graph is that information targeting never seems to fragment the network into multiple components, meaning that it remains largely intact and is able to continue the criminal organisation process. Furthermore, this observation implies that actors that possess the resource *Information* are mainly located at the periphery of the network (i.e., otherwise the network would have split into multiple components when an actor was removed) which is consistent with the resource distribution from Figure 8. While there appears to be some extent of fragmentation of the network, a somewhat similar trend can be observed for the skills/knowledge targeting strategy.

These findings are supported by the results from Figure 11, in which the maximal component size is reported. Especially for information targeting, the largest component still consisted of 19 actors in the step the network became inactive and of 38 actors in the previous step, meaning that the overall network

[8] As the network is never split into more than one active component, for any of the intervention strategies, the total number of components within each step of the simulation is reported, rather than the total number of active components. The effectiveness of network disruption in terms of fragmentation can thus be observed by other means.

remained largely intact throughout the intervention. Though degree targeting results in the smallest possible component size, the steepest and fastest decline in the maximal number of actors in the largest component is caused by betweenness targeting, suggesting that it is the most effective approach for dismantling the network in terms of fragmentation.

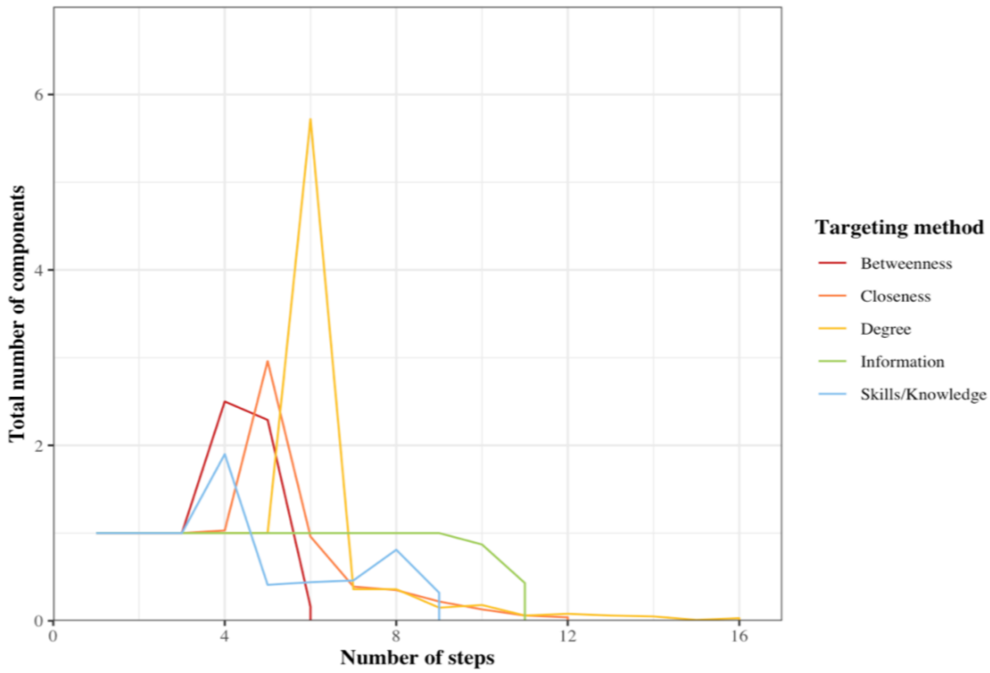

Figure 10. Outcome measure: total number of components

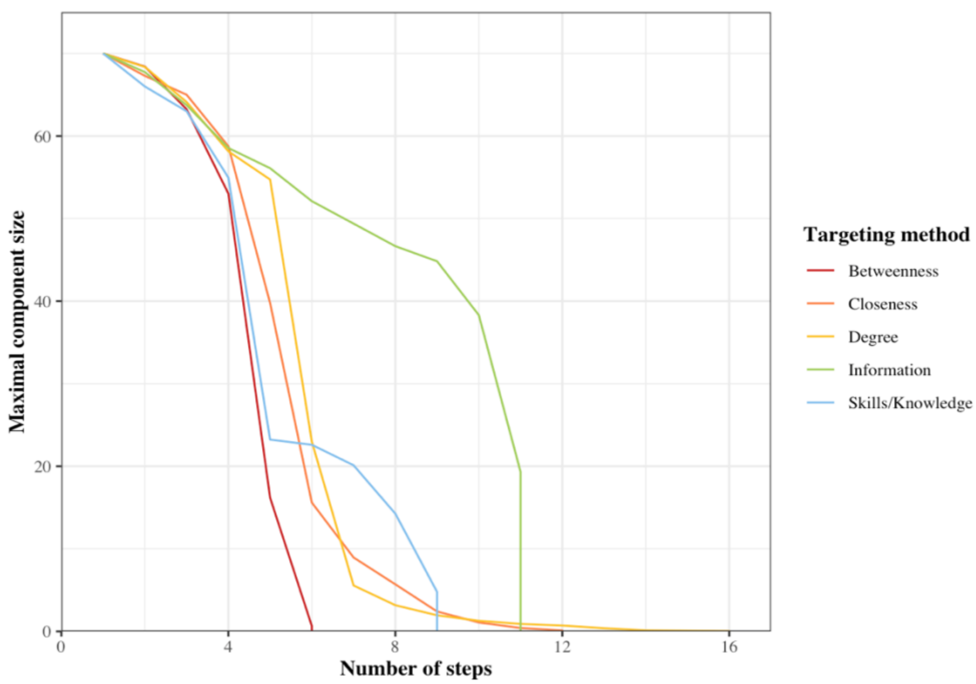

Figure 11. Outcome measure: maximal component size.

Figure 12 shows the network's degree centralization, which represents the visibility of the network – and thus reflects the extent to which *security* is favoured: increased centralization indicates more efficiency and less security (Bichler, et al., 2017; Bright & Delaney, 2013). Therefore, instead of decentralizing the network immediately, an increase in degree centralization in the first few steps is preferred, as this could make other highly centralized actors more visible to law enforcement (Bright, et al., 2017). The results from this graph show that while the degree targeting strategy produces the fastest and steepest decline in the networks degree centralization – thus appearing more effective than betweenness targeting – no initial increase in centralization can be observed. Therefore, actor removal based on degree targeting tends to increase the network's *security*, making it more difficult for law enforcement to further disrupt the network, which corresponds to the relatively slow decline in the maximal component size that can be observed for this strategy (Figure 11). Furthermore, the graph demonstrates that information targeting is, yet again, the least effective strategy to disrupt the network, as it produces merely an increase in degree centralization, which corroborates to the idea that actors possessing this resource are somewhat peripheral actors: when the actors that were targeted by this intervention would have been highly centralized (i.e., in the core of the network), the overall network would become less centralized in the aftermath of their removal. For the other three strategies (i.e., betweenness, closeness, and skills/knowledge targeting), an increase in network centralization can be observed at the start of the simulation, which could explain the steep decrease in the maximal component size in these first few steps (Figure 11).

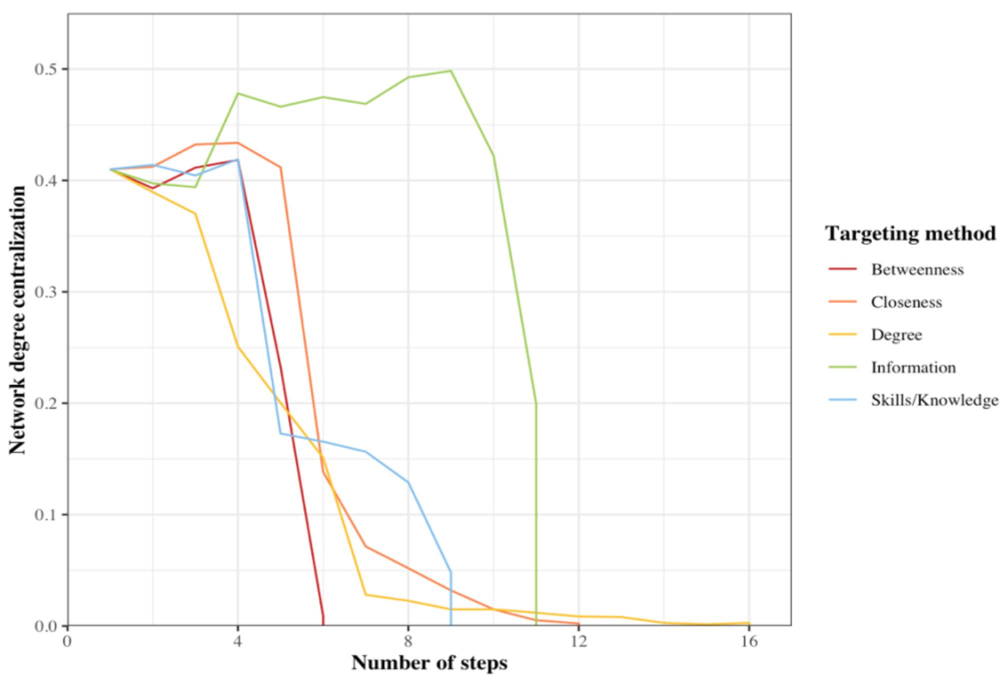

Figure 12. Outcome measure: network degree centralization.

In Figure 13 the results for network density are shown, which can be interpreted both in terms of *security* and *efficiency* (i.e., high density indicates low security and high efficiency: because the actors are highly connected, information and resources are easily exchanged, but actors are also highly visible). As expected, the results from Figure 14, in which the evolution of the network's efficiency throughout the simulation is visualized, therefore share many similarities with the density scores from Figure 13. The figures show that for all strategies the density and efficiency scores remained stable in the first four to five steps of the simulation, which is consistent with the findings from the previous figures: the network did not split into multiple components and the maximal component size and degree centralization did not decrease drastically, meaning that the network was not largely affected by the interventions. In the following steps, density and efficiency scores steeply decreased for all social capital targeting strategies (i.e., degree, betweenness, and closeness centrality targeting) and skills/knowledge targeting, reflecting the idea that – as more actors were removed – the remaining network struggled to (efficiently) continue their criminal operations whilst remaining covert. Furthermore, the increase in density and efficiency, that can be observed for information targeting, implies that – in general – the actors that were targeted by the intervention are not crucial for the continuation of the criminal value chain and even make the network operate more efficiently, as apparently redundant actors are removed.

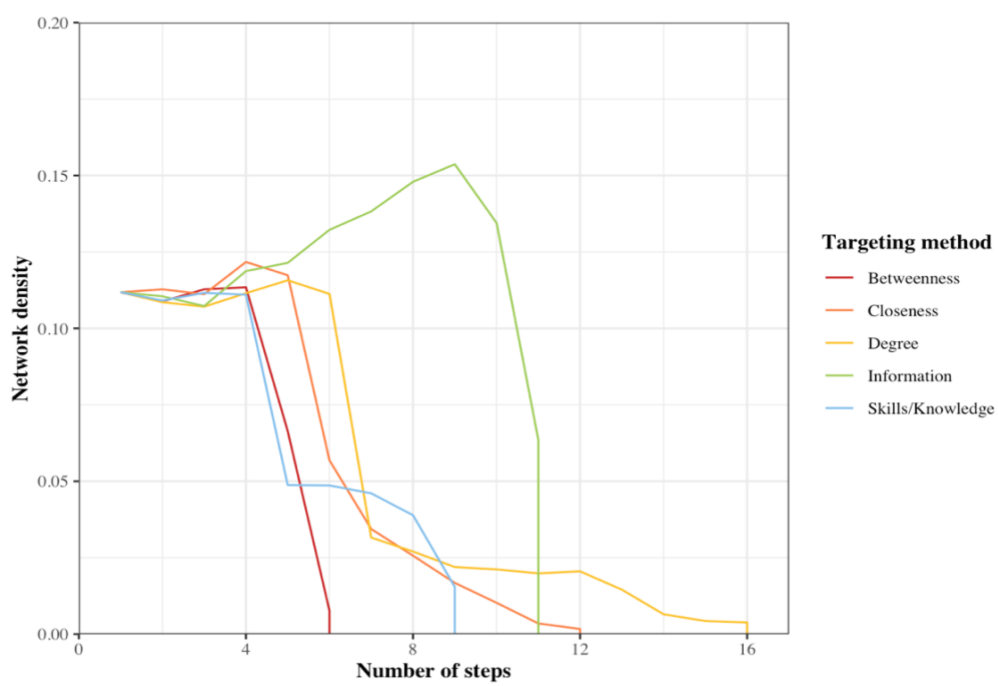

Figure 13. Outcome measure: network density.

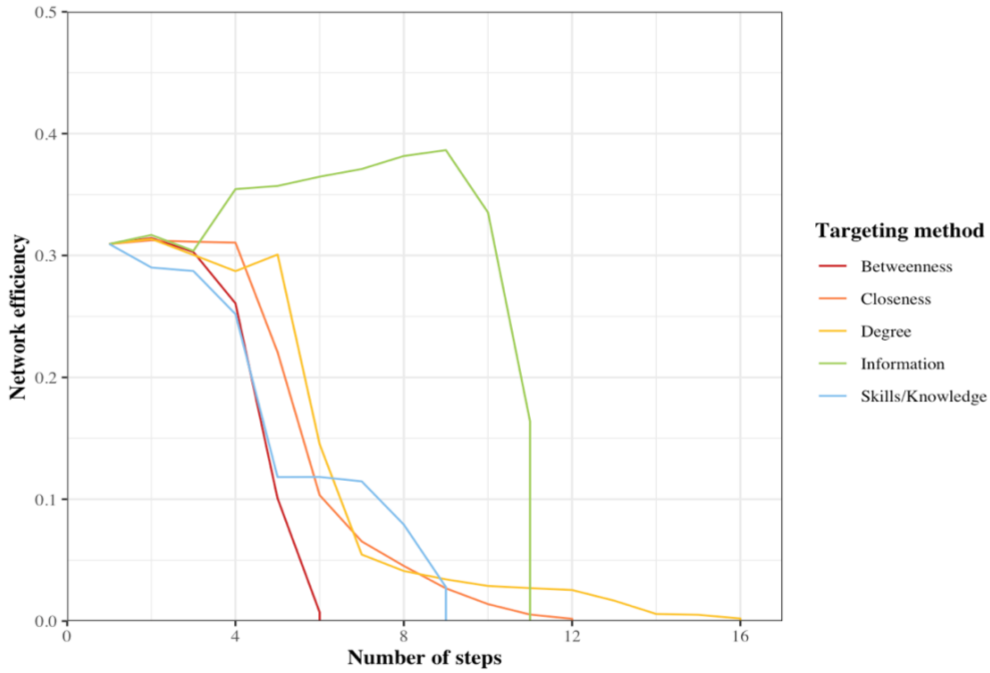

Figure 14. Outcome measure: network efficiency.

Based on the results from the Figures 10-14, which are in line with the findings from Table 4, it can be concluded that betweenness targeting is the most effective law enforcement intervention strategy, both in terms of fragmentation of the network and the extent to which the network can efficiently execute their criminal operations. The closeness, skills/knowledge, and degree targeting strategies followed, all having their own strengths and weaknesses (e.g., while degree targeting causes the greatest fragmentation of the network, it also takes a relatively large number of steps to achieve a decrease in the network's efficiency scores). Finally, the information targeting strategy clearly appears to be the least effective law enforcement intervention, as it not only takes the largest number of steps to disrupt the network, but also does not fragment the network and causes the remaining network to function even more efficiently.

4.2.2. ACTOR-LEVEL OUTCOMES

In order to provide a more in-depth analysis of the law enforcement interventions, the actors that were most likely to be targeted, according to Figures 4-9, were compared with the actors that were actually removed from the network in the social network simulation, which are highlighted in Figure 15. The conclusion from the analysis in section 4.1. was, that the actors *5107*, *10807* and *4436* were most likely to be targeted by the intervention strategies. The results from the simulations show that, indeed, those actors were most frequently targeted – especially by the social capital strategies – in the first steps of the simulation (see Table C.2., Appendix C). Furthermore, there were two actors that were repeatedly targeted within the first four steps of the simulation by both the closeness and skills/knowledge targeting strategies: actor *5394* and actor *6663*. For actor *5394*, BE-registrations revealed that it – presumably – predominately operated on the synthetic drug market, with registrations as dealer, supplier/acquisitor of (pre-)precursors, and laboratory technician/cook. Moreover, the BE-registration data of actor *6663* resulted in multiple registrations for property crimes, dealing cocaine, and – most importantly – owner of weapons/ammunition and/or explosives. Based on these roles in the criminal value chain and position in the network (Figure 15), it is therefore no surprise that these actors emerged as important targets for the law enforcement interventions.

However, there were two actors that appeared to be crucial to the disruption of the network in almost all law enforcement interventions: actor *6523* and actor *7674*. For most targeting strategies actor *7674* was removed in the first few steps of the simulation, and no active components remained immediately or soon after actor *6523* was removed from the network as well. Especially for actor *6523* this is an interesting observation, because this actor was first positioned at the periphery of the network and did not emerge from the initial analysis as a potential target. Therefore, this actor was relatively invisible to law enforcement: with few contacts to other actors, the chance of being discovered – for example, by wiretapping another actor's phone – is relatively small for this actor. Closer inspection of the BE-registration data showed that actor *6523* was registered as owner of a hemp farm and actor *7674* was registered as – amongst other things – owner of a hemp farm, exporter of cocaine, and supplier/acquisitor of synthetic drug chemicals. As a result, these actors were therefore one of the few actors that possessed the resource *Premises* and the only two actors in the network that possessed the resource *Equipment*, causing the overall network to be dismantled after the combination of both actors were removed (see Table C.3., Appendix C). [9]

Finally, for the network capital targeting strategies there were two actors that were always removed from the network within the first three steps of the simulation. For information targeting, actor *9171* was repeatedly targeted in the intervention. According to its position in the network, this actor appeared to connect different regions of the network, which corroborates to the information the from the BE-registrations: actor *9171* was registered as – amongst other things – a broker and operated (i.e., had registrations) on six different criminal markets, thus connecting several subgroups of the network. For the skills/knowledge intervention strategy, actor *3835* was repeatedly removed in the second step of the simulation and sometimes also seemed to emerge as a target for the closeness targeting strategy. Further

[9] To rule out the possibility that the social network simulation was disproportionately influenced by the actors *6523* and *7674*, the simulations were performed excluding the resource *Equipment* – as a requirement for the continuation of the criminal value chain – as well. While the results differed slightly (i.e., skills/knowledge targeting appeared to only be more effective, than betweenness targeting, regarding the mean number of steps and not for the median number of steps), it was decided to keep the resource *Equipment* included in the social network simulation (see Appendix D).

analysis of the available information of this actor, reveals an interesting finding: while the BE-registrations make it seem as though this actor does not have a crucial role in the criminal value chain (i.e., mostly registrations for property crimes), its position and ties to other actors in the network suggest something different. Figure 15 shows that actor *3835* has a relatively central position in the network and – more importantly – connections to other crucial targets, with crucial roles.

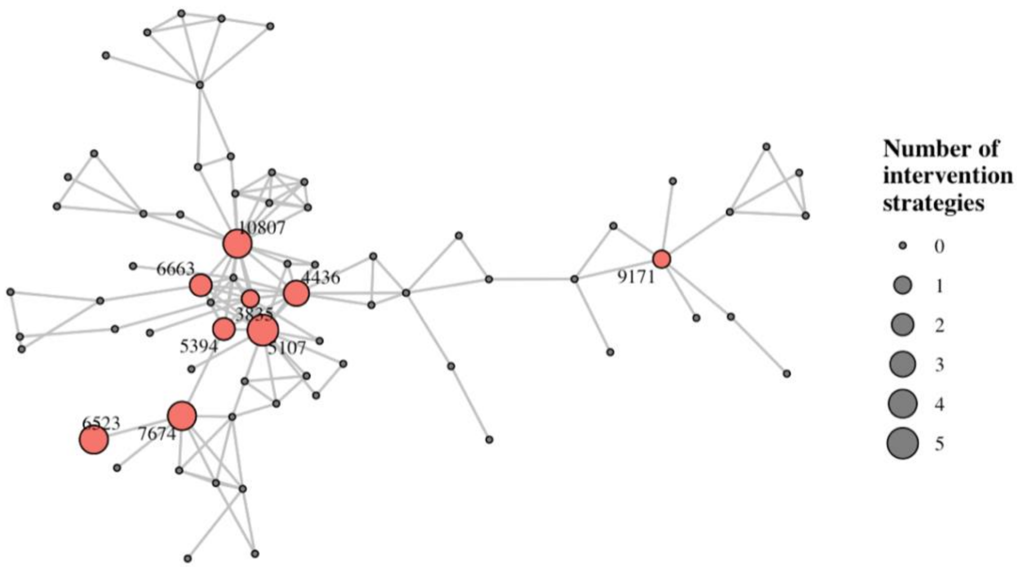

Figure 15. Visualization of the actors that were most often removed from the network in each simulation.

5. CONCLUSION AND DISCUSSION

In the fight against subversive, serious, and organised crime, law enforcers try to create as many barriers or interventions as possible, to disrupt and dismantle criminal organisations. It is therefore of great importance to gain insight into the effects of such interventions. This research has contributed to this goal by simulating the network responses in the aftermath of law enforcement interventions – that aim to disrupt and dismantle criminal organisations – which can support law enforcers to further improve and develop these disruptive barriers. By using unique Dutch Police data on – what was assumed to be – a synthetic drug production and trafficking network, three law enforcement intervention strategies that targeted social capital (i.e., degree, betweenness, and closeness targeting) and two strategies that targeted network capital (i.e., information and skills/knowledge) were tested, as well as a random targeting strategy – which was used as a baseline to compare the effectiveness of the other five law enforcement intervention strategies. Multiple outcome measures – that reflected effectiveness in terms of network fragmentation and the ability to efficiently perform criminal activities – were combined to give an extensive and unified interpretation of the results on a network-level. Furthermore, in-depth, actor-level analyses were performed to examine which actors were most vulnerable to the law enforcement interventions. In doing so, this study has attempted to answer the following research question: "*Which law enforcement intervention strategy is most effective in disrupting and dismantling criminal networks, according to social network simulations?*".

5.1. RESEARCH FINDINGS

The results from the social network simulations showed that the social capital targeting strategy, in which actors that connected different subgroups of actors within the network were removed from the network (i.e., betweenness centrality targeting), was the most effective strategy to disrupt and dismantle a synthetic drug production and trafficking network. Betweenness targeting not only required the fewest number of steps to disrupt the network, but also appeared to fragment the network the fastest and decreased its ability to efficiently continue their criminal operations. These findings are consistent with results from previous research that tested law enforcement interventions and corroborates to the idea that targeting brokers, who connect different parts of the network, is more effective than targeting actors who are highly connected (i.e., degree centrality targeting) or close (i.e., closeness centrality targeting) to other actors in the network (Bichler, et al., 2017; Bright, et al., 2017; Bright & Whelan, 2020; Morselli & Roy, 2008). The actor-level analysis, in which the actors that were removed in each step within the simulation were examined, revealed that this targeting strategy was particularly effective, because the actors that had the highest betweenness centrality scores were also the actors that possessed the scarcest resources. As a consequence, the synthetic drug production and trafficking value chain was disrupted and the network was considered to be dismantled the fastest.

Addressing the other two strategies that targeted actors using the social capital approach, removing actors based on their proximity to others (i.e., closeness centrality targeting), had not been tested in previous research. The closeness targeting strategy appeared to be the third most effective of all five strategies and showed similar patterns to the betweenness targeting strategy in terms of network fragmentation and its efficiency scores. Closer inspection of the actors that were targeted in each step within the simulation revealed that, while the set of actors that were removed was largely the same as the other social capital strategies, an extra actor was added to this set for the closeness targeting strategy, resulting in a different – and less effective – order of removal. The final social capital targeting strategy, in which actors were removed according to their total number of direct social relations within the network (i.e., degree centrality targeting), appeared to be the least effective of these strategies. While the degree targeting strategy was quite effective in terms of network fragmentation, it took a relatively large number of steps before a decrease in network efficiency could be observed – presumably because only redundant actors were removed, which merely caused a decrease in the network degree centralization and allowed the remaining network to recover from the interventions and remain intact for a relatively long time – and was therefore not considered to be a very effective strategy.

Regarding the law enforcement interventions that targeted actors using the network capital approach (i.e., a combination of the social and human capital approach), removing actors that possessed a crucial role as well as a crucial position to the functioning of the network, appeared to have varying success. Removing actors that possessed the resource *Skills/Knowledge,* which was viewed to be a crucial resource for the continuation of the criminal value chain, as it was a scarce resource that would be particularly difficult to replace (i.e., skills/knowledge targeting), appeared to be a highly effective targeting strategy. The skills/knowledge targeting strategy was the second most effective of all five strategies and showed similar patterns – in terms of network fragmentation and efficiency scores – to the betweenness targeting strategy. Furthermore, the actor-level analysis of the simulations revealed that the actors that were targeted by the skills/knowledge strategy, possessed other resources that few actors possessed – that is, precursors, premises, and equipment. These results suggested that having specific skills and/or knowledge, coincides with other resources that are scarce in criminal networks, causing the network to struggle to continue the criminal value chain.

The second network capital strategy targeted actors that possessed the resource *Information* (i.e., information targeting). Information targeting was chosen as an intervention strategy, because it was assumed that actors possessing that resource would have a multi-stage facilitating role, coordinating different groups within the criminal value chain, and would therefore be crucial in continuing the network's criminal operations (Chiu, et al., 2011; Morselli & Roy, 2008). Unexpectedly, however, information targeting was found to be the least effective of all five strategies (excluding random targeting), disrupting the network in the largest number of steps and – more importantly – did not lead to any fragmentation and even increased the degree centralization and efficiency of the network. These results suggested that the actors that were removed in accordance with this targeting strategy, operated predominantly from the periphery of the network, which was supported by the visualizations of the resource distributions. Insights from previous research, however, also suggest that targeting the 'kingpin' leaders of criminal networks does not result in a collapse of the network: although these actors are well informed and issue orders, they often do not actually contribute to these criminal activities and have few direct relations to others – thus operating from the periphery of the network – in order to remain concealed to law enforcement (Duijn, et al., 2014; Morselli & Petit, 2007). When actors possessing the resource *Information* are subsequently targeted, the functioning of the network and the continuation of the criminal value chain are not actually affected by the law enforcement interventions, causing the network to be highly resilient (Duijn, et al., 2014; Morselli & Petit, 2007). The relative ineffectiveness of the information targeting strategy thus corroborates to this idea.

Finally, the random targeting strategy – that was used as a baseline – was, as expected, clearly the least effective in disrupting and dismantling the network. These results are consistent with findings from previous criminal network research and suggest that non-strategic law enforcement interventions – such as vehicle checks – are unlikely to be effective when aiming to disrupt synthetic drug production and trafficking networks from their criminal operations and to dismantle them (Bichler, et al., 2017; Bright, et al., 2017; Bright & Whelan, 2020; Duijn, et al., 2014).

In general, the actor-level results, in which the actors that were removed within each step of the simulation for all five strategies were examined, revealed that there were several actors that were initially the most likely to be removed from the network, based on their centrality scores and the resources they possessed. From the simulation results, it became apparent that indeed those actors were repeatedly targeted in the first few steps of the simulation. This suggests that, when aiming to disrupt synthetic drug production and trafficking networks, performing basic social network analyses (e.g., calculating actors' betweenness centrality scores) and arresting actors accordingly, is an effective strategy to start such intervening operations. However, a surprising finding that followed from the actor-level analysis of the social network simulations was that one of the two actors that were crucial to the disruption of the network for almost all law enforcement interventions, was initially a rather peripheral actor. Because of its position in the network, this actor might not at first be as visible to law enforcement as other actors, but as the network evolved and adapted to the interventions, shifts occurred in the structure of the network. As a result, this further complicates the work of law enforcers and emphasizes that it is important to not only monitor the key actors, but their direct connections as well.

The results from this research form an important step forward in combating organised synthetic drug crime. Especially with the rise of intelligence-led policing, where real-time data can be used to delineate the criminal actors in a network and how they operate (e.g., Operation Trojan Shield (Europol, 2021b)), conducting social network analyses can be of crucial value to the development of new law enforcement interventions. The social network simulations of the law enforcement interventions showed that betweenness targeting was the most effective and consistent strategy to dismantle a synthetic drug production and trafficking network. Pragmatically, this strategy could also be the most efficient targeting method for law enforcement agencies to implement, as the betweenness targeting strategy does not require prior knowledge of the exact roles of the actors in the network. In intelligence-led operations, where criminal actors are monitored in real-time (e.g., by wiretapping or infiltrating in encrypted communication systems), it is then sufficient to know that a social connection exists between two actors, rather than to understand the exact role of these actors. In this way, law enforcement interventions using this targeting strategy can be executed faster, than resource-driven, network capital strategies (e.g., skills/knowledge and information targeting), as no additional information needs to be obtained.

5.2. LIMITATIONS

Due to the covert nature of criminal networks, its actors are obliged to undertake their activities in secrecy to remain concealed and avoid law enforcement (Duxbury & Haynie, 2019; Morselli, et al., 2007). The information position of law enforcement remains limited and it is therefore difficult to obtain a complete view of the actual nature and extent of crime (Diviák, 2019). This often results in missing data, which is in criminological research referred to as 'the dark figure': that part of crime that law enforcement cannot register (van Dijk, Huisman & Nieuwbeerta, 2018). In addition, due to, for example, high workload and the focus of the investigative services, law enforcement data that are registered are vulnerable to error and incompleteness (Bright, et al., 2017). The restricted availability and incompleteness of data has limited this research in several ways.

For the operationalization of the social network simulations, multiple SNA metrics (i.e., degree, betweenness, and closeness centrality) were used in order to determine the targeting strategies for the law enforcement interventions. It was assumed that, by finding the actors with the most social or network capital (i.e., the highest centrality scores), the actors that were most important for the continuation of the criminal value chain, could be targeted to be removed from the network (Bright, et al., 2017; Chiu, et al., 2011; Duijn, et al., 2014). However, the opinions on the use of social network metrics, as a way to assess the importance of certain actors to the functioning of the network, are divided amongst scholars in the field of criminology. That is to say, it is also hypothesized that the most central actors in the network are the ones that are the most visible and are therefore the most likely to be detected by law enforcement (Morselli & Petit, 2007; Peterson, 1994). In addition, the actors' centrality scores could also reflect the focus of law enforcement investigations, rather than the actual social connections within the network (Duijn, et al., 2014). Thus, these actors might be representing vulnerability rather than strength in the network (Peterson, 1994). Therefore, the results from this study should be interpreted with some caution, as the actual impact of the law enforcement interventions might be overestimated.

Moreover, there were many deficiencies in the BE-registrations that were used as a starting point for this research. While the component – or network – that was selected for the social network simulations contained the highest percentage of relevant roles (i.e., 61.1 percent, as opposed to 55.5 and 55.2 percent for the other two largest components in the original data set, see Appendix A), a large share could not be used in this study: roles such as '*Indefinable'*, *'Other'*, and '*Role t.b.d.'*, did not provide any useful information and therefore limited the resource attribution to the actors. As a consequence, there were 20 actors (out of the 70 actors in the full network[10]) that possessed none of the nine resource that were required to continue the criminal value chain and were accordingly not eligible as a replacement node in the adaptation process of the simulation. These deficiencies in the data might have negatively affected the results of the social network simulation: the visualization in Figure 16 shows that there were several actors (e.g., actor *9952* and actor *3017*) that did possess a key position, but did not possess any resources. The key positions – based on, for example, degree or betweenness centrality – suggest, however, that these actors actually are important to the functioning of the network and that some of them might have been chosen as replacement nodes if information on their roles had been available.

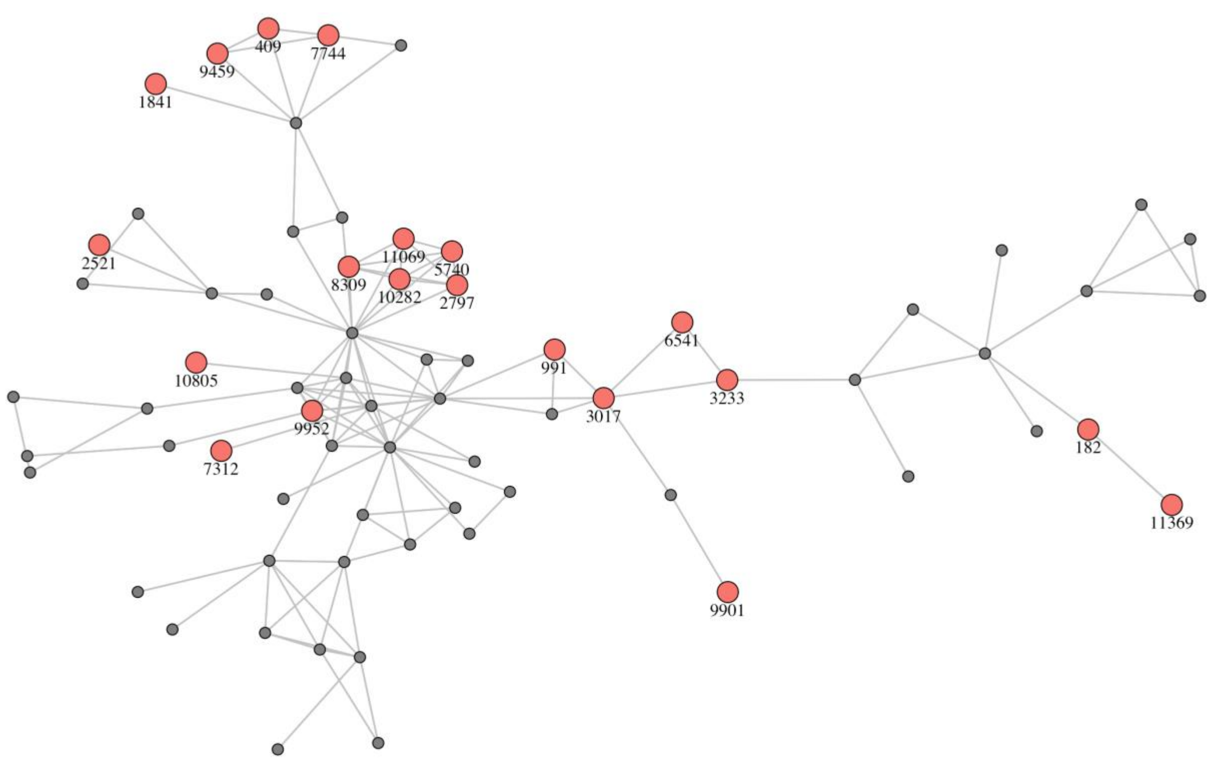

Figure 16. Visualization of the network showing the actors that possessed none of the required resources.

Subsequently, another limitation that resulted from the deficiencies in the data was the resource attribution based on the roles and markets that were presented in the BE-registrations. Because a fairly large share of the BE-registrations from the network (i.e., 20.4 percent, see Appendix A) consisted of registrations on the

[10] It is, however, difficult to say whether this is a relatively large or small share, in comparison to criminal networks from other articles on the subject. In the article of Bright, et al., 2017, for example, it was mentioned that actors that did not possess any resources were not eligible as replacements, but no numbers were reported of how many actors this comprised. Also in the article of Duijn, et al., 2014, such numbers were not presented.

synthetic drug market, it was assumed that the network predominantly operated on this criminal market. Therefore, the crime script, which formed the basis for the social network simulations, schematically presented the seven stages and nine corresponding resources of the synthetic drug production and trafficking value chain. However, there were also many BE-registrations on other markets, such as violence/threat/abduction (21.1 percent), cocaine (12.6 percent), and other property crimes (8.9 percent), suggesting that the network under study might be operating more as a poly-crime network than solely a synthetic drug production and trafficking network (Spapens, 2017). Consequently, resources might have been inaccurately attributed to actors that actually were not in the criminal value chain of synthetic drug production or trafficking, causing for a discrepancy between the crime script and the resource attribution (e.g., actors with the role organiser/investor/financer for the cocaine market also possessed the resources *Money* and *Information*). As a result, the influence of some actors might have been overestimated, which could have affected the results of the simulations: especially for the information targeting strategy, the intervention might appear less effective, as this resource could have been too loosely attributed.

Furthermore, the data that were used in this research – which were retrieved from the Dutch Police – only consisted of BE-registrations from the unit Northern Netherlands. Even though, in this way, extensive conclusions could be drawn on the network actors within this Police district, it is also possible that these actors have criminal links outside this district on a national and perhaps even an international level (Europol, 2021a). From the BE-registrations of the actors from the network that was studied, could be deduced that there were multiple actors that had a nationality other than Dutch (i.e., Iranian, German, and Dutch Antillean). If those (or other) actors – which are highlighted in Figure 17 – would indeed have (inter)national links to other criminal actors or networks, the network structure could be entirely different: actors that seem to be in the periphery of the network could, for example, actually operate as a broker between different cities or countries (Boivin, 2014). Inspections of the BE-registrations showed that both actors with a Dutch nationality, but a different country of birth (i.e., respectively German and Dutch Antillean), were registered as exporter, and organiser/investor/financer and dealer for the cocaine market. Especially the role of exporter suggests that there, indeed, might be connections to other cities or countries that are currently missing in the data. As a result, this actor – that appears to operate from the periphery of the network and therefore might not be as visible to law enforcement as other actors – could actually be an important key player to the functioning of the network.

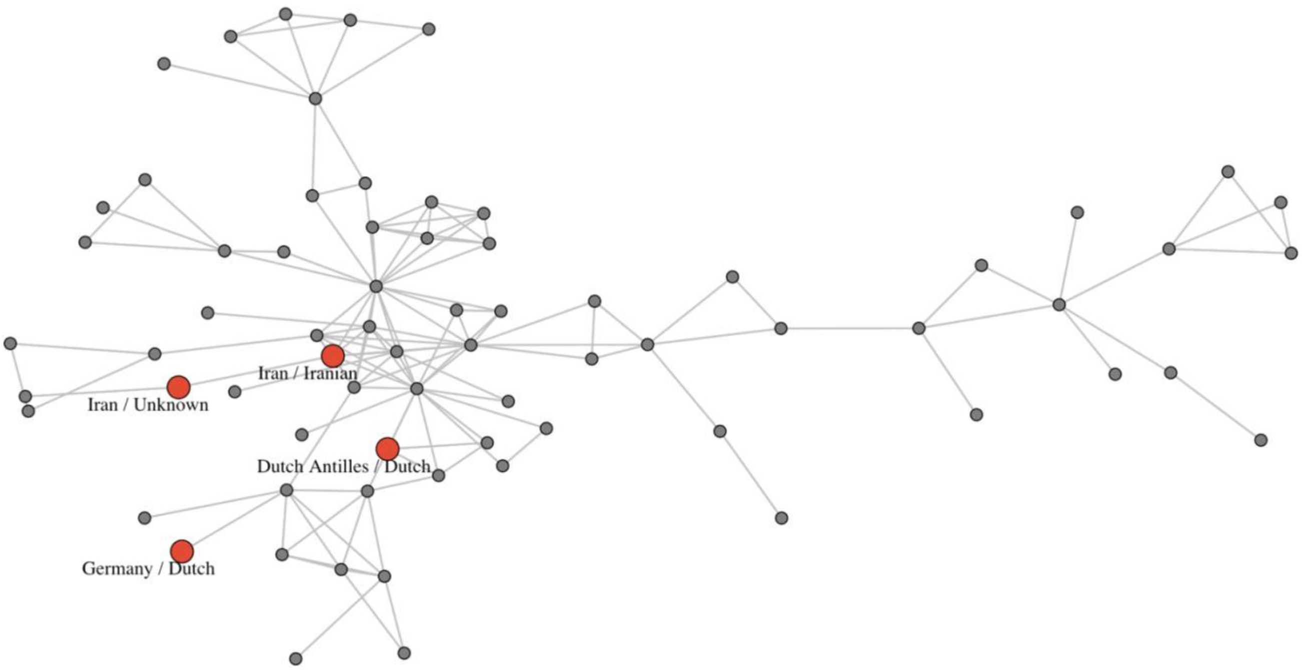

Figure 17. Visualization of actors with a *country of birth/nationality* other than 'Unknown' or 'Netherlands/Dutch'.

5.3. IMPLICATIONS

In order to deal with the aforementioned data deficiencies in future research, the use of crime scripting and social network simulations could, first of all, be supplemented by conducting additional interviews with law enforcement officers, in order to verify the accuracy of the information that is present on the actual nature and extent of the criminal network under study. In this way, it might be easier to establish what the exact role of certain actors is and what the importance of these roles or actors (i.e., actors with a key position, or high centrality score) is for the functioning of the criminal organisation. In addition, information that is not registered as such by law enforcement, for example due to high workload or investigative purposes, can still be included in the research; especially for roles such as '*Indefinable*' and '*Other'*, more information might be known than is apparent from their label (e.g., because they are too complex to capture or embody multiple roles in a single registration). Additionally, it could be verified what the nature of the criminal activities the network performs is or what criminal market it operates on.

Moreover, future research could further adjust and expand the adaptation processes within the social network simulations in several ways to mimic criminal behaviour even more realistically. Following the operationalizations from the article of Bright, et al., 2017, in this current research, the replacement actors could only originate from the existing network and the network was considered to be dismantled when no active components remained – or no replacement actors were present anymore. It is, however, arguable whether this operationalization best reflects real-word criminal behaviour: while actors might seek for replacement within their own network initially, it is more likely that they will subsequently seek replacements outside the network, than quitting their criminal activities altogether (Duijn, et al., 2014). Therefore, by combining these network adaptation operationalizations and allowing the network to seek replacement outside the network, after replacement actors within the original network are not present anymore, could cause for a more dynamic and realistic approach.

In addition, once an actor was removed from the network (i.e., arrested), it could not recur as the simulation progressed. Criminological research, however, shows that recidivism is a common phenomenon: especially in the Netherlands, where penalties for synthetic drug production and trafficking are relatively low on a global scale – which is one of the main reasons it is such an attractive country for these criminal organisations – a prison sentence often has no deterrent effect (van Dijk, et al., 2018; EMCDDA, 2021; Europol, 2021a; LIEC, 2019; Tops & Tromp, 2017; UNODC, 2021). Therefore, in order to enhance realistic modelling of criminal-network behaviour, the possibility of actors to reappear in the network after, for example, six or twelve steps of the social network simulation could therefore be modelled and included in the simulations (i.e., the maximum prison sentence for respectively synthetic drug production and trafficking in the Netherlands (Article 10, Opium Act, 2021)).

Finally, more scientific emphasis should be on the existence of poly-crime and transnational networks (Europol, 2021a; Spapens, 2017; UNODC, 2020; UNODC, 2021). (Inter)national crime assessments have shown that criminal networks are often not limited to one type of crime or one country, as became apparent from the results of this current study as well. That is to say, criminal networks operating in, for example, the trafficking of firearms often also engage in human trafficking and drug trafficking networks appear to engage, for instance, in money laundering as well (Spapens, 2017; UNODC, 2020; UNODC, 2021). By acknowledging the existence of these poly-crime and transnational networks, combining (inter)national criminal data sources, facilitating collaboration between organisations sharing the goal of combatting organised crime, and applying and adapting existing research techniques, interventions aimed at dismantling these networks can be optimized (Boivin, 2014). After all, crime does not stop at borders, so why should law enforcement?

6. LITERATURE

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APPENDIX A – DATA SELECTION AND TRANSFORMATION

In this appendix further specifications on the data selection and transformation processes, that have been carried out in this study, are presented. *R*-scripts that were used can be viewed without request via https://osf.io/ypfsz/?view_only=cdd64d56bef446c5a361477626093333a .

DATA SELECTION

The original data that were used in this study, consisted of two datasets: an edgelist - in which all ties between the actors were noted - and a dataset that consisted the ID-number of the offender, on which of the 29 criminal markets the offence has taken place (e.g., synthetic drugs, weapons, etc.), which role the offender had in the offence (e.g., laboratory technician, burglar, etc.), the age of the offender, the country of birth, and the nationality. In the datasets there was information on 11781 individuals, which together represented 28216 BE-registrations.

For the construction of the social networks, connections - or ties - were considered to be present when two or more actors were jointly registered in one BE-registration. The exact nature of the connections between actors or the offences, however, were unknown. By examining these connections, networks could be identified. These networks, or components, are here referred to as individual connected networks (i.e., all actors were to some extent connected to another actor within the network). Using the R-code provided below, 4307 components could be identified within this dataset.

```
g <- graph_from_data_frame(edgelist, directed = F)
V(g)$component <- components(g)$membership
comp <- data.frame(id = V(g)$name, component_nr = V(g)$component) %>%
as_tibble() %>% arrange(component_nr)
```

For the purpose of the social network simulation, one component was selected from this dataset. As a first selection criterion, the component size was taken into account, resulting in three components that were large enough to be considered eligible for the simulation. The characteristics that were used as selection criteria, of the three largest components are schematically presented in Table A.1. below. Calculations for the results of Table A.1 were performed manually. Therefore, no further R-codes are presented.

Component 7 was eventually chosen for this research, as its characteristics best suited the research objectives. Most importantly, from a theoretical point of view, the criminal markets that the actors within this component were predominantly active in represented *Violence/threat/abduction* and *Synthetic drugs*. The latter is similar to the Methamphetamine network that Bright et al. (2017) studied in their article and as more emphasis should be on the importance of the use of violence and/or weapons within criminal organisations, BE-registrations on this market had to be present. Furthermore, the share of relevant roles was the largest in component 7, which substantially benefits the simulation of the interventions.

DATA TRANSFORMATION

In the original datasets, there was information on the roles that the actors had (e.g., laboratory technician, burglar, etc.) and the criminal markets that they were active on (e.g., synthetic drugs, weapons, etc.). The 70 actors from the selected component represented a total number of 270 BE-registrations, 52 different roles, and 18 different criminal markets. For the purpose of the social network simulation, resources had to be attributed to the actors, using the information from these BE-registrations. Therefore, as a first step, for each role on each criminal market it was determined whether an actor possessed each of the nine resources: money, information, premises, equipment, precursors, skills/knowledge, labour, drugs, and violence/weapons. The resource attribution of the roles is schematically presented in Table A.2 below.

Subsequently, a new dataset was created in which the resources were manually attributed to each of the actors, based on the roles they possessed. If an actor, for example, had been registered as both an Exporter and a Broker (on the cocaine market), it possessed the resources *Information* and *Drugs*. This way, it was possible for actors to possess no, one or more than one resources (see Table 1).

Table A.1. Schematic overview of three largest components and their characteristics: number of actors, numbers of registrations, percentage of relevant roles, total number of criminal markets, and criminal markets with most registrations.

Component characteristics	**Component number**		
	2	**4**	**7**
Number of actors	132	81	70
Number of registrations	564	370	270
Percentage of relevant roles*	55.5	55.2	61.1
Roles with most registrations	Dealer unspecified *(111)*	Owner weapons/ammunition *(32)*	Dealer unspecified *(33)*
*(N)***	Organiser/investor/financer *(27)*	Dealer unspecified *(30)*	Organiser/investor/financer *(14)*
	Executor extortion *(18)*	Fraudster unspecified *(28)*	Executor robbery category 2 *(12)*
Number of criminal markets	21	21	18
Markets with most	Cocaine *(116)*	Fraud/counterfeiting/scamming *(43)*	Violence/threat/abduction *(57)*
registrations *(N)*	Other property crimes *(69)*	Other property crimes *(59)*	Synthetic drugs *(55)*
	Heroine *(65)*	Weapons *(41)*	Cocaine *(34)*

* Some roles were considered to be irrelevant, because they were not necessary for the continuation of the criminal value chain and therefore no resources could be attributed to these roles (e.g., Indefinable, Other, User, Victim, etc.).
** Irrelevant roles excluded.

Table A.2. Schematic overview of the resource attribution of the roles.

Criminal market *(original market in Dutch)*	**Resources**								
Role *(original role in Dutch)*	Money	Information	Premises	Equipment	Precursors	Skills/ Knowledge	Labour	Drugs	Violence/ Weapons
Cocaine *(Cocaïne)*									
Organiser/investor/financer *(Organisator/investeerder/financier)*	Yes	Yes	-	-	-	-	-	-	-
Broker *(Broker)*	-	Yes	-	-	-	-	-	-	-
Owner/possessor batch *(Eigenaar/bezitter partij)*	-	-	-	-	-	-	-	Yes	-
Exporter *(Exporteur)*	-	-	-	-	-	-	-	Yes	-
Stasher *(Stasher)*	-	-	Yes	-	-	-	-	Yes	-
Dealer unspecified *(Handelaar niet gespecificeerd)*	-	-	-	-	-	-	Yes	Yes	-
Courier *(Koerier)*	-	-	-	-	-	-	Yes	Yes	-
User *(Gebruiker)*	-	-	-	-	-	-	-	-	-
Victim/aggrieved *(Slachtoffer/benadeelde)*	-	-	-	-	-	-	-	-	-

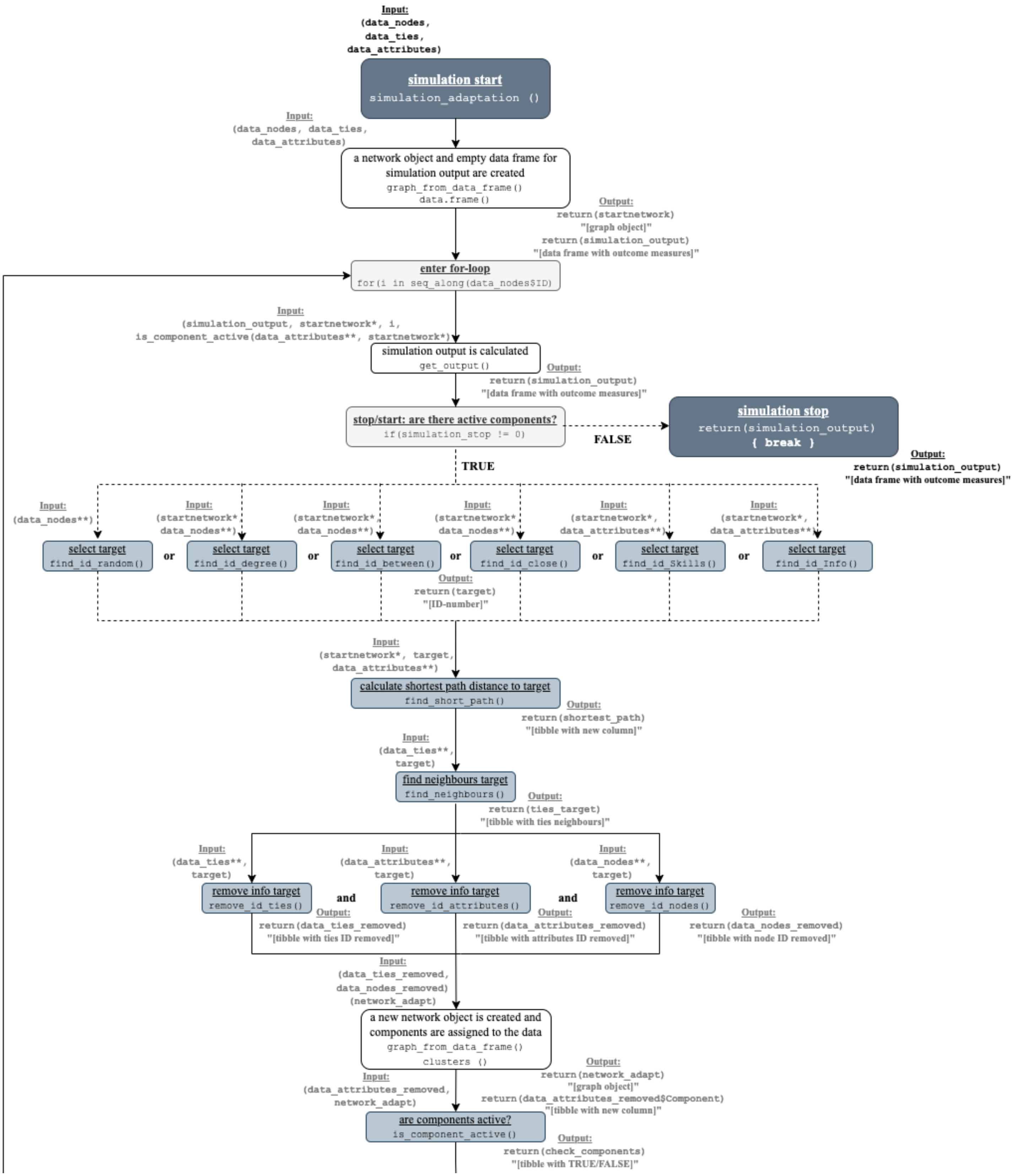
Other *(Overig)*	-	-	-	-	-	-	-	-	-
GHB *(GHB)*									
Broker *(Broker)*	-	Yes	-	-	-	-	-	-	-
Owner/possessor GBL or other (pre)precursors *(Eigenaar/bezitter GBL of andere (pre)precursoren)*	-	-	-	-	Yes	-	-	-	-
User *(Gebruiker)*	-	-	-	-	-	-	-	-	-
Hemp *(Hennep)*									
Organiser/investor/financer *(Organisator/investeerder/financier)*	Yes	Yes	-	-	-	-	-	-	-
Owner/possessor batch *(Eigenaar/bezitter partij)*	-	-	-	-	-	-	-	Yes	-
Owner farm *(Eigenaar kwekerij)*	-	-	Yes	Yes	-	Yes	Yes	Yes	-
Stasher *(Stasher)*	-	-	Yes	-	-	-	-	Yes	-
Transporter *(Transporteur)*	-	-	-	-	-	-	-	Yes	-
Exporter *(Exporteur)*	-	-	-	-	-	-	-	Yes	-
Dealer unspecified *(Handelaar niet gespecificeerd)*	-	-	-	-	-	-	Yes	Yes	-
Heroin *(Heroïne)*									
Organiser/investor/financer *(Organisator/investeerder/financier)*	Yes	Yes	-	-	-	-	-	-	-
Dealer unspecified *(Handelaar niet gespecificeerd)*	-	-	-	-	-	-	Yes	Yes	-
Synthetic drugs: Speed/Amphetamine *(Syndru: Speed Amfetamine)*									
Organiser/investor/financer *(Organisator/investeerder/financier)*	Yes	Yes	-	-	-	-	-	-	-
Supplier/Acquisitor other chemicals *(Leverancier/verwerver andere chemicaliën)*	-	-	-	-	Yes	-	-	-	-
Supplier/Acquisitor (pre)precursors *(Leverancier/verwerver (pre)precursoren)*	-	-	-	-	Yes	-	-	-	-
Laboratory technician/cook *(Laborant/kok)*	-	-	-	-	-	Yes	-	Yes	-

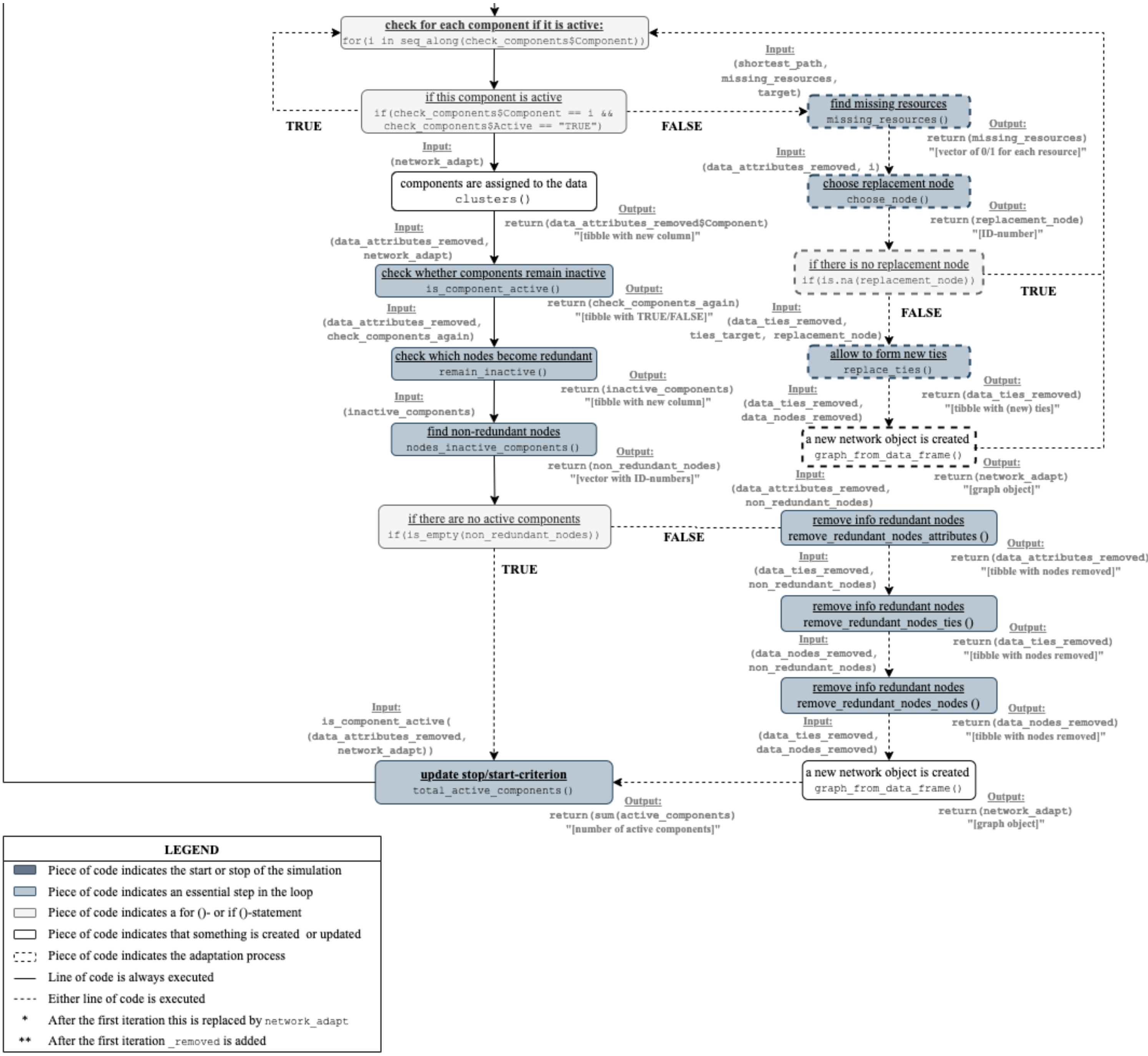
Owner/possessor batch (finished product) *(Eigenaar/bezitter partij (eindproduct))*	-	-	-	-	-	-	-	Yes	-
Dealer 0-100 XTC pills/0-2 kg amphetamine *(Handelaar/dealer 0-100 XTC pillen/0-2 kg afmetamine)*	-	-	-	-	-	-	Yes	Yes	-
Dealer unspecified *(Handelaar niet gespecificeerd)*	-	-	-	-	-	-	Yes	Yes	-
User *(Gebruiker)*	-	-	-	-	-	-	-	-	-
Indefinable *(niet te duiden)*	-	-	-	-	-	-	-	-	-
Synthetic drugs: XTC/MDMA *(Syndru: XTC MDMA)*									
Owner/possessor batch (finished product) *(Eigenaar/bezitter partij (eindproduct))*	-	-	-	-	-	-	-	Yes	-
Dealer unspecified *(Handelaar niet gespecificeerd)*	-	-	-	-	-	-	Yes	Yes	-
User *(Gebruiker)*	-	-	-	-	-	-	-	-	-
Indefinable *(niet te duiden)*	-	-	-	-	-	-	-	-	-
Human trafficking *(Mensenhandel)*									
Pimp/madam *(Pooier/madam)*	-	-	-	-	-	-	-	-	-
Prostitute under coercion *(Prostituee onder dwang)*	-	-	-	-	-	-	-	-	-
Sex offences *(Zedenmisdrijven)*									
Rapist *(Verkrachter)*	-	-	-	-	-	-	-	-	-
Victim *(Slachtoffer)*	-	-	-	-	-	-	-	-	-
Indefinable *(niet te duiden)*	-	-	-	-	-	-	-	-	-
Fraud/counterfeiting/scamming *(Fraude vervalsing oplichting)*									
Organiser/investor/financer *(Organisator/investeerder/financier)*	Yes	Yes	-	-	-	-	-	-	-
Money laundering (criminal) assets *(Witwassen (crimineel) vermogen)*									

Stasher money/luxury goods *(Stasher geld/luxe goederen)*	Yes	-	Yes	-	-	-	-	-	-
Owner money *(Bezitter geld)*	Yes	-	-	-	-	-	-	-	-
Robberies/ram cracks/ explosive cracks *(Overvallen ram- en plofkraken)*									
Executor robbery category 2 *(Uitvoerder overval categorie 2)*	Yes	-	-	-	-	Yes	-	-	Yes
Executor robbery unspecified *(Uitvoerder overval niet gespecificeerd)*	Yes	-	-	-	-	-	-	-	Yes
Healer *(Heler)*	Yes	-	-	-	-	-	-	-	-
Victim/aggrieved *(Slachtoffer/benadeelde)*	-	-	-	-	-	-	-	-	-
Other property crimes *(Overige vermogensmisdrijven)*									
Principal *(Opdrachtgever)*	-	Yes	-	-	-	-	-	-	-
Executor theft *(Uitvoerder diefstal)*	Yes	-	-	-	-	Yes	-	-	-
Burglar *(Inbreker)*	Yes	-	-	-	-	Yes	-	-	-
Healer *(Heler)*	Yes	-	-	-	-	-	-	-	-
Role t.b.d. *(Rol tbd)*	-	-	-	-	-	-	-	-	-
Indefinable *(niet te duiden)*	-	-	-	-	-	-	-	-	-
Extortion debt collection *(Afpersing incasso)*									
Principal extortion *(Opdrachtgever afpersing)*	Yes	Yes	-	-	-	-	-	-	Yes
Principal debt collection *(Opdrachtgever incasso)*	Yes	Yes	-	-	-	-	-	-	Yes
Executor extortion *(Uitvoerder afpersing)*	Yes	-	-	-	-	-	-	-	Yes
Executor debt collection *(Uitvoerder incasso)*	Yes	-	-	-	-	-	-	-	Yes
Ripping *(Rippen)*									
Ripper hemp *(Ripper hennep)*	-	-	-	-	-	-	-	Yes	Yes
Victim ripping *(Slachtoffer rip)*	-	-	-	-	-	-	-	-	-
Liquidation/murder/homicide *(Liquidatie moord doodslag)*									
Principal/financer *(Opdrachtgever/financier)*	Yes	Yes	-	-	-	-	-	-	Yes
Executor shooter/offender *(Uitvoerder schutter/dader)*	-	-	-	-	-	-	-	-	Yes

Executor other *(Uitvoerder overig)*	-	-	-	-	-	-	-	-	Yes
Other *(Overig)*	-	-	-	-	-	-	-	-	-
Victim *(Slachtoffer)*	-	-	-	-	-	-	-	-	-
Indefinable *(Niet te duiden)*	-	-	-	-	-	-	-	-	-
Violence/threat/abduction ***(Geweld bedreiging ontvoering)***									
Executor attempted homicide/murder *(Uitvoerder poging doodslag/moord)*	-	-	-	-	-	-	-	-	Yes
Executor deprivation of liberty *(Uitvoerder vrijheidsbeneming)*	-	-	-	-	-	-	-	-	Yes
Executor serious assault *(Uitvoerder zware mishandeling)*	-	-	-	-	-	-	-	-	Yes
Executor simple assault *(Uitvoering eenvoudige mishandeling)*	-	-	-	-	-	-	-	-	Yes
Executor threat *(Uitvoerder bedreiging)*	-	-	-	-	-	-	-	-	Yes
Executor domestic violence *(Uitvoerder huiselijk geweld)*	-	-	-	-	-	-	-	-	Yes
Victim threat *(Slachtoffer bedreiging)*	-	-	-	-	-	-	-	-	-
Victim other violence *(Slachtoffer geweld overig)*	-	-	-	-	-	-	-	-	-
Role t.b.d. *(Rol tbd)*	-	-	-	-	-	-	-	-	-
Weapons ***(Wapens)***									
Owner weapons/ammunition and/or explosives *(Bezitter wapens/munitie en/of explosieven)*	-	-	-	-	-	-	-	-	Yes
Dealer 1 item *(Handelaar 1 stuk)*	-	-	-	-	-	-	-	-	Yes
Other *(Overig)*	-	-	-	-	-	-	-	-	-
Role t.b.d. *(Rol tbd)*	-	-	-	-	-	-	-	-	-
Indefinable *(niet te duiden)*	-	-	-	-	-	-	-	-	-
NA ***(NA)***									
NA *(NA)*	-	-	-	-	-	-	-	-	-

APPENDIX B – SIMULATION FLOW DIAGRAM




check for each component if it is active:
for(i in seq_along(check_components$Component))
if this component is active
if(check_components$Component == 1 &&
check_components$Active == "TRUE")
TRUE
FALSE
Input:
(network_adapt)
components are assigned to the data
clusters()
Output:
return(data_attributes_removed$Component)
"[tibble with new column]"
Input:
(data_attributes_removed,
network_adapt)
check whether components remain inactive
is_component_active()
Output:
return(check_components_again)
"[tibble with TRUE/FALSE]"
Input:
(data_attributes_removed,
check_components_again)
check which nodes become redundant
remain_inactive()
Output:
return(inactive_components)
"[tibble with new column]"
Input:
(inactive_components)
find non-redundant nodes
nodes_inactive_components()
Output:
return(non_redundant_nodes)
"[vector with ID-numbers]"
if there are no active components
if(is_empty(non_redundant_nodes))
FALSE
TRUE
Input:
is_component_active(
(data_attributes_removed,
network_adapt))
update stop/start-criterion
total_active_components()
Output:
return(sum(active_components)
"[number of active components]"
Input:
(shortest_path,
missing_resources,
target)
find missing resources
missing_resources()
Output:
return(missing_resources)
"[vector of 0/1 for each resource]"
Input:
(data_attributes_removed, i)
choose replacement node
choose_node()
Output:
return(replacement_node)
"[ID-number]"
if there is no replacement node
if(is.na(replacement_node))
TRUE
FALSE
Input:
(data_ties_removed,
ties_target, replacement_node)
allow to form new ties
replace_ties()
Output:
return(data_ties_removed)
"[tibble with (new) ties]"
Input:
(data_ties_removed,
data_nodes_removed)
a new network object is created
graph_from_data_frame()
Output:
return(network_adapt)
"[graph object]"
Input:
(data_attributes_removed,
non_redundant_nodes)
remove info redundant nodes
remove_redundant_nodes_attributes ()
Output:
return(data_attributes_removed)
"[tibble with nodes removed]"
Input:
(data_ties_removed,
non_redundant_nodes)
remove info redundant nodes
remove_redundant_nodes_ties ()
Output:
return(data_ties_removed)
"[tibble with nodes removed]"
Input:
(data_nodes_removed,
non_redundant_nodes)
remove info redundant nodes
remove_redundant_nodes_nodes ()
Output:
return(data_nodes_removed)
"[tibble with nodes removed]"
Input:
(data_ties_removed,
data_nodes_removed)
a new network object is created
graph_from_data_frame()
Output:
return(network_adapt)
"[graph object]"
LEGEND
Piece of code indicates the start or stop of the simulation
Piece of code indicates an essential step in the loop
Piece of code indicates a for ()- or if ()-statement
Piece of code indicates that something is created or updated
Piece of code indicates the adaptation process
Line of code is always executed
Either line of code is executed
* After the first iteration this is replaced by network_adapt
** After the first iteration _removed is added

APPENDIX C – SUPPLEMENTARY RESULTS

DESCRIPTION OF THE NETWORK

Actor-level analysis of the network

In Figure C.1. on the next page, the visualizations of the network are presented highlighting the resource distributions per resource. These figures can be used to illustrate where certain resources are located and whether patterns can become visible in the resource distribution. For example, for the resource *Skills/Knowledge,* actors appear to be generally located in between different subgroups: they connect different parts of the network. Furthermore, in Table C.1. the roles of the actors that were most likely to be targeted by the simulations, that could be deduced from the BE-registrations, are presented. An interesting observation that can be deduced from this table is that, for actor *5107,* the BE-registrations give a strong indication of its role within the network, while that is not the case for the other two actors. For actor *10807* and actor *4436*, the markets that they operate on reveal some information of what their role might be, but it remains unclear what the exact nature of their position in the network is.

Table C.1. Overview of the roles and markets of the actors that were most likely to be targeted.

Actor*	**Market**	**Role**	**(frequency)**
5107			
	Cocaine	Dealer unspecified	(2)
	Other property crimes	Healer	(1)
		Victim/aggrieved	(1)
		Role t.b.d.	(1)
	Synthetic drugs: Speed/Amphetamine	Organiser/investor/financer	(2)
		Laboratory technician/cook	(1)
		Supplier/acquisitor other chemicals	(1)
10807			
	Extortion debt collection	Executor debt collection	(1)
	Other property crimes	Principal	(1)
		Role t.b.d.	(1)
	Violence/threat/abduction	Role t.b.d.	(2)
4436			
	Other property crimes	Healer	(1)
		Role t.b.d.	(1)
	Weapons	Indefinable	(2)

*In order likeliness.

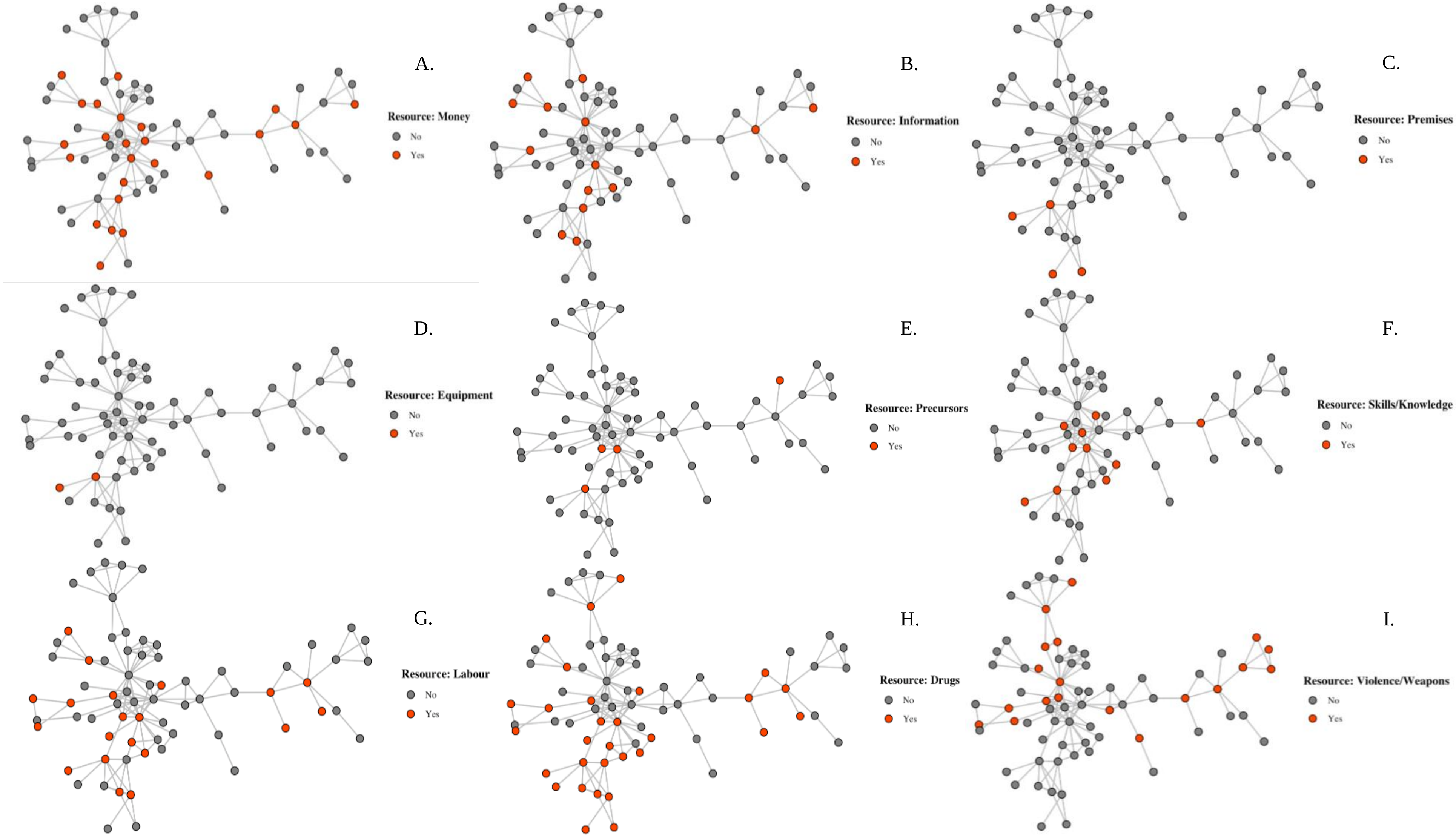


Figure C.1. Visualization of the resource distribution across the overall network for the resources: (**A.**) Money, (**B.**) Information, (**C.**) Premises, (**D.**) Equipment, (**E.**) Precursors, (**F.**) Skills/Knowledge, (**G.**) Labour, (**H.**) Drugs, and (**I.**) Violence/Weapons.

ACTOR-LEVEL OUTCOMES

In order to compare the actors that were most likely to be targeted and actors that were actually targeted in the social network simulation, for each targeting strategy, 10 runs of the simulation were performed manually. The results from these simulation runs are shown in Table C.2. below, to see whether any patterns can be deduced from the actor removal strategies. An interesting observation that results from this table is that, for almost all targeting strategies, there was little to no variation in the actors that were removed from the network in the first three steps of the simulation; only for closeness targeting those actors were different in each simulation run.

Table C.2. Overview of the actors that were removed in each step within the simulation for each targeting strategy.

Targeting strategy	**Step**	**Simulation**									
		1	2	3	4	5	6	7	8	9	10
Degree											
	1	**10807**	**10807**	**10807**	**10807**	**10807**	**10807**	**10807**	**10807**	**10807**	**10807**
	2	5107	7674	7674	5107	7674	5107	5107	5107	5107	5107
	3	7674	5107	5107	7674	5107	7674	7674	7674	7674	7674
	4	4436	4436	4436	4436	4436	4436	4436	4436	4436	4436
	5	**6523**	**6523**	**6523**	6934	**6523**	**6523**	**6523**	6934	**6523**	**6523**
	6				**6523**				3835		
	7								9171		
	8								**6523**		
Betweenness											
	1	**10807**	**10807**	**10807**	**10807**	**10807**	**10807**	**10807**	10807	**10807**	**10807**
	2	**7674**	**7674**	**7674**	**7674**	**7674**	**7674**	**7674**	**7674**	**7674**	**7674**
	3	**4436**	5107	**4436**	**4436**	**4436**	**4436**	**6523**	**6523**	**6523**	**4436**
	4	**6523**	**4436**	**6523**	**6523**	**6523**	**6523**				**6523**
	5		**6523**								
Closeness											
	1	**4436**	**4436**	**4436**	**4436**	**4436**	**4436**	**4436**	**4436**	**4436**	**4436**
	2	3835	10807	6663	5107	10807	10807	7674	6663	10807	6663
	3	11439	7674	9952	9952	7674	7674	10807	3835	7674	7674
	4	5394	**6523**	5394	5394	6523	5107	**6523**	9952	**6523**	5107
	5	10030		5107	3017		**6523**		7674		**6523**
	6	10907		7674	6541				5394		
	7	5107		**6523**	7674				10907		
	8	7674							10030		
	9	**6523**							5107		
	10								3017		
	11								3233		

Skills/Knowledge											
	1	**5107**	5107	**5107**	**5107**	**5107**	**5107**	**5107**	**5107**	**5107**	**5107**
	2	**3835**	3835	**3835**	**3835**	**3835**	**3835**	**3835**	**3835**	**3835**	**3835**
	3	**7674**	7674	**7674**	**7674**	**7674**	**7674**	**7674**	**7674**	**7674**	**7674**
	4	6663	6663	5394	5394	5394	5394	5394	5394	5394	6663
	5	5394	5394	**3464**	**3464**	**3464**	**3464**	**3464**	**3464**	**3464**	5394
	6	3464	3464								3464
	7	10907	10907								**6523**
	8	**6523**	**6523**								
Information											
	1	**10807**	**10807**	**10807**	**10807**	**10807**	**10807**	**10807**	**10807**	**10807**	**10807**
	2	**5107**	**5107**	**5107**	**5107**	**5107**	**5107**	**5107**	**5107**	**5107**	**5107**
	3	**9171**	**9171**	**9171**	**9171**	**9171**	**9171**	**9171**	**9171**	**9171**	**9171**
	4	11436	3268	11436	3268	11436	11436	11436	11436	3268	3268
	5	9998	9998	9998	9998	3268	9998	9998	9998	9998	9998
	6	3268	11436	3268	11436	8159	3268	3268	3268	11436	11436
	7	8159	8159	8159	8159	7747	8159	8159	8159	8159	8988
	8	7747	7747	8988	7747	11429	7747	7747	8988	7747	8159
	9	11429	11429	7747	11429		11429	11429	7747	11429	7747
	10			11429					11429		11429

In Table C.3. the roles of the actors that were most often removed from the network, according to the different targeting strategies, are presented. These actors were chosen based on the results from Table C.2. and had to either be removed in the first three steps of the simulation in at least three runs, or in the first four steps in at least three runs and appear in at least one run of another strategy. An exception to this selection criterion was made for actor *6523* as for most strategies the simulation stopped running – and the network was considered fully disrupted – immediately after this actor was removed from the network.

Table C.3. Overview of the roles and markets of the actors that were most often targeted in the simulations.

Actor*	**Market**	**Role (frequency)**	
5107			
	Cocaine	Dealer unspecified	(2)
	Other property crimes	Healer	(1)
		Victim/aggrieved	(1)
		Role t.b.d.	(1)
	Synthetic drugs: Speed/Amphetamine	Organiser/investor/financer	(2)
		Laboratory technician/cook	(1)
		Supplier/acquisitor other chemicals	(1)
10807			
	Extortion debt collection	Executor debt collection	(1)
	Other property crimes	Principal	(1)
		Role t.b.d.	(1)
	Violence/threat/abduction	Role t.b.d.	(2)

4436			
	Other property crimes	Healer	(1)
		Role t.b.d.	(1)
	Weapons	Indefinable	(2)
6523			
	Hemp	Owner farm	(1)
7674			
	Cocaine	Exporter	(1)
	Hemp	Dealer unspecified	(1)
		Owner farm	(1)
		Transporter	(1)
	Synthetic drugs: Speed/Amphetamine	Supplier/acquisitor other chemicals	(1)
3835			
	GHB	User	(1)
	Other property crimes	Burglar	(2)
		Executor theft	(1)
		Role t.b.d.	(1)
9171			
	Cocaine	Other	(1)
	GHB	Broker	(1)
	Other property crimes	Undefinable	(1)
	Robberies/ram cracks/explosive cracks	Executor robbery category 2	(4)
	Synthetic drugs: Speed/Amphetamine	Dealer unspecified	(3)
		Owner/possessor batch (finished product)	(4)
		Undefinable	(2)
		User	(4)
	Synthetic drugs: XTC/MDMA	Dealer unspecified	(1)
		Undefinable	(1)
		User	(1)
6663			
	Cocaine	Dealer unspecified	(1)
	Human trafficking	Prostitute under coercion	(1)
	Other property crimes	Burglar	(1)
		Healer	(1)
		Role t.b.d.	(1)
	Weapons	Owner weapons/ammunition and/or explosives	(1)
5394			
	Other property crimes	Role t.b.d.	(1)
	Synthetic drugs: Speed/Amphetamine	Dealer unspecified	(1)
		Laboratory technician/cook	(1)
		Supplier/acquisitor (pre)precursors	(1)

*In no particular order.

APPENDIX D – SIMULATIONS WITH EQUIPMENT EXCLUDED

In the overall network, there were only two actors that possessed the resource *Equipment* (see Table 1). Further analyses of the social network simulation showed that for all social capital targeting strategies (i.e., degree, betweenness, and closeness centrality targeting), the network was completely disrupted immediately after those two actors – actor *6523* and actor *7674* – were removed from the network. To ascertain whether the influence of the actors that were responsible for provision of equipment was disproportionate, the simulations were performed without this resource as well.

Table D.1. shows the results for the simulation without adaptation, in which equipment was excluded as a resource that a component had to require in order to remain active. Except for a slight increase in the total number of steps for the random targeting strategy (i.e., one additional step for the median), the results did not seem to be affected by the exclusion of equipment at all.

Table D.1. Outcomes for the number of steps required until there are no active components remaining for all interventions without adaptation, this time with **Equipment** excluded.

Targeting strategy	Mean	Standard deviation	Median	Minimum	Maximum
Random	22.9	8.1	24	5	41
Degree	5.0	0	5	5	5
Betweenness	5.0	0	5	5	5
Closeness	5.0	0	5	5	5
Skills/Knowledge	4.0	0	4	4	4
Information	8.0	0	8	8	8

The results from Table D.2. however, reveal that indeed, for most strategies, the simulation was slightly influenced by the two actors that possessed the resource *Equipment*: for closeness targeting the median number of steps increased with three steps, for degree and betweenness targeting with two additional steps, and for skills/knowledge targeting with one additional step. Where skills/knowledge targeting at first appeared the third most effective law enforcement intervention, according to the total number of steps, it is now the most effective intervention. The relatively large standard deviation for skills/knowledge targeting (2.2) however, also indicates that it is one of the least robust interventions. While it is important to take these findings into account for the interpretation of the results, no changes were made to the social network simulation, as the results did not substantially differ when the resource *Equipment* was excluded.

Table D.2. Outcomes for the number of steps required until there are no active components remaining for all interventions with adaptation, this time with **Equipment** excluded.

Targeting strategy	Mean	Standard deviation	Median	Minimum	Maximum
Random	34.0	9.4	34	6	53
Degree	9.8	3.0	8	4	18
Betweenness	6.9	0.8	7	6	10
Closeness	8.1	1.4	8	5	13
Skills/Knowledge	**6.4**	**2.2**	**7**	**4**	**9**
Information	10.3	0.5	10	9	11