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The Identification & Ranking of Organised Crime Groups and Members: Combining the Crime Harm Index (CHI) and Social Network Analysis (SNA)

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Abstract

This research aims to examine the performance of combining the Crime Harm Index (CHI) with Social Network Analysis (SNA), to assist in the identification and ranking of known and previously unknown Organised Crime Groups (OCGs) and Group Members. The results are then compared to the current policing methods used in the OCG Mapping Tracker.

Data set 1 consists of 760 known OCG members recorded in 3,092 crimes and 22,588 intelligence logs. Data set 2 consists of all crime and intelligence in the Wycombe policing area involving 17,938 persons, recorded in 21,516 crimes and 17,810 intelligence logs. The data period for both sets is from 1st April 2014 to 31st March 2017. The descriptive variables include aggregated Crime Harm Index (CHI) values, Network Degree Centrality measures, and OCG Mapping Tracker scores.

This is a cross-sectional explorative analysis. In both data sets, the CHI values were attributed to each crime and then aggregated for each person and OCG. Crime and Intelligence Data was charted, and the network degree centralities calculated. Principal Component Analysis was performed on the CHI, Crime Degree, and Intelligence Degree measures for persons and groups to create a new metric called the Network Harm Index (NHI). Community Detection was then used to partition the network. The CHI Power Few, NHI Power Few and Detected Communities were compared to existing OCG structures recorded in the police force's OCG Mapping Tracker.

The results showed that the NHI and Tracker agreed on 5 out 29 OCGs ranked in the power few. Analysis of the crime types showed that the NHI prioritised OCGs specialising in Drug Supply and Exploitation, whereas the Tracker prioritised OCGs

specialising in Fraud. This reveals that data external to local systems was being considered in the Tracker which was not available to the NHI, and suggests improvements need to be made to crime and intelligence recording practices. The CHI was successfully implemented as an objective way to measure the harm perpetrated by OCGs and OCG Members. A power few of 474 (3%) were shown to be perpetrating the most harm in the Wycombe LPA, 24 of which were OCG members in the Tracker. The NHI identified a power few of 103 (0.57%), 30 of which were OCG members recorded in the Tracker. The NHI identified an additional 21 offenders matching the definition of organised criminal activity, that were not being monitored by police.

Implications Statement

This is the first study that jointly applies SNA & the CHI to create a single objective index for the purposes of identifying and ranking known and previously unknown OCGs and OCG members. It therefore offers a new tool for targeting, resource allocation, and the setting of priorities. The analysis uses simple data points which can be applied by any law enforcement agency and presents a methodological foundation for the design of computer systems, which can identify and prioritise organised crime. Investment in such a system would deliver valuable insights and the ability to develop cost effective proactive and preventative strategies, particularly if scaled to a national level.

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1. Introduction

Organised crime gains considerable political, public, and media attention. Towards the end of 2016, there were an estimated 5,866 Organised Crime Groups (OCGs) operating in the UK, consisting of 39,414 individuals (NCA, 2017). Organised criminals are some of the most serious offenders in society, responsible for the most harmful and costly crimes. They are difficult to detect, and the spectrum of offences has become ever more complex with technology playing an increasing role. The UK is entering a period of growing economic uncertainty, the conditions of which tend to foster increases in organised criminality (Van Dijk, 2007). It is therefore more important than ever, that law enforcement is doing everything it can to improve its capability in combatting organised crime.

Law enforcement agencies around the world employ various risk assessment methodologies to prioritise organised crime and enable the implementation of cost effective proactive and preventative strategies (Tusikov, 2011). However, academics have pointed out serious methodological weaknesses and concerns surrounding law enforcement claims of analytical objectivity and suggest that offender targeting processes are just confirmatory tools for the police to forward an already established agenda (Innes et al., 2005). Many of the assessments purport to measure “harm”, however there is a lack of research as to how this is achieved, which might reflect the implementation of an unstructured or weak methodology (Zoutendijk, 2010).

The Crime Harm Index (CHI) is an opportunity to introduce greater objectivity into the assessment of OCGs, and its usefulness in ranking and understanding the concentrations of harm in crime is well documented (Bland and Ariel, 2014; Dudfield et al., 2017; Sherman et al., 2016; Weinborn, 2017). The CHI is designed using sentencing guidelines to provide a standardised, objective means to apply a measure of harm to varying crime types (Sherman et al., 2014). By using the CHI to measure the harm perpetrated by OCG members it will be possible to address some of the limitations in current law enforcement risk assessment processes.

This research proposes a new approach to identifying and ranking Organised Crime Groups and Group Members, by using the Crime Harm Index (CHI) to measure concentrations of harm and Social Network Analysis (SNA) to measure the degree of co-offending and intelligence association. With the exceptions of Hallworth (2016) and Jeffery (2012 cited Crocker et al., 2016), few studies have formally identified whether OCG members engage in higher harm offences. However, increased co-offending is associated with a sustained criminal career (Andresen and Felson, 2011; McAndrew, 2000) and OCG members are known to co-offend more frequently than typical offenders (Campana and Varese, 2013; Morselli, 2009). In addition to co-offending data, intelligence association is also used in the network to fill the gaps in undetected crime. By combining crime and intelligence data sources, the network will have further information to increase the reliability of SNA (Rostami, 2015).

SNA has now become a mainstream approach in Criminology and has secured notable improvements over traditional methods of measuring social structure and influence (Bouchard & Malm, 2016). Its roots can be traced back as far as Auguste Comte, who posited that the scientific study of society should focus on patterns in social connections, while Emile Durkheim made references to the importance of social ties (Gravel & Tita, 2017). SNA is often thought of as a novelty, but in reality it is an example of where methodological and technological advances are finally catching up with theoretical ideas (Morselli, 2009).

This cross-sectional exploratory research will break new ground by using data reduction techniques to combine the CHI and Degree Centralities for OCGs and OCG members into a new index to measure organised crime. This single measure will provide an objective means of assessing organised crime and has been termed the Network Harm Index.

The techniques are performed on Police Crime and Intelligence data sets to extract information, and are arguably almost impossible for Crime Analysts or Serious and Organised Crime Teams to achieve by traditional methods. Firstly, the research will aim to determine if the objective measures of harm and degree network centrality can be used as an effective means of ranking known OCGs and OCG members. Secondly, the research uses the same methods to identify previously unknown OCGs and OCG members in a larger data set.

In this research, two data sets will be analysed. The first includes 126 OCGs consisting of 760 OCG members, being monitored by Thames Valley Police between 01/04/2015 and 31/03/2017. The total number of intelligence logs recorded for OCG members is 22,588 and the total number of crimes recorded for OCG members is 3,093. There are a total of 756 instances of association between OCGs.

The second data set includes all offence and intelligence that occurred in the Wycombe Local Policing Area (LPA) between the dates of 01/04/2014 and 31/03/2017. The network consists of 17,938 persons, 21,516 crimes and 17,810 intelligence reports. The total number of associations via crime and intelligence is 29,738.

The production of the Network Harm Index involves four main sections of analysis: 1) The application of the CHI; 2) the networking of crime and intelligence data; 3) Principal Component Analysis of the CHI values and SNA Degree Centralities and; 4) Community Detection algorithms. The results are then compared to current methods of OCG assessment to determine the performance of the methodology. Firstly though, the available body of work will be reviewed on Organised Crime, OCG Risk Assessments, the Crime Harm Index (CHI), and Social Network Analysis (SNA), before returning to the study in Thames Valley Police.

2. Literature Review

The nature of organised crime constitutes a problem for law enforcement. Firstly, there is difficulty in defining organised crime, which is sculpted by the society in which it operates. Secondly, organised crime is inherently clandestine, meaning it is impossible to know the extent to which it is taking place in society and by whom. Thirdly, organised crime may or may not, be structured in such a way that there exists a permanent set of individuals who conspire to commit crime, for whatever reason, over a sustained duration. The successful detection and apprehension of individuals engaging in prolonged organised crime is therefore illusive.

This literature review will examine the nature of organised crime and illustrate how UK Police Forces currently prioritise organised crime threats. It will discuss the advantages of a Crime Harm Index (CHI) and how this can be used to objectively measure harm concentrations. Furthermore, the technique of Social Network Analysis (SNA) will be discussed regarding its ability to understand organised crime though patterns in co-offending and intelligence networks. There will also be a review of the quality of different data types and how these can be best used to measure organised activity.

2.1 Organised Crime

Organised crime is difficult to define, and the terminology covers a range of activities from the traditional concept of the Mafia, to more contemporary examples of drug supply lines and street gangs. Definitions of organised crime tend to differ considerably at international, national, and even organisational levels. Indeed, von

Lampe (2012) compiled a list of some 190 definitions of organised crime by different countries, agencies, institutions and academics. Legislation in some countries, such as Italy, makes it a crime to be associated to organised crime groups such as the Mafia (Campana and Varese, 2013).

Within England and Wales there is no legal definition, and various government agencies and police forces work to different criteria when classifying organised crime. Definitions also differ between the criminal justice world and that of academia, possibly affecting the validity of findings when applied to a law enforcement setting. Most experts agree however, that the standard criteria for identification of organised criminals should be the extent to which individuals are involved in crime (Tayebi & Glasser, 2012; Tusikov, 2011; Wortley, 2010).

Thames Valley Police uses a paragraph from a 2013 Home Office report for a definition, which states, "O*rganised crime is serious crime planned, coordinated and conducted by people working together on a continuing basis. Their motivation is often, but not always, financial gain. Organised crime is characterised by violence or the threat of violence and by the use of bribery and corruption"* (Home Office, 2013).

The Crown Prosecution Service (CPS) provides the definition of an organised crime group, but not of organised crime. "*An organised crime group is defined as a group which has at its purpose, or one of its purposes, the carrying on of criminal activities and consists of three or more people who agree to act together to further that purpose"* (CPS, 2015).

These definitions are quite vague and therefore it is easy to see how organisations can take different interpretations. Organised crime is always evolving, and divergent interpretation by law enforcement could result in the irregular inclusion or exclusion of individuals for the focus of police activity. This makes it very difficult to assess the reliability and validity of various law enforcement tactics in different jurisdictions.

The very nature of an OCG makes activity particularly difficult to detect. For many OCGs, their ability to operate covertly, directly impacts their ability to evade detection. To avoid being targeted by the police, groups need to keep their activities covert, but at the same time, the group needs to communicate to plan activities and forge new relationships (Fielding, 2016). This is known as the Efficiency -Security Trade Off (Morselli, 2007) and creates an operational conflict and opens the OCG to risk. Indeed, nearly all organised crime groups that come to police attention do so because of a tip off, meaning that highly professional organised groups are unlikely to be identified (Morselli, 2009). This means that the true number of OCGs remains unknown and those that are successfully disrupted are likely to be the least competent or most overt.

Another issue that complicates the successful apprehension of organised criminals is that they are transient. OCGs in the UK have been shown to differ from the traditional concepts such as the Mafia, in that they are a series of temporary social arrangements between a constantly changing group of individuals (Hobbs, 1997). As a result, OCG members may only be aware of their own activities, and therefore completely naïve to the fact they are part of a greater network (Morselli, 2009). This organic and fluid social structure makes defining a group of organised collaboration particularly difficult.

2.2 OCG Risk Assessments

To manage the resources deployed on OCGs, law enforcement requires a means to prioritise the most harmful. Thames Valley Police currently uses two models to score OCGs. The first is the Organised Crime Group Mapping (OCGM) index, in operation since 2009, which collects data from police forces and is periodically aggregated at a national level by the National Crime Agency (NCA). The second includes the Management of Risk in Law Enforcement (MoRiLE), which is a risk assessment model that attempts to score organisational, strategic, operational, and tactical risks through a series of questions. The model is designed to provide consistent assessment across a number of business areas, of which organised crime is but only one. MoRiLE is still in development and has been in use for less than a year within Thames Valley Police, so the necessary data is not available for analysis over an extended period. For this reason, the thesis will be analysing data obtained through the OCGM model.

The OCGM process has three elements which include criminal activity, intent and capability, and intelligence quality and coverage (Organised Crime Partnership Board, 2010). The criminal activity scores represent proxy measures of the physical, community, financial, and political impact of organised crime. Intent captures the motivation of an OCG, and capability is determined by both the resources accessible to a group and the skills and knowledge available. The last element provides an assessment of the intelligence quality and coverage that has been utilised. The resulting output is a matrix which supports law enforcement decision making on how to invest resources for further intelligence gathering and operational activity.

The model has been designed to ask the questions relevant to making informed decisions on how to invest resources. The methods address a wide range of issues that contribute to risk and harm, however they rely on the user to correctly interpret the question, attribute the correct score, and record it correctly. To ensure a quality output, comprehensive understanding is required on behalf of the practitioner on information from a number of disparate and complex data sources. This results in a subjective process in which forces users take a 'best guess' approach to assessment (Tusikov, 2012).

Law enforcement assessments address threat, risk, and harm, however they do not do so in the most accurate and measurable way (Tusikov, 2012). A study of clinical versus statistical analyses performed by Paul Meehl (1952) in patient prognosis and treatment, found that 60% of statistical analyses outperformed human intuition, and that the remaining 40% of analyses were equally as good as human intuition. Moreover, the statistical analysis was conducted at a far lesser financial cost than when performed by a practitioner (Kahneman, 2011). Currently, Thames Valley Police employs an Organised Crime Group Mapping (OCGM) Coordinator and Researcher, to conduct the risk assessments and compile scores from OCGs across the jurisdiction, into a coherent product. In an ideal environment, assessment would be performed via a software solution that sources data stored in police systems, which frees up the time for the coordinator to work on novel resourcing solutions. However, the IT infrastructure does not exist for this to be a reality and until such time that algorithms can produce a risk assessment from all objective data available, it would be wise to focus efforts on automating feasible elements in isolation.

2.3 The Crime Harm Index (CHI)

It has long been known that crimes are not distributed evenly in space and time. In Minneapolis, Sherman et al., (1989) showed that over half of all calls to police were concentrated in just 3.3% of places. The distributions observed reflect those frequently observed in nature and in disciplines such as economics, business, and more. This is described by the Pareto Principle, or more commonly known as the 80/20 rule, where roughly 80% of effects originate from 20% of causes (Sherman, 2007). Regarding crime, this concentration of persons, places, or events has been coined the "power few" (Sherman, 2007). This finding has gained a strong evidence base in policing and it stands to reason that if law enforcement were to target the power few, then the finite resources available will be utilised to premium effect and maximum return on investment.

Recently, it has been acknowledged that not all crimes are created equal, and counting them as such fosters distortion of risk assessments, resource allocation, and accountability (Sherman, 2016). Some crimes are far more harmful than others and are worthy of greater resourcing. An extreme example would be the resources allocated to a murder in comparison to a shoplifting. By measuring the severity of different crime types, it is possible to take a triage approach to the prioritisation of resources.

The Crime Harm Index (CHI) is designed for this purpose and is formed using sentencing guidelines to provide a standardised, objective means to apply a measure of harm to varying crime types (Sherman et al., 2014). These measures are obtained from the Sentencing Council Guidelines which show the recommended number of days sentencing for particular crime types. Sentencing guidelines are designed to ensure that

Courts across England and Wales have a consistent approach. The technique of applying the CHI to prioritise particular persons, places, or events has been gaining traction in law enforcement over the recent years and this has led to considerable changes to the way that some agencies approach the allocation of resources (Dudfield et al., 2017).

For example, research into 36,000 domestic violence offences in Suffolk Constabulary between 2009 and 2014 showed that only 2% of couples accounted for 80% of the total harm (Bland and Ariel, 2015). Another example includes victimisation data from Dorset Police, where Dudfield et al., (2017), found that over one year, under 4% of victims suffered 85% of total harm. Further recent evidence comes from Weinborn et al., (2017) who used harm as an alternative to crime frequency in the identification of “hotspots”. In councils across the UK, the spatial analysis of crime concentrations compared to harm concentrations, showed that half of all crime events were concentrated within 3% of locations, whereas half of all harm was located in just 1% of locations. These findings show distributions consistent with those found by Sherman in Minneapolis and they have profound implications for the development of cost effective prevention strategies.

Thames Valley Police’s 3rd Strategic Objective in 2017 is “To protect our communities from the most serious harm”. Yet we do not currently measure harm in such an objective way and therefore we cannot triage as effectively as possible. As previously argued, current models rely on the practitioner to report the type and extent of offending subjectively. The danger is that the practitioner will have limited capability to assess harm across varying crime types and may unwittingly place too much emphasis on the frequency of crime rather than the severity. There is a risk that current models ask the practitioner to do the impossible and any resulting highly scored OCGs may not correlate with OCGs perpetrating the most harm in reality. The inclusion of the CHI into this research aims to provide a more accurate measure of harm perpetrated by OCGs for the purposes of identifying organised crime and ranking those groups so that the most serious can be allocated the fair share of resources available.

2.4 Network Analysis

Networks analysis enables law enforcement to look at criminality in terms of social systems rather than the individual perspective and theorises that individual behaviours are shaped by the influences around them (Borgatti et al., 2013). Network analysis has been shown to provide great value to crime enforcement and prevention (Berlusconi, 2017), however the complexity of the literature has often meant the techniques are overlooked (Coles, 2001). Network analysis allows the practitioner to seek out the structure of an organised crime group (Morselli, 2009) and allows the use of empirical evidence rather than just assume key players via clinical experience or an incomplete intelligence picture (Varese, 2010). Network Analysis can be used with any type of data where associations exist between entities. Associations are called ties or links and entities are known as nodes.

In this research, the node is either the OCG or an offender, and the tie is an intelligence event or instance of co-offending. Algorithms known as network centrality measures, are used to study the links in a network to identify prominent or important actors. These techniques have been shown as especially effective for ongoing investigations to identify key individuals and sub-groups within large networks of co-offenders (Strang, 2014). The term centrality refers to a whole family of concepts, however there are a small number that are regularly used such as degree, betweenness, closeness, and eigenvector (Borgatti, Everett, & Johnson 2013).

This research focusses on the degree centrality, which is described by Freeman (1978) as the number of other nodes to which a given node is adjacent. Therefore, a node with high degree centrality has multiple connections with other nodes in the network and is often positioned near the centre. These individuals have access to, and influence over, others and therefore act as a source or facilitator of information exchange or resources.

Previous research has endeavoured to understand how organised crime groups are distinguishable from normal social arrangements, based upon a number of characteristics including network centrality measures. A systematic review by Bichler et al., (2017) regarding the structure of OCG drug networks, showed that leaders could be accurately identified using centrality measures, as long as enough data was available in police systems. Many of the studies in the review looked at group structure over time, before and after operational activity. The review found that the best disruption technique was to target individuals with high degree centrality to split networks into smaller groups. There was corroboration throughout the studies that this form of law enforcement activity can impact upon the structure of organised crime groups, normally increasing the density and lowering the centrality. This shows that, as a result of using degree centrality for disruption, OCGs suffer operationally and close ranks to increase security.

Another aspect of Social Network Analysis is Community Detection, which works by creating partitions in the network based upon the degree centrality of connected nodes. This technique has been used by Tayebi & Glasser (2012) to that organised group members engage in continuous collaboration, with fewer peripheral members than non-organised groups. However, these collaborations do not persist over long periods of time. This finding was also shared by Sarnecki (2001), showing that criminal relationships among juveniles in Sweden do not frequently develop into the long term.

Social exchange theory suggests that co-offending is an interpersonal exchange of material and immaterial goods, in which each offender profits from the cooperation of the other (Weerman, 2003). Research by Campana and Varese (2013) shows that continued cooperation among co-offenders can increase instances of violence through the receipt of mutually compromising information. Further support for this comes from Morselli (2009), who corroborates that OCG members tend to have higher rates of co-offending than non-members. OCG members also tend to be older, commit more harmful crimes that increase in severity over time, and engage in criminal activity for longer Jeffery (2012 cited Crocker et al., 2016). If so, then we should expect to see OCG members co-offending in the form of high harm network clusters over a duration of time. This research proposes that degree centrality to measure co-offending incidents and association through intelligence will provide a strong indicator of organised activity.

2.5 The Importance of various data sources for SNA

Research into organised crime is often made difficult by researcher access to data. In this study, the researcher has complete direct access to intelligence and crime data, thereby overcoming this hurdle. Social Network Analysis relies upon having complete datasets and therefore different types of data can have an impact on the validity of any analyses. For example, crime data contains either offences that have been reported, or those that have been proactively targeted by law enforcement. This means that offences that were committed yet never reported are unable to be used to create a complete dataset (Rostami, 2015). Additionally, crime data may contain suspects yet to be confirmed by the available evidence.

Intelligence is essential to control, reduce, and prevent organised crime (Ratcliffe, 2010). It allows law enforcement to understand the context behind recorded criminality. However, it also has its limitations in that the data collection methods can become self-fulfilling and subject to confirmation bias. This could take the form officers suspecting particular individuals of organised criminal activity, and therefore focussing their investigations more heavily towards those individuals (Rostami, 2015). Crime data is therefore a more complete and reliable dataset than intelligence, however intelligence can help to fill the gaps where crimes have gone undetected (Tayebi & Glasser, 2012). The conclusion is that the analysis of multiple data sources can increase the reliability of SNA (Rostami, 2015).

The study will utilise intelligence in two ways. It is logical that intelligence will capture some of the illicit activities performed by undetected offenders. For this reason, each person will be attributed with their total number of intelligence logs and the number of associations they have to other offenders. These values will act as another metric to understand organised activity in undetected offenders. Secondly, an intelligence network will be constructed to supplement the existing co-offending network. This will be analysed to determine if intelligence associations can provide more insight into the harm perpetrated by OCGs. Additionally, intelligence will be reviewed to evaluate identified high harm clusters in relation to the definition of organised crime groups. This will allow a greater understanding of the associations between individuals in a cluster.

The literature review has highlighted the issues regarding the nature of organised crime in the UK and the difficulties in defining organised crime groups. High harm offending has been identified as a characteristic of organised crime group members and the CHI has been introduced as a method of measuring the severity of crime. Degree centrality has been shown to be successful in identifying influential organised crime group members and an effective means of disrupting organised crime groups. By measuring organised crime groups in the terms of harm and degree centrality, this research will aim to provide an improved means of identifying and ranking known and unknown OCGs and members. This will allow law enforcement agencies to target OCGs more efficiently and use the finite resources at their disposal to premium effect.

3. Methods

This chapter details the methods that have been used to test the research questions presented in the introductory chapter, and starts with some key definitions that will be used throughout the thesis. The nature of the data sources will be explained, and any data issues or limitations highlighted. Finally, this chapter will describe the analytical procedures used to arrive at the results. This research is a cross-sectional exploratory analysis to establish a procedure for the identification and ranking of OCGs and OCG members, using the Crime Harm Index (CHI) and Social Network Analysis (SNA) centrality measures.

3.1 Research Questions

The research sets out to provide an objective means of ranking known OCGs and OCG members. Efforts are then made to use the techniques to identify previous unknown OCGs and unknown members from a much larger data set.

1. Can the objective measures of harm and degree network centrality be used as an effective means of ranking known OCGs and OCG members?
2. How successful is this method in identifying previously unknown OCGs and OCG members?

3.2 Definitions

Crime Harm Index (CHI) by the Person and by Group

As discussed in the literature review, it is possible to attribute a total CHI score to persons, places, or events by aggregating the CHI for crimes associated to the entity in question. In this research, persons will have their scores aggregated when they were associated to a crime in which they acted in an offender capacity.

The same process is repeated with groups, however it is important to note the distinction between aggregating person CHI scores and group CHI scores. The Total CHI for groups is the aggregation of CHI scores for unique crimes, that individuals in the group have committed, opposed to the aggregation of CHI scores for everyone in that group. This prevents the duplication of scores for crime in which individuals within the same group had co-offended.

Social Network Analysis

This technique is the investigation of social structures by visualisation and statistical analysis in a network. Nodes, which can be people or other entities, are connected by ties, which can be associations or events. The analysis is used in a wide range of disciplines to understand how actors influence others around them. The advantage of this in a criminological context is the ability to assess all interactions at the same time, rather than a person centric approach that is often used during law enforcement investigations.

Principal Component Analysis (PCA)

PCA, sometimes referred to as Factor Analysis, is a data reduction technique that combines multiple variables and produces a single factor. In this research, the aim is to use Crime Degree, Intelligence Degree and the CHI to create a proxy measure of organised activity. PCA takes the 3 variables and combines them into a single score, whilst maintaining variance, that allows the researcher to rank by all three variables at the same time.

3.3 Variables

Total CHI

The Total CHI is an aggregation of CHI scores for crimes perpetrated by an individual or group. This variable is used to measure the volume of harm that an individual or group commits. As organised criminals are shown to commit higher harm offences than the typical criminal (Hallworth, 2016; Jeffery, 2012 cited Crocker et al., 2016), this variable will be used to score individuals who are potentially organised in their approach to crime. Average CHI was considered as a variable, however this would not provide an accurate representation of the harm perpetrated. For example, an individual who had committed 10 robberies would achieve the same score as someone who had committed just one. Equally, individuals with a single high harm offence such as sexual assault would score nearly twice as much as someone with a sexual assault and shoplifting offence, because shoplifting scores are very low.

To ensure that the CHI was measuring harm in proportion to the Tracker values, the scores were only aggregated for when each OCG was being actively monitored. Due to the emergence and dissipation of different OCGs over the data period, it was not possible to simply aggregate the CHI scores for each OCG. Tracker risk assessments take into consideration the previous 3 months of crime and intelligence and therefore it was necessary to only aggregate CHI scores that fit within this time frame for each OCG. This provided a proportionate comparison between the Tracker and the CHI scores.

Crime Degree

This variable uses the degree centrality to measure co-offending. The measure reflects the extent to which individuals commit crime together with other individuals. For instance, members of the same OCG may both engage in the same offences, such as drug dealing together or a violent assault by two OCG members toward someone in their debt. Organised criminals are shown to engage in more co-offending than the typical criminal (Campana and Varese, 2013; Morselli, 2009) and so this variable will be used to score those who are potentially organised in their approach to crime. The literature shows that co-offending is a reliable data source for network analysis and therefore increased crime degree is an indicator of greater involvement in organised crime (Bichler et al., 2017).

Intelligence Degree

This variable uses the degree centrality to measure association through intelligence. Although co-offending provides a reliable indication of criminal involvement and association, there are many crimes that go unreported or undetected. Intelligence fills in some of those gaps to provide a picture more coherent with law enforcement understanding (Tayebi & Glasser, 2012). For example, law enforcement may receive intelligence of a meeting between OCG members, or a police officer may observe an exchange between members. Equally, an informant may provide intelligence on how an OCG operates or with whom. This type of information does not exist in co-offending data alone.

Network Harm Index (NHI)

The NHI is the score resulting from the data reduction performed on the CHI, Crime Degree, and Intelligence Degree variables, through Principal Component Analysis (PCA). This new variable encompasses the objective measurement of harm and structured organised activity for each offender. It is hypothesised that the higher the NHI score, the more likely that the individual engages in organised crime. Individuals are ranked by the NHI and the power few are selected for comparison to the Tracker.

Average Tracker Score

The Tracker score is calculated from the values obtained through current assessment methods. Each OCG is scored on a semi structured basis. Ideally each OCG would be scored each month, however the resources are not available to do this, so more pertinent OCGs tend to take priority. This causes an issue for identifying a final score for an OCG. To address this, the average score for each OCG was calculated over the 3 year data period, taking into consideration when each OCG was active.

Considerations were given to Total Tracker score, however this would have inflated OCGs that were scored more frequently. In the scenario where an OCG is considered an urgent concern, multiple risk assessments may be performed in the same month, whereas lower priority OCGs may only be scored every other month. Using the Total Tracker Score would therefore provide an inconsistent measure.

Consideration was also given the highest score that each OCG had achieved, however this did not consider when OCGs scored particularly highly in one-off instances. An example of this is when new intelligence is obtained that an OCG is in possession of firearms. Later it may be identified that this intelligence is inaccurate and therefore a re-assessment takes place and the score is quickly downgraded. The highest score attained by an OCG would not be able to account for these situations.

3.4 Data Sources

Data Selection

Data on OCGs, OCG members and their corresponding assessment scores was retrieved from the OCG Mapping Tracker, for those active during the data period. This takes the form of an Excel spreadsheet which contains a record of the details for each OCG and the scores resulting from the assessment process. The average Tracker score was calculated from this data, which is fundamental in rating the effectiveness of the NHI.

The OCG member unique identifier from the Tracker was used in data mining software called IBM iBase. This allowed the extraction of OCG member details from the Niche crime and intelligence system. Once these had been obtained, all crime and intelligence for OCG members during the data period was extracted using iBase.

For the identification of unknown OCGs and OCG members, all crime and intelligence data was extracted from the Niche system for Wycombe LPA in the data period to create a second, new data set. Individuals involved in an offender capacity were identified and the person details were also extracted. This provided all crime and intelligence data within a geospatial boundary, to which the NHI could be applied.

3.5 Data Issues & Limitations

Data Quality

Niche data quality should be consistent throughout the data period. Niche was introduced one month before the start of the data period, ensuring that all crime and intelligence was being recorded in the same way. There are still instances where a crime may be recorded twice or a person on the system is not identified and given a new unique identifier. A quality assurance team is responsible for ensuring that duplications of events, people, and places are rectified, which relies on users of the system bringing it to their attention. In the more prolific offenders this is usually effective.

The Tracker process had been established for a number of years prior to the start of the data period and therefore OCGs were being consistently recorded. However, the recording method is manual and requires the OCG Mapping Coordinator to type in the details of all OCGs, members and Tracker results into an Excel workbook. This resulted in a number of typographical errors when recording local system person identifiers. Having observed this in the data, a confirmation check was performed on the Police National Computer (PNC) identifiers to ensure the local identifiers matched, or that any missing or inaccurate identifiers were found. Not all OCG members had PNC identifiers and therefore some data was missing. System checks on OCG Member names then filled in the missing identifiers but some could not be retrieved, mainly because those members did not exist in our system or they had been recorded incorrectly. All efforts were made to ensure that as many OCG member omissions as possible were addressed.

An issue with the OCGM Tracker assessment application, is that it overwrites the results of any previous OCG assessment. The last assessment is manually copied over into the Excel Tracker but this only keeps the final score for the assessment on each OCG. This means it is impossible to determine the conditions that lead to Tracker reaching a particular score for an OCGs in the past. This limits the insights the Tracker is available to offer.

Additionally, the Tracker uses information that is not held on local police systems. This puts the NHI at a disadvantage. For example, OCG members could be active in the Thames Valley jurisdiction but offend in other areas. Also, the individuals could be managed under the Confidential Unit which maintains a covert intelligence function. This intelligence is ring-fenced and only disclosed to those completing the assessment. Intelligence could also have come from another Force and never entered onto our local systems. Furthermore, the Serious and Organised Crime Unit (SOCU) don’t always release the intelligence they have gathered onto local systems due to resourcing. This means that tacit knowledge regarding the OCG is being implemented into the assessment, with which the NHI cannot compete.

One final issue with the Tracker is that some Operations are kept running even after completion because they are either suspected to be operating within prison or expected to continue operating immediately after a short sentence. In some instances, the Tracker score could have remained unchanged, as there was no motive to re-score. This could have affected the average Tracker score for some OCGs.

Offender Roles

For the analysis to be possible, it was necessary to decide upon a threshold for classifying an individual as an offender in crime. The main offender roles within crime include Suspect, Arrested, Charged, and Cautioned. The inclusion of the suspect role was given consideration, as suspects will sometimes be incorrect. By taking a random sample of 50 crimes within one LPA and interviewing Lead Analyst with knowledge of the offences, it was determined that excluding the suspect role would be of detriment to the overall analysis.

This was because although some offenders would be incorrectly attributed to a crime, there were far more instances where there was a lack of evidence despite the Officer in Charge being convinced they had the perpetrator, which resulted in the suspect being filed as no further action. Although this is a matter of opinion that cannot be measured, it was decided that the suspect role should be included in the offender role criteria on the side of caution. If this analysis was to be used to identify high harm offenders, then it would be safer to have a false positive result than a false negative.

Crime Related Incidents

Crime Related Incident (CRI) is a term used to describe a record of an incident which has come to the attention of the police, which, on the balance of probabilities would normally amount to a notifiable crime, but a resultant crime has not been recorded for a number of circumstances, such as the victim declined to confirm the crime occurred. This happens often in organised crime and therefore the decision was made to include CRIs.

No Crimes

An offence can only be 'no crimed' if it has been recorded as a crime. The situations when a crime can be 'no crimed' are governed by the Home Office Counting Rules for Recorded Crime. This includes circumstances such as confirmation that no crime occurred or if a crime constitutes part of another crime. These were omitted from the data collection.

Excluded Crimes

Due to the sheer number of Shoplifting offences, this crime type was excluded from the data collection. Despite OCG members being involved in very little shoplifting, other associates were prolific. This reflects the proportion of Drug Supply OCGs being monitored by Thames Valley Police, as Shoplifting is commonly seen in the drug user community. In the initial data collection, Shoplifting was included, however the volume of offences had a serious impact on the network resulting in overinflated centralities, giving a false interpretation of organised activity. As Shoplifting is the lowest scoring crime on the CHI, it was decided to remove this crime type completely as it would have limited impact on offender Total CHI scores.

Operational Activity and Proactive Policing

In Thames Valley Police there is no way to single out crime records that were created as a result of proactive police work, other than to exclude all crime except for those reported to the police by victims or witnesses (Sherman et al., 2014). Many crimes committed by organised groups, which were not proactively identified, involve a victim or witness that is unwilling to report the crime. Therefore, exclusion would have a serious detrimental effect on the types and volume of crime captured. For this reason, all recorded crime was used in the research with the exception of Shoplifting. This research acknowledges that the variables will be influenced by some offences that were generated as a result of proactive policing and special operations.

External Validity

The analysis performed in this research should be replicable in any law enforcement agency, however there is no guarantee that the structure of organised crime in the Thames Valley area is the same in other jurisdictions. Wider replications of the study would be required to assert the findings more generally.

3.6 Analytical Procedures

There were two data sets used for the research. The first was for known OCGs and OCG members and the second was for the identification of previously unknown OCG members and OCGs in the Wycombe LPA. This section details the steps that were applied to each data set.

Application of CHI

All crimes were extracted from local police systems into an Excel workbook. All unique Home Office codes were assigned the appropriate CHI value from the index published by Cambridge University (Sherman et al., 2016). The CHI scores were aggregated for each crime in which the individual was in an offender role. In the case of OCGs, the CHI scores were aggregated for each unique crime perpetrated by OCG members in that group.

Application of the Tracker Score

The Tracker scores were obtained from the OCG Mapping Coordinator for the data period. These were averaged during the active period for each OCG and attributed to the appropriate OCG in Excel along with the CHI.

Social Network Analysis (SNA)

The application used for the SNA was Gephi, which is an open-source network visualisation and statistical software package. To import data into Gephi, it was necessary to change the format of the data. Niche Crime records are extracted on a 'Person by Crime' basis. This means that a new row is produced for every person involved in a crime. In networking terms, this is known as a two-mode network. The nodes of the network consist of both the person and the crime. For network analysis centralities to be calculated, it was necessary to convert this into a one-mode network, which consists of the person being represented by the node and the crime becoming the tie that links them together. This was achieved using a Visual Basic script and meant that nodes and their details, including CHI values, are saved into one spreadsheet and the ties and associated details are saved into another. These are then imported into Gephi and the degree centrality calculated.

Bivariate Correlations, Principal Component Analysis (PCA) and the NHI

To perform the Principal Component Analysis, data with the new crime and intelligence degree centralities is extracted from Gephi and imported into SPSS, which is a statistical software package. Principal Component Analysis is run as a standard function of the software to create the Network Harm Index (NHI). SPSS is then used to run bivariate correlations on the CHI, Crime Degree, Intelligence Degree, NHI and the Tracker score. The data is then extracted from SPSS with the new NHI scores and imported back into Gephi to allow visualisation of the network.

Community Detection

A large network consists of many interconnected nodes, some of these ties are random and some are a product of organisation. Community detection algorithms split the network into partitions of highly interconnected nodes to uncover the underlying organised structure. This research uses the inbuilt statistical tool of Gephi to detect communities. This is based on the Louvain Method of community detection, which is a heuristic algorithm that measures the density between nodes to form small communities, which are then grouped, and the process repeated to establish a larger community (Blondel et al., 2008). Once the community detection analysis is performed, the data is exported from Gephi into Excel for comparison with known OCG formations in the Tracker.

Analysis of Outliers

This involved representing the variables in a scatter chart and identifying the OCGs that scored high for one variable but low for the other. Examination of the OCG Tracker and NHI scores allows the identification of any conditions that caused these outliers to occur. A comparison is then made to determine the difference in characteristics between the types of OCGs in both groups.

Comparison of NHI and Tracker

The last Results section deals with the identification of previously unknown OCGs and OCG member in the Wycombe LPA. The comparison looks at how many OCG members from the Tracker appear in crime and intelligence for the data period. It then looks at how many were identified in the analysis and compares them to those that exist in the Tracker to give an indication of how effective the NHI is at identified organised crime. Any individuals in the NHI power few that do not exist in the Tracker are researched, to identify if they qualify as OCG members and an exploration of crime and intelligence is performed to determine the reasons why they were not prioritised.

4. Results

This chapter is divided into three sections, presenting the results from the analysis of known OCGs, known OCG members, and the analysis on Wycombe LPA. The first section details the network structure, the power few concentrations, and analysis of the outliers for both the CHI and the NHI for OCGs. This aims to address the first research question as to whether a combination of harm and degree network centrality be used as an effective and alternative means of ranking OCGs that are currently being monitored.

The second section details the network structure and the power few concentrations for known OCG members. It also analyses the network structure through community detection algorithms to determine if it is possible to correctly partition the network into already established OCGs.

The third section addresses the second research question of how successful the techniques are in identifying previously unknown OCG members and OCGs. This will be done by comparing the NHI results to the Tracker and then reviewing the crime and intelligence for those individuals identified, which do not appear in the Tracker as OCG members. Further analysis with community detection will further determine the effectiveness of the technique.

4.1 Known OCGs

The analysis will start by looking at the groups in which Thames Valley Police have placed offenders. Police Forces deal with organised crime at the group level as this facilitates tactical options. Each group is scored and ranked in the Tracker, which ultimately dictates the resources that will be dedicated to dealing with each group. This section focusses on how the CHI and NHI compare to the Tracker in terms of ranking and offers some insights on the differences.

4.1.1 Descriptive Analysis

One hundred and thirty OCGs were being monitored by Thames Valley Police between 01/04/2015 and 31/03/2017. One hundred and twenty-six of those contained OCG members who were active on local police crime and intelligence systems. This resulted in 760 OCG members in total. On average, OCGs consist of 6 members but they are not evenly distributed; 109 (87%) OCGs had between 1 and 10 members and only 3 (2%) OCGs had between 20 and 25 members.

The total number of intelligence logs recorded for OCG members was 22588 and the total number of crimes recorded for OCG members was 3093. There are 756 instances of association between OCGs resulting in 202 ties.

4.1.2 Network-based Measures

Network Analysis would typically be performed at the individual level, however in the law enforcement arena there is a need to target groups, as to disrupt on an individual basis would place resources too sparingly across all OCGs.

The purpose of this section is to show the network structure of OCGs in the Thames Valley Police area and present an illustrative depiction of each variable being examined. The figures show the 126 OCGs that have been active in the Thames Valley Police area during the data period. Each node consolidates the individuals in an OCG and the tie represents a consolidation of all the co-offending incidents and intelligence associations between OCG members in connected groups. Where colours are present, the node colour represents its position on a high to low scale of the respective variable, and the tie colour is a mixed representation of the variable values for each node. Tie thickness shows the number of combined co-offending incidents and intelligence associations between each group.

Figure 1: The OCG Network shows the combined co-offending and intelligence links between OCGs in Thames Valley Police. The first thing to be noted is that OCGs do associate with one another. This can be measured by network density, which in this case is 0.026.

Figure 1: The OCG Network

Typically, this would be considered a low-density network, but in the case of organised crime, we would expect little cooperation between OCGs who could be in direct competition or even conflict. The cooperation evident here is likely to take the form of assistance in crime, or the exchange of information, tactics and commodities.

Research has shown that organised crime group members engage in more co-offending than the typical criminal. Crime Degree Centrality provides an objective measure of co-offending in the network. Degree Centrality has been repeatedly shown to successfully identify key players in many fields, including criminology.

Figure 2: OCG Crime Degree Centrality shows that a small number of OCGs, in red, have a high crime degree centrality. This means that these OCGs have a tendency to co-offend with other OCGs more frequently.

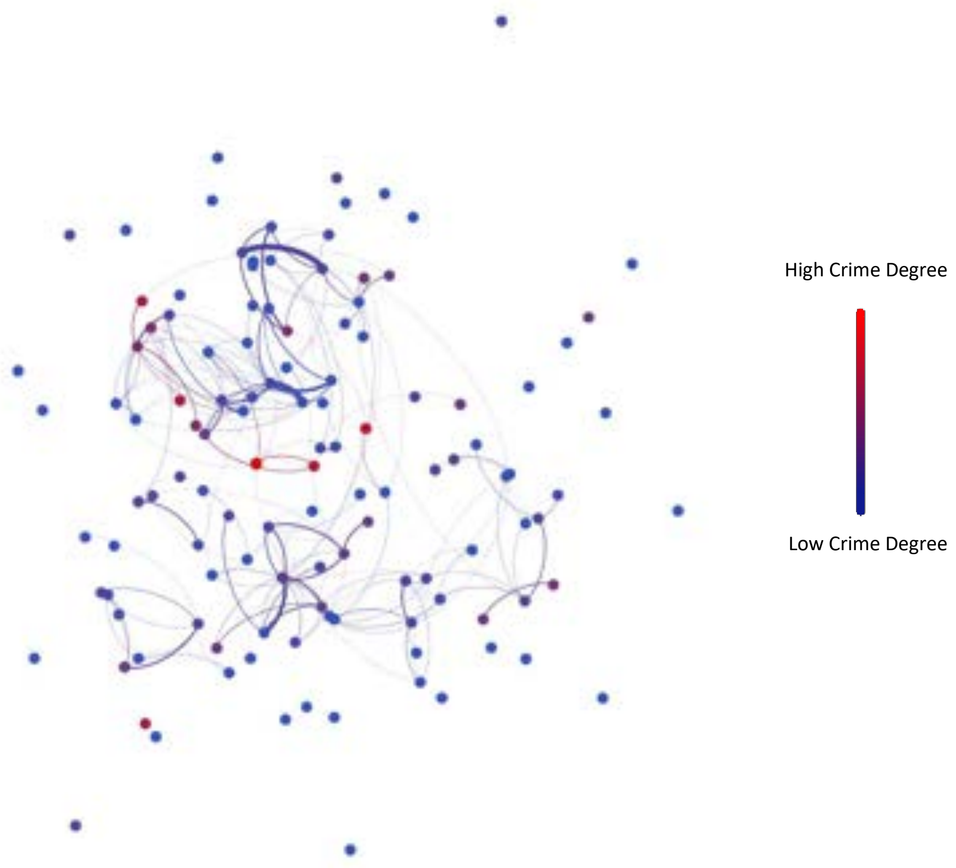

Figure 2: OCG Crime Degree Centrality

Figure 3: OCG Intel Degree Centrality highlights the nodes with a high intel degree centrality. This is an objective measure of intelligence associations between OCGs. Those with high degree centrality are more frequently associated with other OCGs in police intelligence.

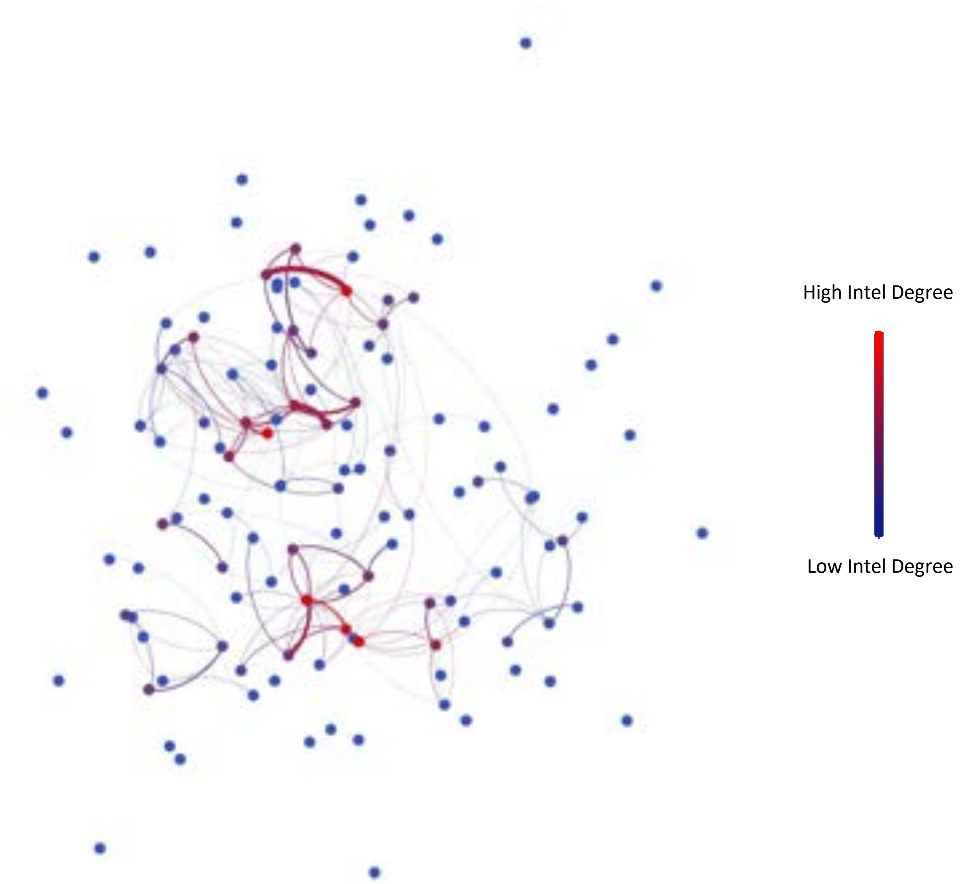

Figure 3: OCG Intel Degree Centrality

Figure 4: OCG Crime Harm Index shows OCGs with high CHI scores in the network. Research has shown that organised crime group members engage in higher harm offences than the typical criminal. The CHI is calculated by aggregating the number of recommended sentence days for each crime committed by members of that OCG. The CHI network shows that only a small number of OCGs have a high CHI score. This is common in the application of the CHI and represents the power few OCGs that are responsible for the majority of harm.

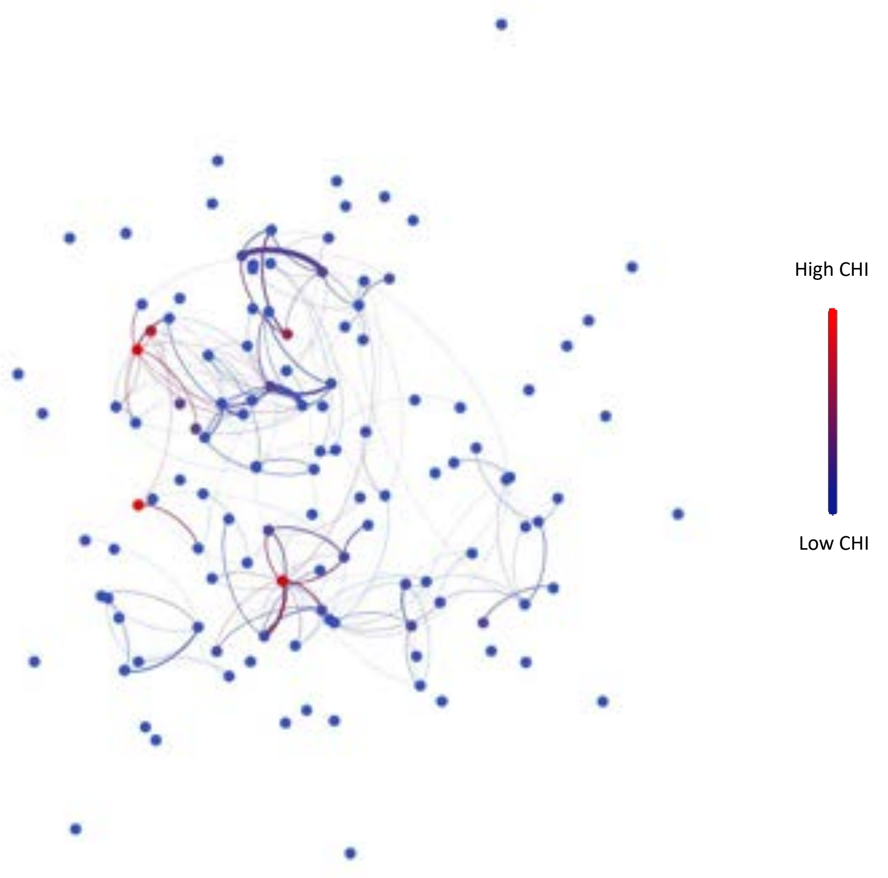

Figure 4: OCG Crime Harm Index

Figure 5: OCG Network Harm Index combines the attributes of the Crime degree, Intel Degree and the CHI. By prioritising the OCGs with a high CHI and degree centrality, tactical activity would not just disrupt the OCG being targeted, but also those OCGs in association. Figure 5: OCG Network Harm Index shows the NHI score for each OCG, resulting from the combination of the previously presented variables. It can be seen that only a few OCGs have a very high NHI and that many fall into the mid-range of the scale. This reflects how the NHI has prioritised high harm, high degree OCGs.

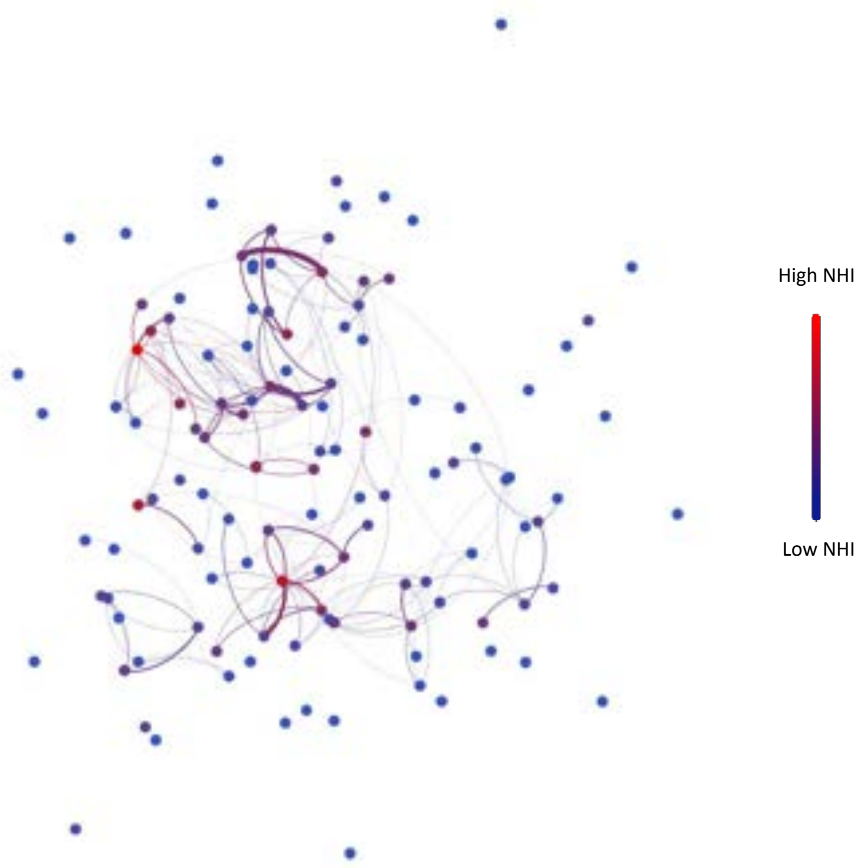

Figure 5: OCG Network Harm Index

Thames Valley Police, like all Forces, only has the resources to deal with a finite number of OCGs. For this reason, it is vital to prioritise to make the best use of resources.

The intended use of the NHI is to allow law enforcement to pick out the OCGs the are the most influential and the most harmful.

Figure 6: OCG Mapping Tracker shows that many OCGs fall into the high end of the scale. This is because the Tracker score, calculated through current assessment methods, has little variance in its calculation of a final score, making it more difficult to prioritise.

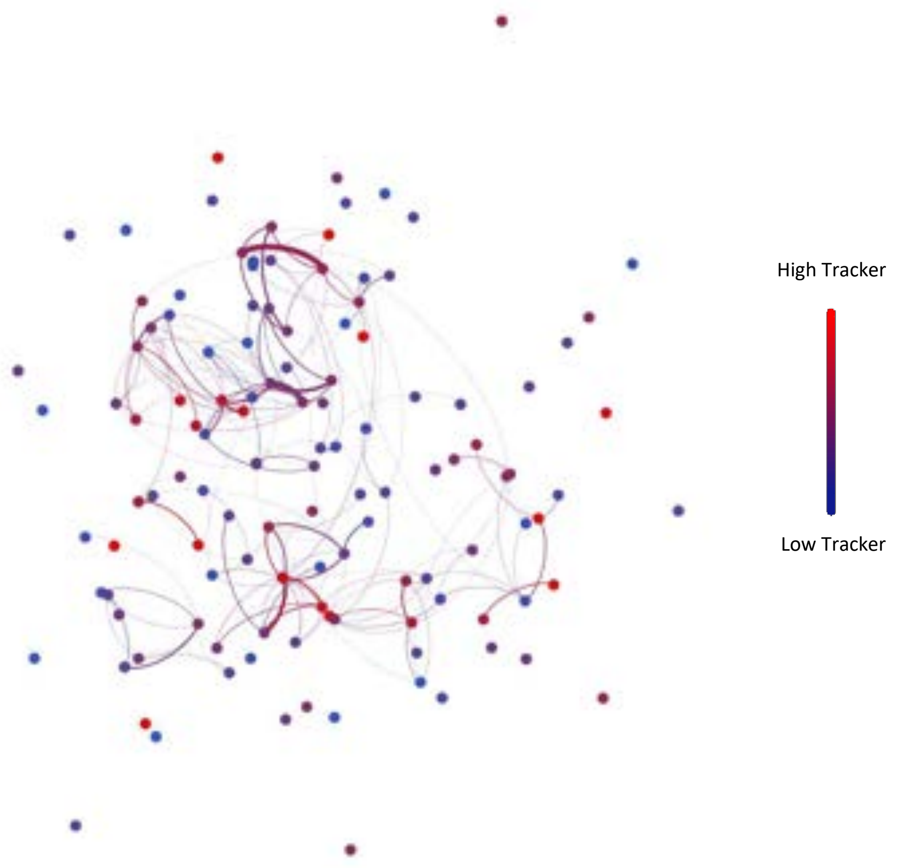

Figure 6: OCG Mapping Tracker

4.1.3 Power Few Analysis

By looking at the power few concentrations within the three scoring mechanisms, it is possible to interpret the types of OCG that each method favours. It is first necessary to identify the power few OCGs, so that their attributes can be compared.

These are the groups that sit at the top of the priority list for each method. This can be done using the Pareto principle, more commonly known as the 80/20 rule, which states that in many events roughly 80% of effects result from 20% of causes.

Figure 7: OCG CHI Distribution shows that a small number of OCGs perpetrated most of harm. When analysing at the CHI distribution, 23% (29) of OCGs were responsible for 80% of Harm. This is consistent with the characteristics of the Pareto principle when applied to criminality in a number of previous studies.

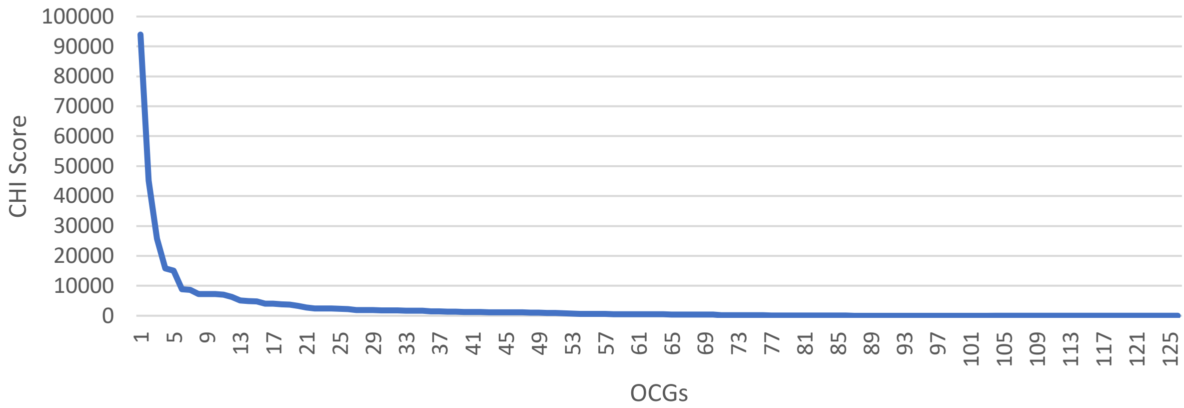

Figure 7: OCG CHI Distribution

The application of Principal Component Analysis means that a Pareto distribution is not seen in the NHI scores, due to the inclusion of crime and intelligence degree centralities and the creation of a new scale. However, 16 OCGs (13%) achieve 3.0 or above before a rate of change is observed.

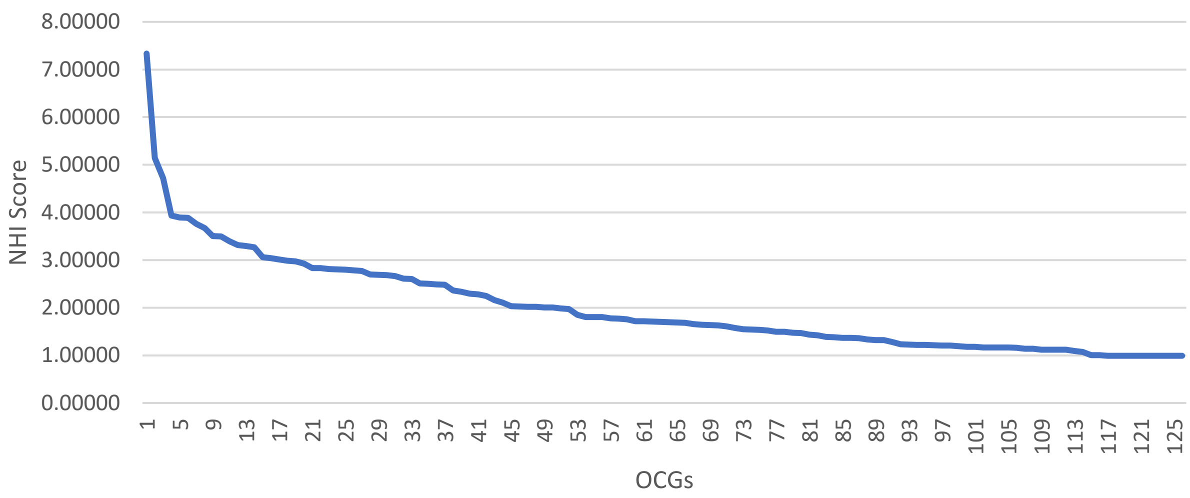

Figure 8: OCG NHI Distribution

In the case of the Tracker power few, a Pareto distribution is not observed in the data as the scores result from the OCG assessment. However, by looking at Figure 9: OCG Tracker Distribution, it can be seen that the top 18 OCGs (14%) show disproportionately higher scores than the other OCGs.

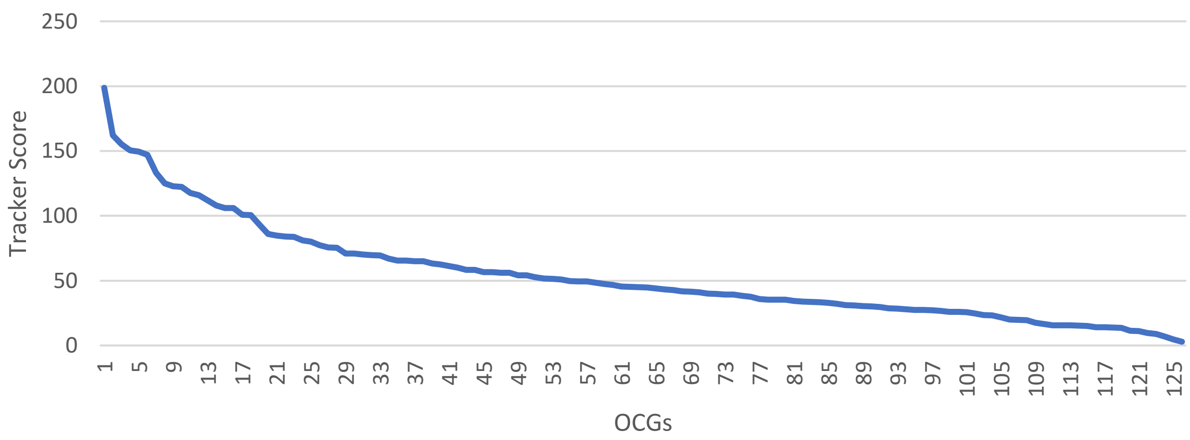

Figure 9: OCG Tracker Distribution

4.1.4 Ranking Comparison

The OCG tracker records the type of criminality in which each OCG specialises and this will be used to compare the types of OCGs in each power few. The criminality types for all 126 OCGs can be reduced to 7 main categories, as seen in Table 1: OCG Criminality Categories**.**

Table 1: OCG Criminality Categories

Crime Category	# OCGs	Description
Damage	1	Large number of criminal damage offences on vehicles.
Exploitation	9	Human Trafficking. Sexual Exploitation. Managing Prostitution.
Family	3	Crime Family orientated offending. Various criminality.
Firearms	1	Importation and Supply of Firearms.
Fraud	12	Fraud. Money Laundering. Rogue Trading.
Supply	85	Importation and/or Supply of Drugs. Nearly all Class A.
Theft	15	Burglary. Vehicle Theft. Plant Theft.

Table 2: OCG Ranking Comparison shows which OCGs are prioritised in the CHI, NHI and the Tracker, highlighted in red.

Table 2: OCG Ranking Comparison

Group Ref	TotalMembers	TotalCHI	IntelDegree	CrimeDegree	AveTracker	NHI	Type
13	25	93966	0.8781	1.0232	71	7.89318	Exploitation
48	17	45199	1.1955	0.4561	86	4.95549	Exploitation
62	20	25760	2.2357	0.6719	116	4.95400	Supply
4	17	15820	2.1616	0.4256	81	4.12411	Supply
50	15	602	0.2168	3.1351	42	3.85321	Supply
52	18	2330	0.3162	2.7132	47	3.68179	Supply
22	21	2810	2.4235	0.0860	106	3.33658	Fraud
85	10	6249	0.6992	1.6280	108	3.32249	Supply
124	3	0	2.0597	0.6027	106	3.29616	Supply
16	19	8817	1.8143	0.2584	53	3.28705	Supply
88	11	790	0.8869	1.7147	43	3.25295	Supply
79	8	747	0.7724	1.8090	15	3.22992	Damage
92	2	10	2.4390	0.1290	45	3.22909	Supply
76	12	203	2.1272	0.4092	51	3.20357	Supply
11	9	15067	1.2646	0.2868	77	3.18181	Family
78	5	7295	1.3334	0.6200	42	3.08620	Supply
122	2	0	0.2440	0.0000	162	1.20368	Supply
51	3	185	0.1087	0.1720	155	1.24073	Exploitation
104	10	1696	0.4390	0.1032	150	1.55601	Supply
107	4	571	0.6910	0.3878	149	1.95242	Supply
115	8	1	0.2034	0.0000	147	1.16827	Firearms
2	8	417	0.0000	1.5503	133	2.31927	Fraud
120	2	21	0.8945	0.2580	125	1.98996	Supply
26	2	10	0.1630	0.0000	123	1.13353	Fraud
35	12	3867	1.0568	0.5168	122	2.56548	Theft
113	2	0	0.0000	0.9045	118	1.75219	Supply
86	9	1809	1.5356	0.3731	101	2.74688	Exploitation
100	9	3685	0.2530	1.0623	101	2.31279	Supply
116	3	1	1.6260	0.3443	93	2.70013	Family

There is agreement on just 5 of 29 (17%) power few OCGs in both the NHI and Tracker lists. Eleven OCGs were identified by the NHI that were not a high priority in the Tracker and 13 existed in the Tracker but not the NHI. OCG 13 was ranked first because of the extremely high CHI score whereas OCG 4 was ranked 4th as a result of a very high

Intel Degree coupled with a relatively high CHI. OCG50 was ranked 5th due to a very high Crime Degree and the same is true for OCG52.

By looking at the percentage of the total for each crime category, it is possible to see how each scoring method prioritises those categories. Table 3: OCG Criminality Comparison shows that 85 out of 126 OCGs (67%) specialise in the importation and/or supply of drugs, followed by Theft (12%), Fraud (10%) and Exploitation (7%).

Table 3: OCG Criminality Comparison

	All OCGs		Tracker Power Few		CHI Power Few		NHI Power Few	
	Count	% of Total	Count	% of Total	Count	% of Total	Count	% of Total
Damage	1	0.79%		0.00%		0.00%	1	6.25%
Exploitation	9	7.14%	2	11.11%	3	10.34%	2	12.50%
Family	3	2.38%		0.00%	1	3.45%	1	6.25%
Firearms	1	0.79%	1	5.56%		0.00%		0.00%
Fraud	12	9.52%	5	27.78%	3	10.34%	1	6.25%
Supply	85	67.46%	9	50.00%	20	68.97%	11	68.75%
Theft	15	11.90%	1	5.56%	2	6.90%		0.00%
Total	126	100%	18	100%	29	100%	16	100%

The Tracker can be seen to decrease the priority of Supply OCGs in favour of Exploitation, Firearms and particularly Fraud. The CHI ranking is similar to the count of all OCGs but places slightly more emphasis on Exploitation and less on Theft. These results mirror those of Sherman et al., (2016) in which a similar change in distribution was observed. The NHI places more emphasis on Supply and Exploitation, with reductions in Theft, which reflects the increased emphasis that high degree network measures and CHI score have on the distribution.

4.1.5 Correlations

Appendix 1: OCG Correlations shows a table for all variables in the OCG data set and the correlations. There was a moderate correlation between the number of members in an OCG and the number of intelligence logs recorded, $r = .638$, $p < .01$. This is to be expected as more members will result in more intelligence, however it may indicate that large OCGs are less secure or that intelligence officers place more resources on intelligence gathering for larger groups. Weak correlations can also be seen between the number of members and the intel degree and crime degree. It stands to reason that as the number of members increases with an OCG, so does their association through crime and intelligence.

There was a moderate correlation between the number of members in an OCG and the Total CHI, $r = .556$, $p = < .01$. This is to be expected as the higher number of offenders will result in more harm being perpetrated. There was a weak correlation between the number of members in an OCG and the Average Tracker score, $r = .275$, $p < .01$. This suggests there is little relationship between the size of the OCG and their prioritisation through current assessment methods, despite more harm being perpetrated.

There was a weak correlation between the number of crimes recorded and the number of intelligence logs recorded, $r = .247$, $p < .01$, however one OCG has a staggering 1561 offences, which is more than 10 times the next highest count. Removing this OCG results in $r = .783$, $p < .01$, indicating that groups with more intelligence have also been involved in more crime. There is no correlation between the number of crimes and the Total CHI, $r = .089$, $p =$ n.s. This is a strange result as the more crimes committed would inevitably lead to greater harm, however the same OCG with 1561 offences is skewing the results. Removing this OCG provides in $r = .481$, $p = < .01$.

There was a weak correlation between the number of intelligence logs recorded and the Average Tracker score, $r = .208$, $p < .01$. If an OCG has many intelligence logs this indicates they may not have a high score under current assessment methods. There was a weak correlation between the Total CHI and the number of intelligence logs recorded, $r = .318$, $p < .01$. This indicates that, to a small extent, OCGs that have more intelligence are involved in higher harm offences. There was also a weak correlation between the Total CHI and the Average Tracker score, $r = .152$, $p < .01$. This weak correlation indicates that to a small extent, the two methods are measuring something similar but with some fundamental differences. The exploration of the outliers can help to identify these differences which are detailed in the next sub-section.

4.1.6 CHI and NHI Outliers

When plotting the CHI and NHI on a scatter chart against the Tracker score, it is possible to identify OCGs which are outliers. These may be OCGs that have a particularly high Tracker Score and low CHI or NHI, or vice versa. Understanding the attributes of these OCGs will provide insight into how each scoring method prioritises different group types.

Figure 10: OCG CHI & Tracker Outliers shows there are 3 OCGs that score very highly for CHI yet do not have particularly high average Tracker scores. Additionally, there are 10 OCGs that have high Tracker scores but low CHI scores. The highest scoring OCG involved a high-profile Child Sexual Exploitation ring. Despite convictions being obtained in 2013, a spate of historical offences were reported during the data period. Also, members of the OCG were still committing crime however these tended to involve

low level violence and drugs offences. This is also true of the second highest scoring OCG. It appears that investigation into this OCG unearthed some historical sexual offences however the OCG continued to engage in sexual, drugs and violence offences during the data period. The third OCG is regarding a street gang which engaged in considerable violence and weapons offences throughout the data period.

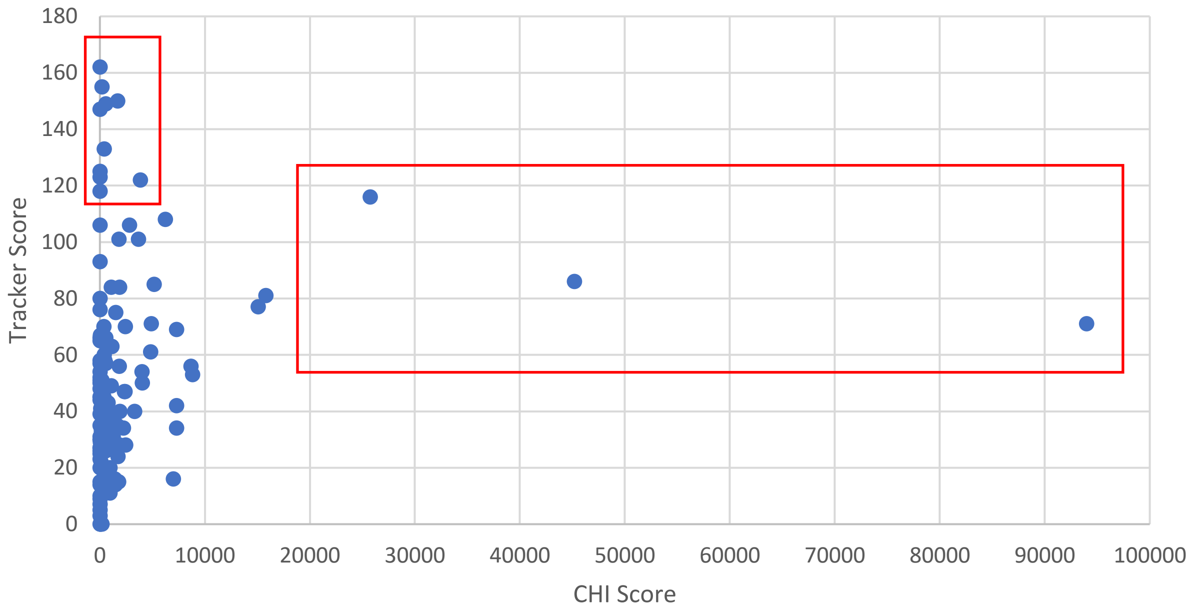

Figure 10: OCG CHI & Tracker Outliers

All of the low harm high tracker OCG's, with the exception of one, have very low crime totals meaning on average they each only have 10 offences on which to score harm. The number of intelligence logs for these OCGs is variable indicating that something else is a factor for such a high score and highlights the issues raised about the sources of information used in the tracker assessment (see 3.5 Data Issues & Limitations). There appears to be no pattern for crime type except for Fraud which has a very low number of reported crimes. This is likely a result of long and complex investigations where a single crime report is created to encompass a whole range of criminal activity.

Figure 11: OCG NHI and Tracker Outliers shows there are 3 OCGs that score highly for NHI yet do not have high average Tracker scores. These 3 are the same as those identified by the CHI. Additionally, there are 8 OCGs that have high Tracker scores but low NHI scores. All 8 are contained within the 10 identified by the CHI.

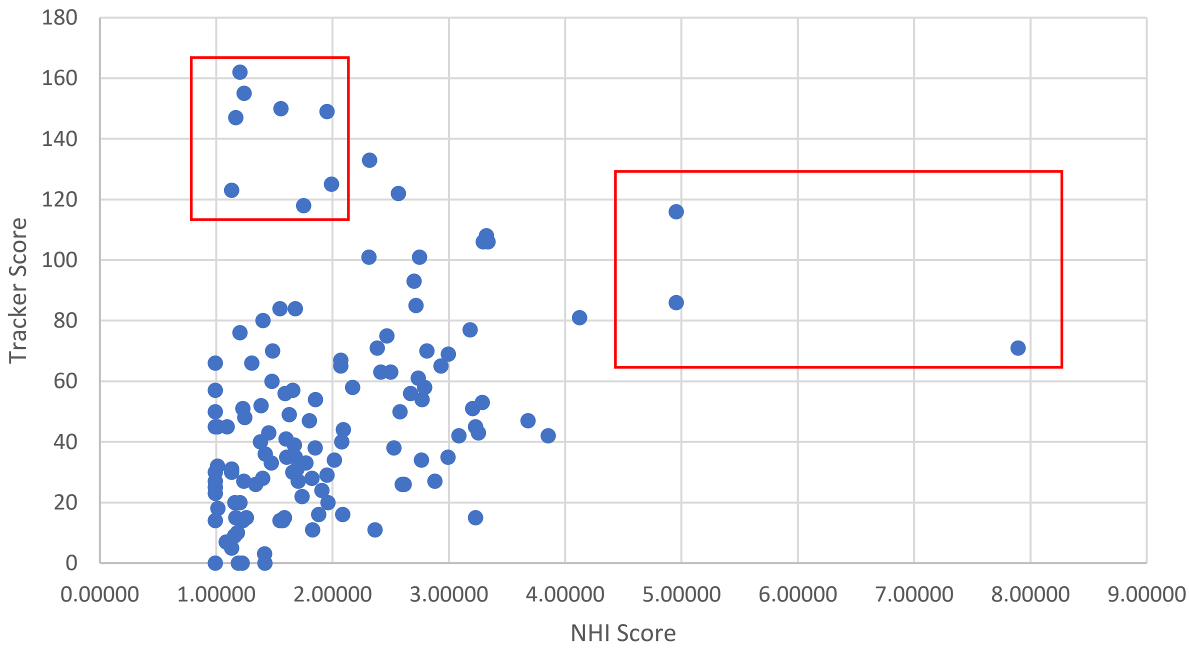

Figure 11: OCG NHI and Tracker Outliers

These results pose a question regarding the inclusion of historical offences and OCGs involved in a low number of crimes. In this data, 98 historical offences were found in the first and second high ranking OCGs. This represents 67% of all historical records in the dataset. All other historical records are distributed in single figures across 26 different OCGs. If historical offences were taken out and a threshold of less than 5 crimes was enforced, then a more positive correlation would be seen with the tracker whilst maintaining the integrity of the power few.

If this was to be completed, then 33 OCGs with less than 5 crimes would be removed. These have Total CHI scores of under 2000, meaning they are very low priority. Removal of these outliers results in a moderate correlation between the NHI and the Tracker, $r = .460$, $p < .01$, which provides a stronger case that the two methods are measuring a similar phenomenon. The importance of this will be addressed in **4.3 Previously Unknown OCGs and OCG Members**, where attempts will be made to identify OCGs and members from a large data set of crime and intelligence.

4.2 Known OCG Members

Police Forces deal with organised crime at the group level for tactical purposes, but it also valuable to examine how individuals interact. This is because membership to an OCG is fluid and individuals may drop in or out of a group due to varying situational and motivational factors. It is also possible that individuals are inaccurately included in or excluded from a group because the police do not have a complete picture. This section focusses on how CHI and NHI scores for individuals compare to their respective OCG Tracker score and whether network analysis can group individuals into their respective OCGs using the characteristics of the network structure alone.

4.2.1 Network-based Measures

Figure 12: Crime Degree Centrality, shows the individuals most closely associated through crime in the network. It can be observed that some clusters in the network engage in far more co-offending than others.

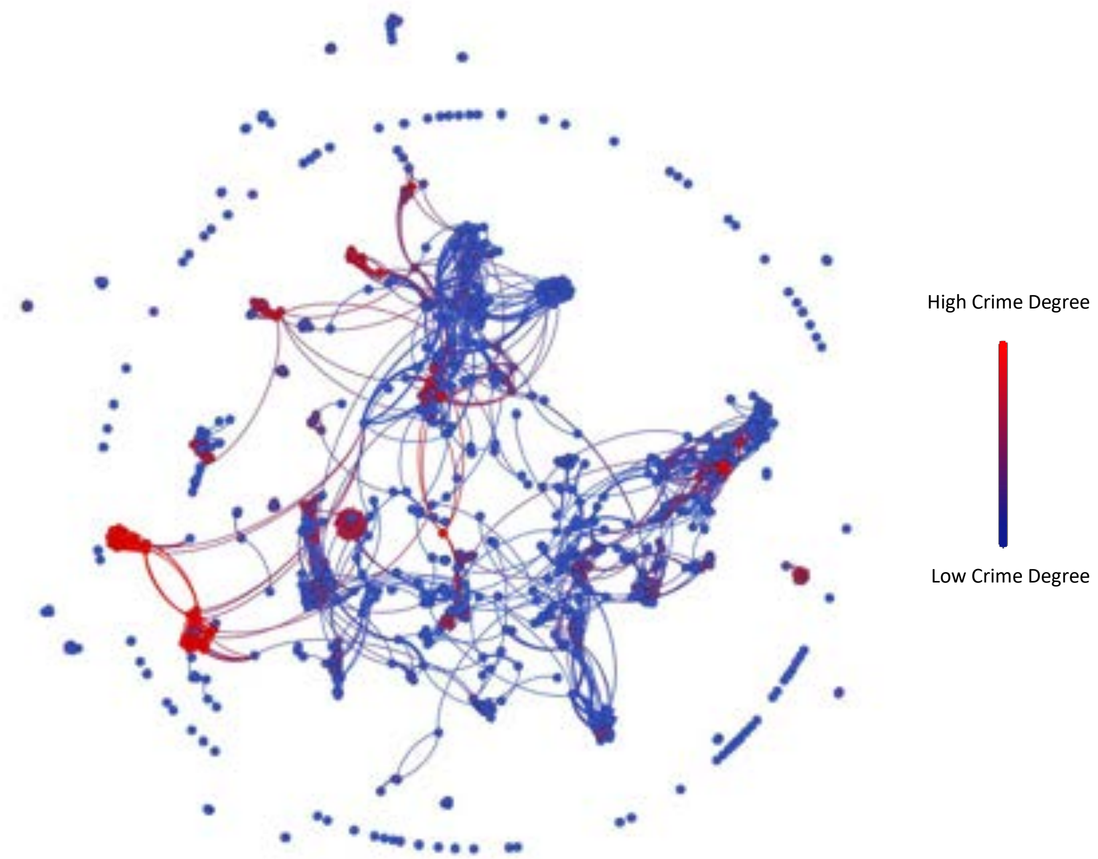

Figure 12: Crime Degree Centrality

Figure 13: Intelligence Degree Centrality shows the individuals most closely associated through intelligence in the network.

There is a clear difference between which individuals have a high crime degree and those which have a high intelligence degree. This means that the two measures do complement each other by providing a different picture of association, and highlights the importance of including both intelligence and co-offending data sets in the analysis.

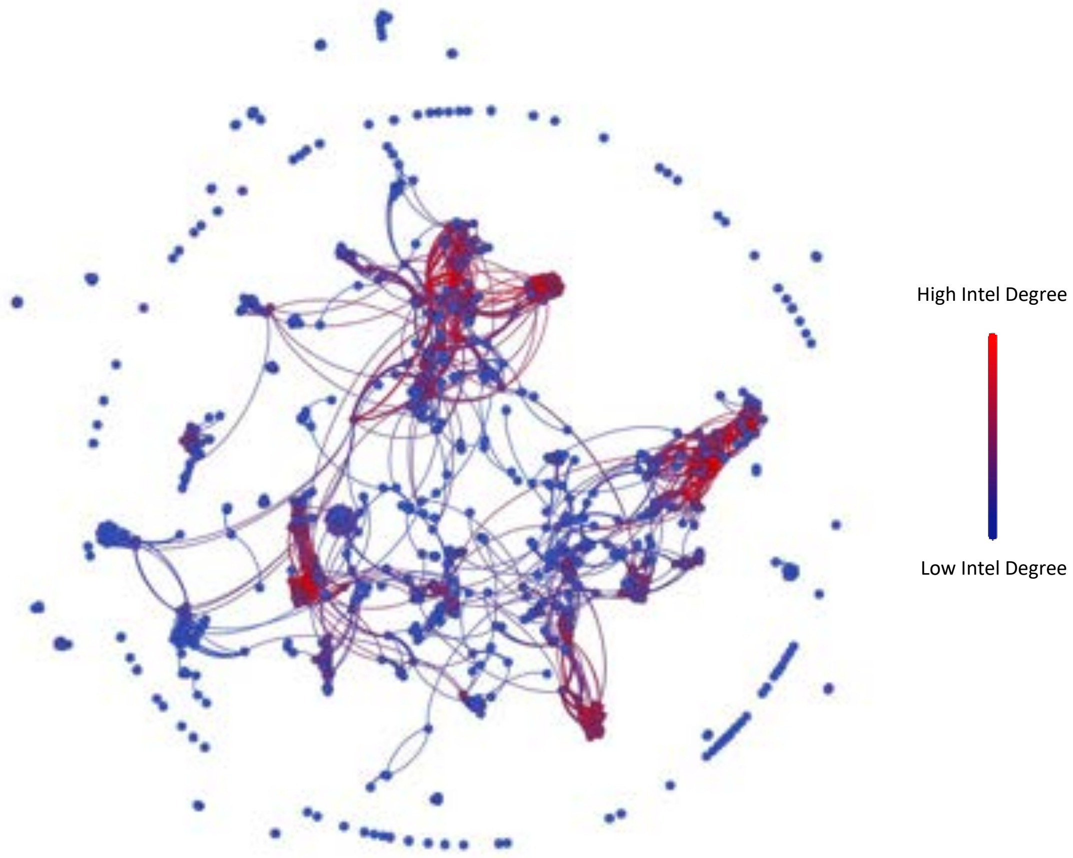

Figure 13: Intelligence Degree Centrality

The charts also show that frequent co-offenders are often separate from the dense sections of the network, whereas individuals with many intelligence associations are situated more closely. This is because there are far more intelligence logs, but also highlights that either police systems do not contain as much intelligence for frequent co-offenders, or that these individuals are more clandestine by nature.

Figure 14: Crime Harm Index shows that just a small number of individuals have high scores, which is typical of the CHI distribution in previous research. High harm individuals are also clustered in small groups indicating that high harm offences take place between individuals who are closely associated rather than one-off offences.

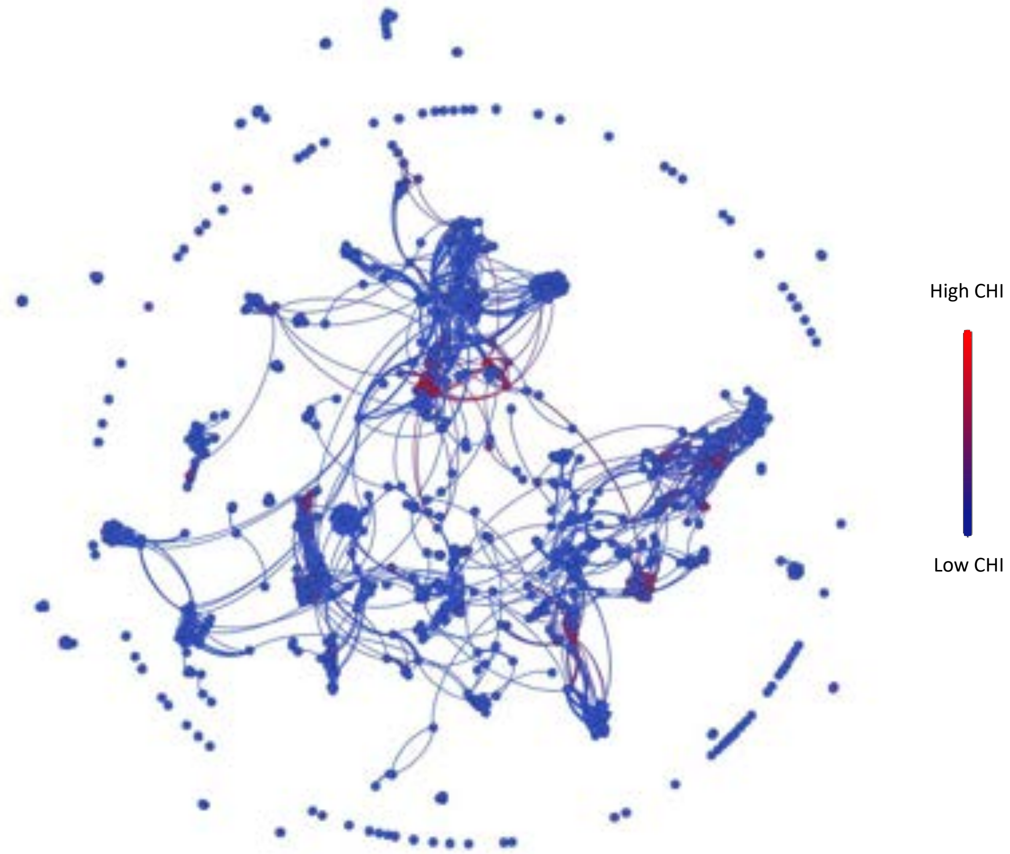

Figure 14: Crime Harm Index

Figure 15: Network Harm Index shows the combined attributes of the Crime degree, Intel Degree and the CHI, produce through the data reduction technique of Principal Component Analysis. Nodes that encapsulate high scores in the other variables have been prioritised.

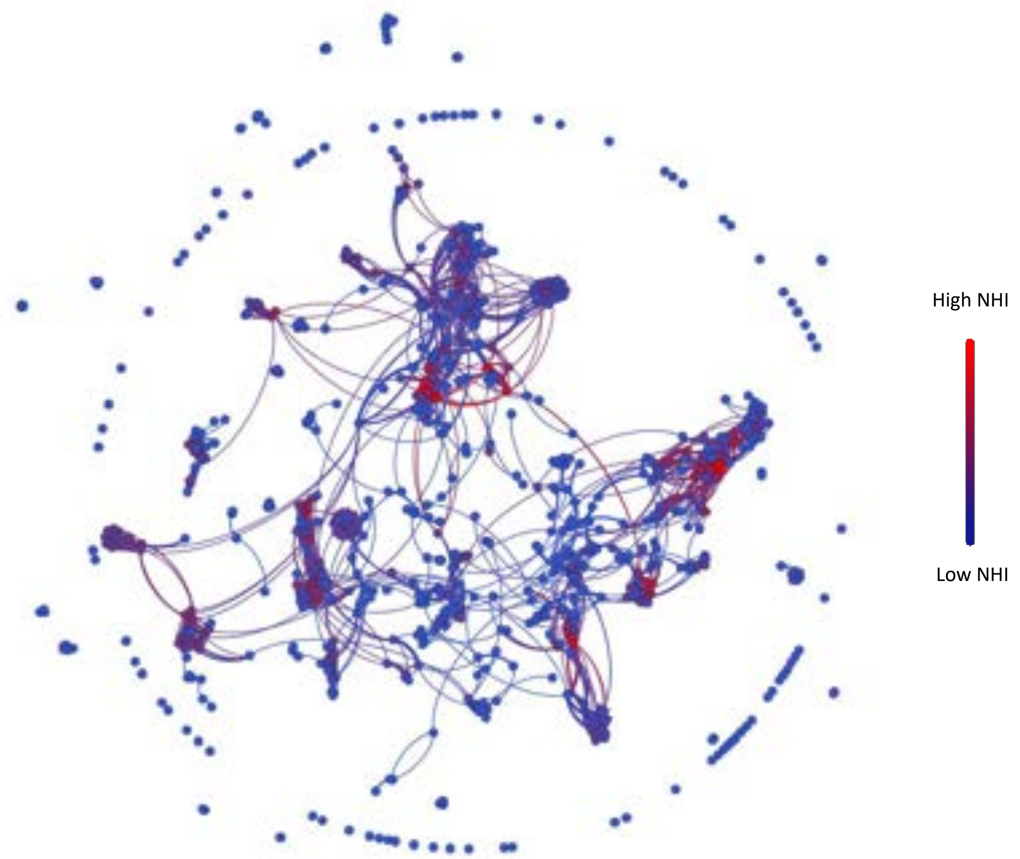

Figure 15: Network Harm Index

Figure 16: OCG Mapping Tracker shows that many individuals belong to OCGs that score highly in the OCG Tracker. The OCG Tracker does not keep scores for individuals, so the score for each individual has been appropriated from their respective OCG.

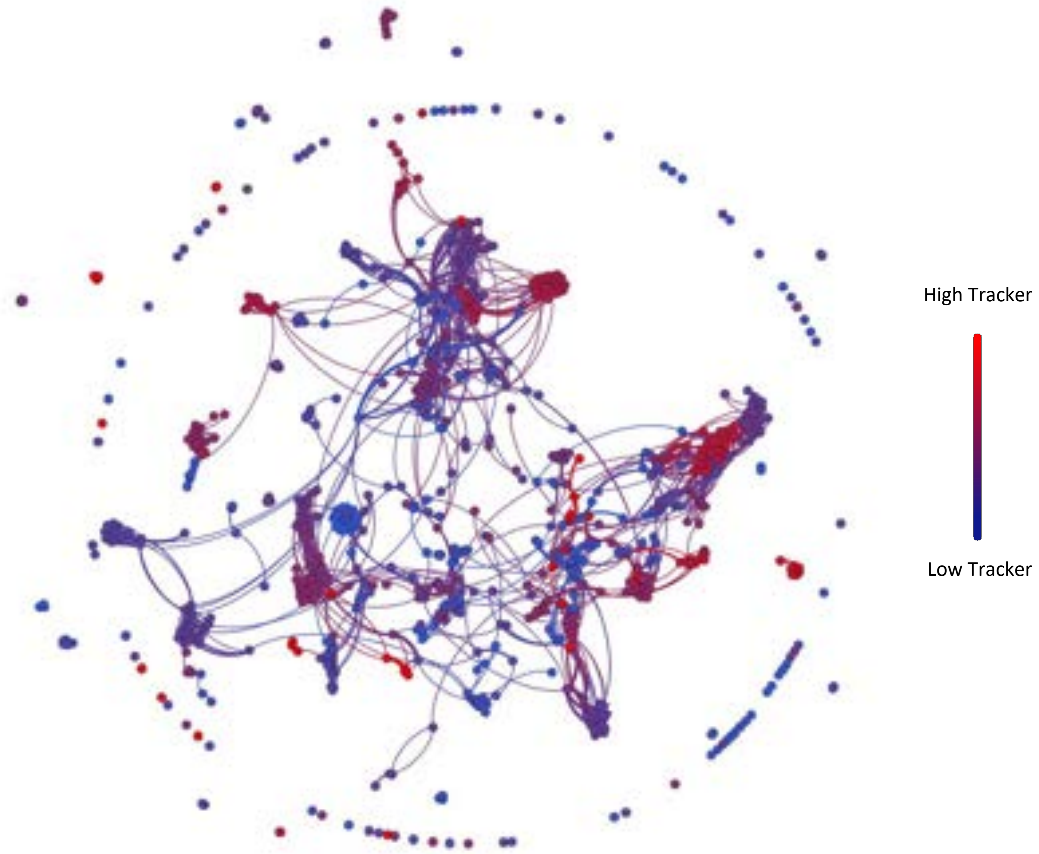

Figure 16: OCG Mapping Tracker

4.2.2 Power Few Analysis

The power few concentrations for the CHI at the individual level, seen in Figure 17: OCG Member CHI Distribution, closely resemble the distributions at the group level. The CHI power few are 156 of 760 individuals (21%), which reproduces the observations in the Pareto principal.

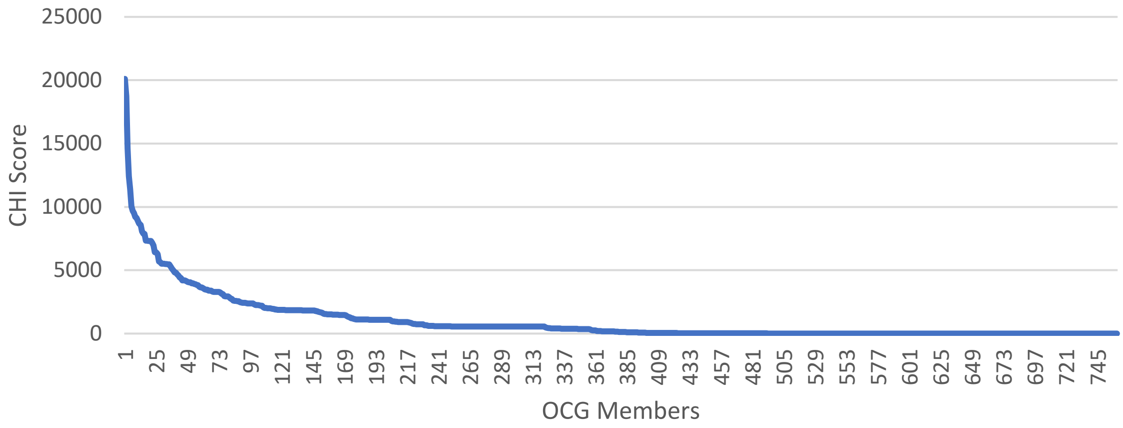

Figure 17: OCG Member CHI Distribution

The NHI distribution does adhere to the Pareto principal, but a power few of 79 OCG members (10%) can be seen above the NHI score of 3.0.

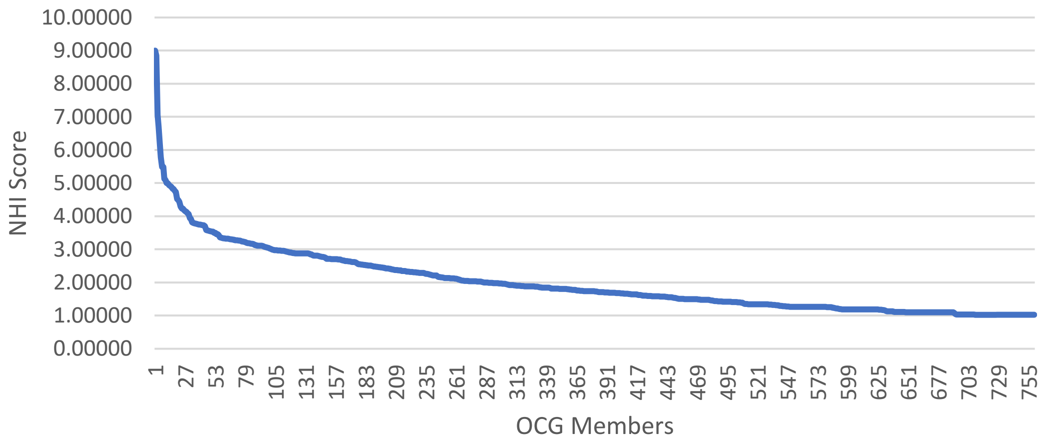

Figure 18: OCG Member NHI Distribution

The Tracker distribution also does not adhere to the Pareto principal, but a rate of change is evident after the first 120 OCG Members.

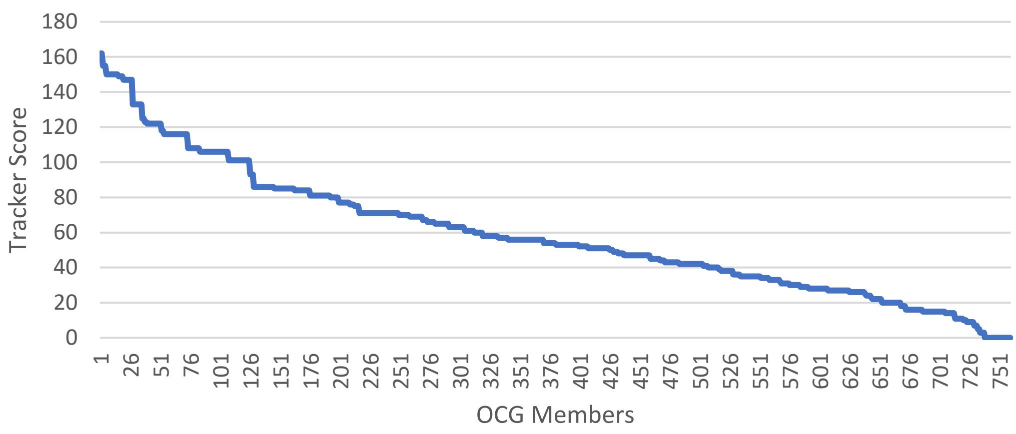

Figure 19: OCG Member Tracker Distribution

4.2.3 Community Detection

Community Detection was conducted on all 760 OCG members. This analyses the internal structure of the network to identify communities which are closely connected. These communities have been shown to have real world meaning (Blondel et al., 2008). By looking at the communities identified in the analysis and comparing them to known OCG membership formations, it was identified that the community detection was accurate to 77%.

A network visualisation using Community Detection compared to known OCG formations is shown in Appendix 3: Comparison of Community Detection and Known OCG Formations. For known OCG formations a unique colour was attributed to each OCG. For the Community Detection network, a unique colour was attributed to each detected community. Although the colours do not correspond between the community and the OCG formation for technical reasons, it is very clear that the pattern of differentiation between colours within each network shows that community detection is broadly accurate (it is important to note that the colours in each network do not describe the same OCGs in both networks). This has real implications for the identification of OCGs from communities of high harm and well associated offenders in the next section, 4.3.5 Community Detection.

4.2.4 Correlations

Correlations between Crime Degree, Intel Degree and the CHI can be viewed in **Appendix 2: OCG Member Correlations**. There are no moderate or strong correlations between the main variables. A weak correlation can be seen between Intelligence Degree and Total CHI, indicating a small tendency for individuals associated through intelligence to be involved in higher harm offending. There is also a weak correlation between Intelligence Degree and Average Tracker indicating a small tendency for individuals associated through intelligence to be scored more highly in current assessment processes. A weak correlation was seen between the NHI and the Average Tracker, , $r = .205$, $p < .01$.

4.3 Previously Unknown OCGs and OCG Members

Police Forces deal with organised crime at the group level. These groupings, which are based upon intelligence and surveillance, are built around the suspects initially identified. Networks built on this data collection method are known as Egocentric. This thesis proposes an alternative method, known as a Sociometric network, to identifying organised crime. This involves analysing all criminality within a spatial and temporal boundary (Morselli, 2009). An Sociometric method is considered superior to building a network around already established individuals.

4.3.1 Descriptive Analysis

The Wycombe Local Policing Area (LPA) was selected for this analysis between the dates of 01/04/2014 and 31/03/2017. This LPA has a dense population of 180,000 (ONS, 2016) and 16 established OCGs, which makes it suitable for comparing the results of the analysis. The network consists of 17938 persons, 21516 crimes and 17810 intelligence reports. The total number of associations via crime and intelligence is 29738.

There are 104 OCG members in the tracker who were active in the Wycombe LPA, however only 53 of these had co-offended or been associated in intelligence during the data period. The 53 OCG members had an average CHI score of 1248 compared to non OCG members who had an average CHI score of 152. In regard to network measures, the 53 OCG members had an average Intelligence Degree of 71 and an average Crime Degree of 160, whereas non OCG members had an average Intelligence Degree of 2 and an average Crime Degree of 2.

4.3.2 Network-based Measures

Figure 20: Network Visualisation of NHI Scores for Wycombe, shows the entire NHI network. Due to the size of the network it is difficult to draw any conclusions from a paper illustration, however a red cluster of high NHI individuals can be seen in addition to a collection of red node in the dense centre of the network. The NHI network represents the combination of network variables that can be seen in Appendix 4, 5 and 6.

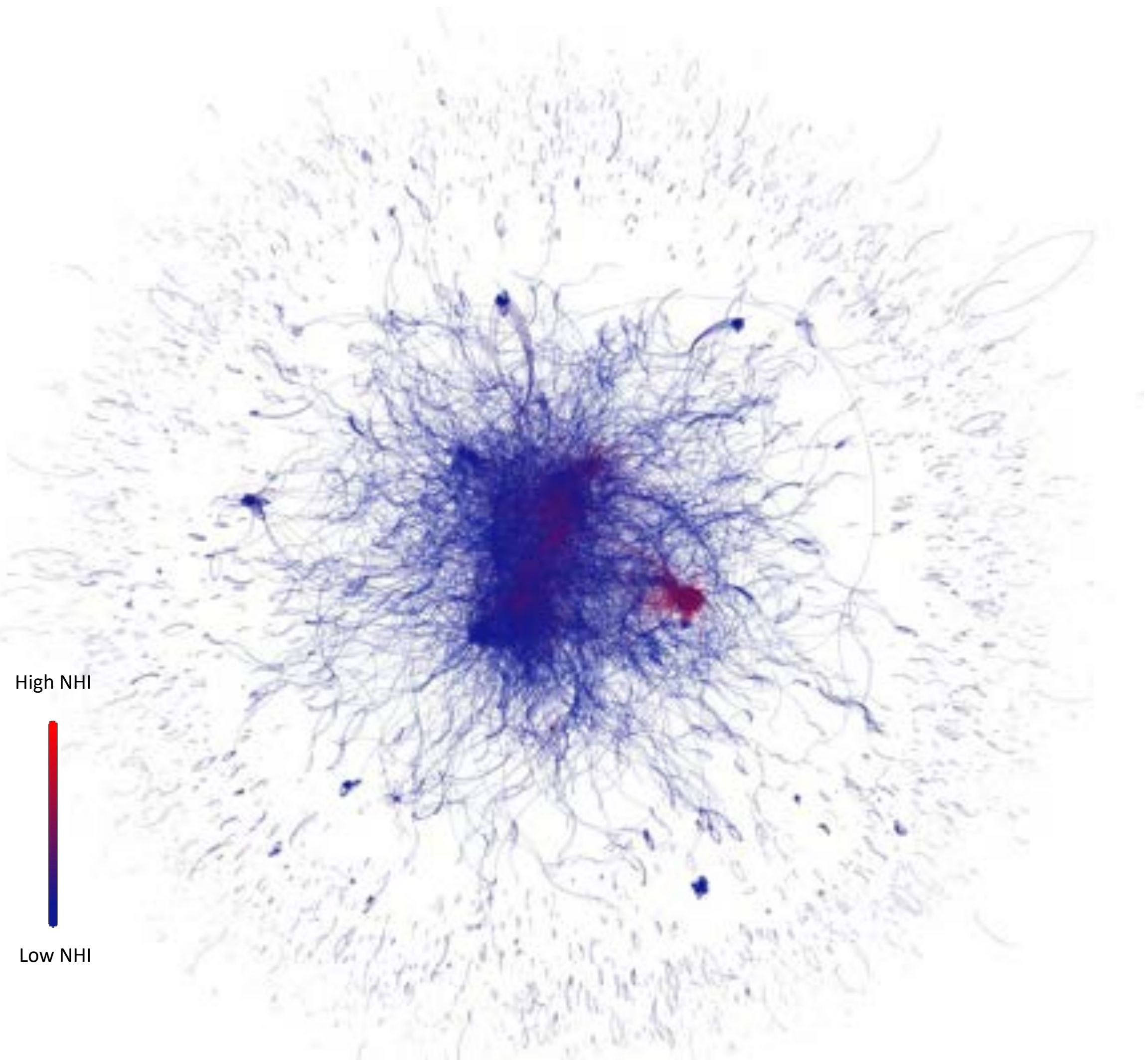

Figure 20: Network Visualisation of NHI Scores for Wycombe

Later in the section, the network will be distilled into the power few so that more specific observations can be made. Network charts displaying the other variables for Wycombe can be found in the Appendix.

4.3.3 Power Few Analysis

Figure 21: Wycombe Offenders CHI Distribution shows a powerful concentration of offenders responsible for harm. From the total 17938 individuals, 474 (3%) perpetrated 80% of harm. There are 104 OCG members in the tracker who were active in the Wycombe LPA, however only 53 of these had co-offended or been associated in

intelligence during the data period. The CHI power few included 24 of the possible 53 OCG members active in Wycombe.

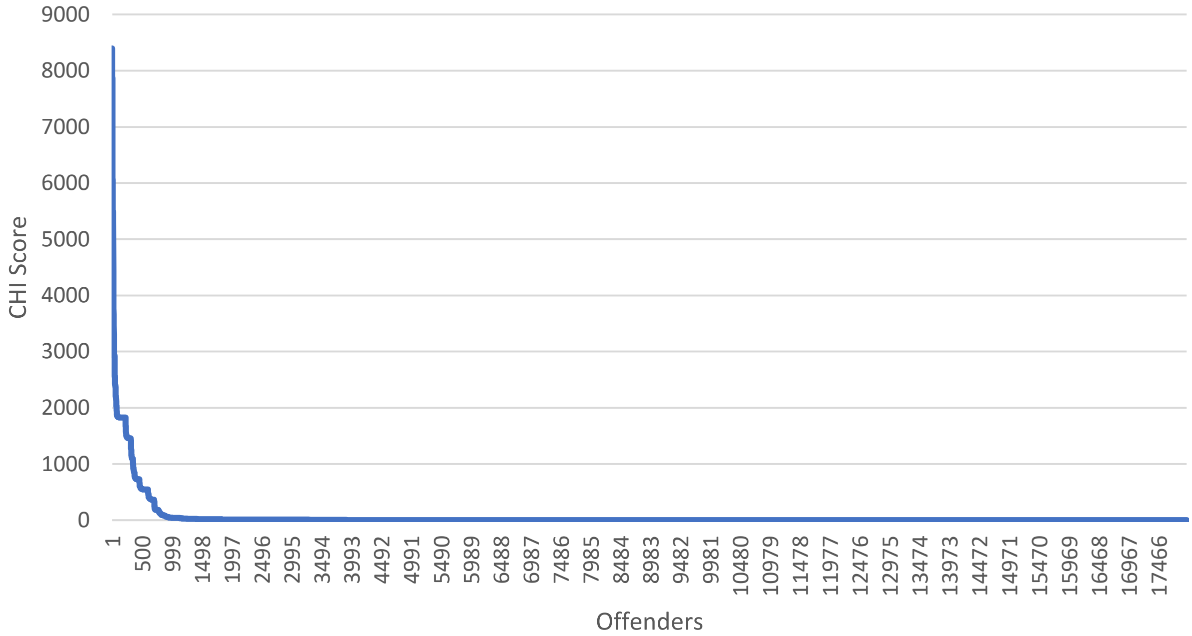

Figure 21: Wycombe Offenders CHI Distribution

Figure 22: Wycombe Offenders NHI Distribution shows that there are powerful concentrations of NHI scores, however due to the size of the data set it is not possible to use the Pareto principle. There are an abundance of individuals with low scores which dwarfs the score of any power few. For the purposes of identifying a power few, any offender with a score of 5 NHI or above was used. This provided a suitable pool of 103 top scoring offenders to be compared to the Wycombe OCGs recorded in the Tracker.

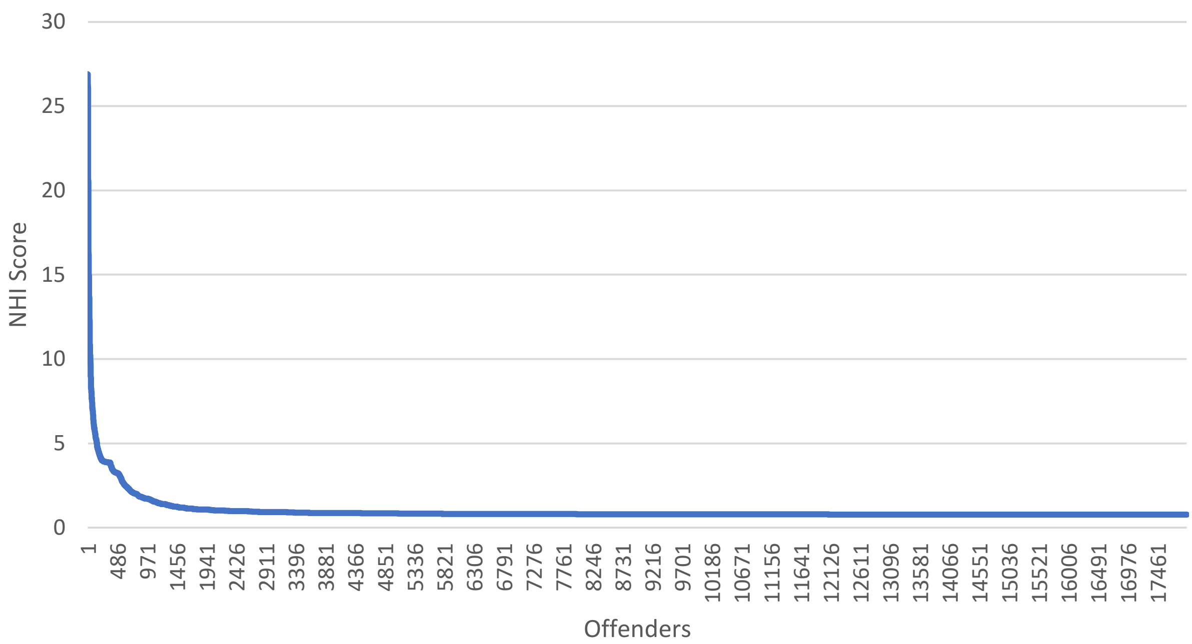

Figure 22: Wycombe Offenders NHI Distribution

When removing all individuals except for the NHI power few, the number of offenders reduces from 17938 to a power few of 103 (0.57%). There are 104 OCG members in the tracker who were active in the Wycombe LPA, however only 53 of these had been involved in co-offending or associated in intelligence during the data period. In the NHI power few, 30 of the 53 active OCG members in Wycombe were correctly identified. The accuracy of the NHI was particularly evident in the top 14 of the power few, where 11 tracked OCG members were identified.

4.3.4 Correlations

The correlations for the Wycombe data set can be seen in Appendix 7: Wycombe Offender Correlations. There is a weak correlation between Intelligence Degree and CHI, $r = .232$, $p < .01$. This is a similar result to what was seen in the correlations between these variable for both OCGs and OCG members, and could indicate that offenders more frequently associated through intelligence are, to a small extent, more likely to commit high harm offences.

4.3.5 Community Detection

Figure 23: NHI Power Few partitioned by Community Detection shows the power few from the NHI network. By performing a community detection analysis on the 103 offenders, 16 communities are identified.

Figure 23: NHI Power Few partitioned by Community Detection

The 30 individuals identified in the NHI power few and who were present in the Tracker, fall into 5 distinct communities.

- Community 1 accurately captured all 5 OCG members in OCG79.
- Community 2 captured 3 OCG members from OCG74.
- Community 3 accurately captured all 8 OCG members from OCG4.
- Community 4 accurately captured all 4 members from OCG67.

- Community 5 accurately captured all 3 OCG members from OCG119.
- 7 members of OCG74 were captured in communities of isolation or in OCG119 or OCG4.

The community detection analysis accurately identified the correct groups for all members except those of OCG74. To see why this was the case, it is necessary to look at the crime and intelligence reports. Table 4: Intelligence Association Matrix and Table 5: Co-offending Matrix**,** display all the intelligence and crime counts, in which OCGs interacted.

Table 4: Intelligence Association Matrix

		OCG				
		4	67	74	79	119
OCG	4		1	97	2	3
	67	1		1	1	4
	74	97	1			22
	79	2	1			
	119	3	4	22		

Table 5: Co-offending Matrix

		OCG			
		4	67	74	79
OCG	4			2	
	67			1	
	74	2	1		2
	79			2	

OCG4 and OCG74 have the highest number of associations. The context of these events is that the OCGs operate in very close proximity to one another. Members belong to the same gangs and operate the same drugs lines. They often exchange resources, prepare drugs and deal in conjunction. There have been two offences over the data period where these OCGs collaborated. The first was a drive by shooting and the other was possession of firearms.

The second highest number of associations is between OCG119 and OCG74. Members of these OCGs are close associates and have been sighted together on many occasions. They have also been in possession of bank cards belonging to the other, suggesting financial cooperation. There have been no co-offending incidents for this group.

This analysis shows that, with the exception of OCG74, all OCG members identified in the NHI power few were correctly sorted into the appropriate OCG through community detection. The basis for how the communities were formed appears to be well grounded, however the process has not mirrored the separation of highly cooperative OCGs as recorded in the Tracker.

4.3.6 Comparison of NHI results to Known Wycombe OCGs

Only 53 of the 104 known Wycombe OCG members were involved in co-offending or associated in intelligence during the 3 year data period. There could be many reasons for this including the sources of information used in the tracker assessment, which have been already addressed in 3.5 Data Issues & Limitations. In summary, intelligence not entered onto local systems, either because it was either confidential or from another source such as the NCA or another Police Force, has a detrimental effect on the performance of the NHI.

There are 73 individuals identified by the NHI not in the tracker, whom Thames Valley did not attribute to an OCG. They are all responsible for high harm offences and they frequently associate with known OCG members. To establish if these individuals should be considered for OCG membership, it will be necessary to look at the intelligence reports. The definition this research is applying to Organised Crime is *"serious crime planned, coordinated and conducted by 3 or more people working together on a continuing basis for often, but not always, financial gain".*

All of the individuals are prolific and well known to law enforcement, however 21 of the 73 identified individuals exhibited characteristics of organised criminal activity related to drug supply and gang involvement. The 52 individuals who did not match the characteristics of an OCG member were supporters of organised activity who were not instrumental in making decisions.

The 21 who were instrumental, engaged over a period of time, with currently known OCG members for the purposes of supplying Class A drugs, firearms and performing extortion and violence. Their absence in the Tracker was likely for operational reasons such as resourcing shortages or OCG member imprisonment. There are 23 individuals who appeared in the Tracker but not in the NHI power few. This means that the NHI failed to pick up on these individuals despite Thames Valley Police considering them OCG members. The main reason for this was that 17 OCG members had been involved in low levels of criminality during the data period. Six OCG members scored within the CHI power few, with just a few high harm offences meaning that the crime degree centrality was low. Four of these individuals did have a moderately high intelligence degree centrality, however not enough to provide them with a qualifying

NHI score. In total, 6 of the 23 individuals showed characteristics of organised criminality in the intelligence which was not picked up by the NHI.

4.4 Summary of Results

The results of the first section show that there is a correlation between the NHI and the Tracker when outliers were removed, $r = .460$, $p < .01$. These outliers contained OCGs with a very high number of historical sexual offences and others with a very low number of offences. The NHI found a power few of 16 OCGs whereas the Tracker found a power few of 18 OCGs. Both power few sets contained 5 OCGs in agreement.

Analysis of the OCG specialisations in the power few shows that the NHI tends to give slightly higher priority to OCGs involved in Drug Supply and the Tracker gives slightly higher priority to OCGs involved in Fraud. This reflects the source of information available to the Tracker however the number of OCGs in the power few was relatively small, weakening the validity of the findings.

The second section found a 77% accuracy rate in the allocation of OCG members to their recorded OCG. This is a strong indication that it is possible to successfully group OCG members on the basis of the crime and intelligence associations in the network.

The third section as shown the NHI to be effective in identifying 30 out of 53 OCG Members (57%) from a pool of 17938. This was an improvement over the CHI alone, which identified 24 OCG members (45%). Additionally, the NHI identified another 21 individuals whose criminality fits the definition of organised crime. Community Detection has shown to adequately group these individuals into communities that almost exactly resemble established OCGs recorded in the Tracker. Twenty-three individuals (43%) in the Tracker were not identified by the NHI. This was because their activity during the data period was too low to achieve a qualifying NHI score.

5. Discussion

This research set out to develop an objective means of identifying and ranking organised crime. Previous research has shown that organised criminals tend to commit higher harm offences (Hallworth, 2016; Jeffery, 2012 cited Crocker et al., 2016) and that they are more likely to co-offend (Campana and Varese, 2013; Morselli, 2009).The Crime Harm Index (CHI), and Social Network Analysis (SNA) degree centralities were used to measure these characteristics and the results were subject to data reduction to create the Network Harm Index (NHI).

The results have been presented in three sections. The first compared the rankings of Organised Crime Groups (OCGs) by their NHI scores to the corresponding OCG Mapping Tracker scores. The second section compared individual OCG members NHI scores to their respective OCG Mapping Tracker scores. The third section used an entirely different data set to see how the techniques fared on a much larger scale, with all offenders in the Wycombe LPA. The research firstly aimed to answer whether the objective measures of harm and degree network centrality could be used as an effective means of ranking known OCGs and OCG members. The second section aimed to take this a step further and explore how successful this method could be in identifying previously unknown OCG members and their respective OCGs.

5.1 New Evidence Groups

The first stage of the thesis aimed to understand if OCGs could be ranked by using the CHI and Network Analysis. This was conducted through the use Principal Component Analysis which is a data reduction technique, to produce a single measure that combines Crime Degree, Intelligence Degree, and the CHI. Organised crime is clandestine by nature, so it is impossible to test any new method with 100% accuracy. However, law enforcement in the UK does collate OCG activity using the OCGM process. Therefore by using established OCGs recorded in the Tracker, it should be possible to get an understanding of the general effectiveness of the NHI. The Tracker is not infallible however and this does leave the possibility that not all organised criminality has been identified and entered into the Tracker. Therefore any comparison between the results of this research and the Tracker are only as good as the information already collected by Thames Valley Police.

The first finding was that a power few of 29 OCGs (23%) perpetrated 80% of harm. This finding replicates the distribution described by the Pareto Principle. Many other criminological applications of the CHI have produced a far more concentrated power few at around the 5% mark (Bland and Ariel, 2014; Dudfield et al., 2017; Sherman et al., 2016; Weinborn, 2017). A credible explanation is that this research has already narrowed the sample down and therefore the power few is a concentration within an already established pool of high harm offending groups. It is therefore surprising that a power few distribution is maintained and shows that even within a police force's most serious criminal groups, there remains a minority that perpetrate the most harm.

The next step was to see how the application of the NHI would affect the power few. It was determined that 16 OCGs (13%) were positioned in the power few, showing that the NHI produces a high concentration than that of the CHI. This is the first application of a harm index in conjunction with degree centrality measures and so no comparison can be made to previous research, however the results indicate that the technique has greater targeting precision than the CHI on its own.

To test whether the NHI could adequately rank OCGs, the NHI results were compared to the Tracker and showed conformity in only 5 out of 29 of OCGs (17%) in the power few. This conformity was lower than expected. Interestingly, the CHI and the Tracker agreed in 6 out of 29 of OCGs (21%). This was due other OCGs with particularly high degree centralities, deposing OCGs at the lower end of the harm scale. To understand why this disparity exists, it was necessary to compare the criminal specialities of the OCGs in each power few. This showed that the NHI prioritises Drug Supply and Exploitation offences to the detriment of Fraud offences.

The difference in OCG speciality prioritisations highlights the difference in the source information that each technique is measuring. The NHI uses the CHI to measure high harm offences which prioritises extreme violence and sexual exploitation and the Network Analysis is measuring the associations between OCGs which is quite often higher in Drug Supply OCGs. Fraud is a very different type of crime and offences are often not recorded in the same way on police systems. It would be logical to think that a Fraud OCGs would be committing numerous criminal acts to a multitude of victims, however research shows that only a small percentage of Fraud offences are ever directly investigated by police (ONS, 2017). Furthermore, Fraud is not restricted geographically, therefore it is likely that crime and intelligence data used to score Fraud OCGs is being obtained from other jurisdictions and not entered onto local systems.

The results indicate a fundamental difference in what is being measured in comparison to the OCGM Tracker. The Tracker undervalues the objective harm being perpetrated by OCGs and the NHI is missing certain sources of information that the Tracker uses for its assessment. In summary, the NHI could be an effective means of ranking OCGs, if all available intelligence and crime data, internal and external to the law enforcement agency in question, is recorded accurately on local systems.

5.2 New Evidence Individuals

The next section of the research deals with known OCG members to confirm whether the same concentrations occur in individuals as they do in groups. This was found to be true as 156 OCG members (21%) were responsible for 80% of harm. This finding reaffirms the power few concentrations identified in OCGs. The same pattern was found in the application of the NHI where 79 OCG members (10%) were positioned in the power few. This corroborates the findings of the group based analysis that the NHI has a more precise targeting capability than the CHI on its own.

The advantage of analysing individuals was the opportunity to see in Community Detection algorithms could place OCG members back into their respective OCGs on the basis of network structure alone. The results showed that Community detection could be completed with 77% accuracy. Appendix 3: Comparison of Community Detection and Known OCG Formations, shows an illustrative example of the accuracy of Community Detection. This analysis could have a considerable beneficial impact in the way the Serious and Organised Crime teams determine subjects for operational activity.

5.3 New Evidence Wycombe

The final stage of the research aimed to see if the techniques performed could identify known and previously unknown OCG members and their respective OCGs in a much larger data set. The nature of this data set is quite different to the one used in the first two sections. The data used was all crime and intelligence with a spatial and temporal boundary, as opposed to starting out with a predefined list of individuals. This is known as a Sociometric network and is considered superior to analysis built around already known individuals, as it removes any bias that led to the identification of those individuals in the first place (Morselli, 2009).

The application of the CHI and the identification of the power few showed that 474 individuals (3%) were responsible for 80% of harm. This is consistent with prior research in crime harm concentrations in normal offender data sets. When analysing for concentrations with the NHI however, it was identified that just 103 offenders (0.57%) were in the power few. This is a very high concentration and presents a tiny fraction of offenders as potential organised criminals.

To determine whether the NHI power few were indeed involved in organised criminality, a comparison was made to OCGs members active in Wycombe during the data period. This comparison found that 30 of the 53 active OCG members (57%) were present in the NHI power few. Interesting the CHI power few only identified 24 OCG members (45%). This is especially pertinent when it is considered that the NHI power few contained just 103 offenders in comparison to the CHI which contained 474 offenders.

The next stage was to take another opportunity to test Community Detection algorithms. This successfully partitioned the power few into communities which exactly reflected established groupings in the tracker, with the exception of one OCG which was highly cooperative with two others. This is a reassuring result which indicates that not only can organised criminals be identified using the NHI, but also groups and will allow law enforcement the ability to more appropriately allocate resources.

There was a remainder of 73 power few individuals who were not recorded in the tracker, 21 of which were identified through further research as being involved in organised crime. This result shows that a sociometric approach to OCG member identification can include offenders that have been overlooked or excluded for some reason by investigators.

There were also 23 OCG members recorded in the tracker that the NHI did not identify, mostly due to low activity. This is an unfortunate yet unavoidable issue. OCGs consisting of members who are not linked to crime will inevitably not get prioritised into the CHI or NHI power few. OCG members recorded in the Tracker that have a hands-off approach to organised crime may be far more difficult to identify, but it may be possible to include other data points such as flags, code 5 intelligence, or links to group entities in computer software architecture that will allow for a more accurate identification of these individuals in future analysis.

5.4 Unexpected Findings

There were some unexpected findings in the research that deserve a mention. The first was the previously unknown interdependencies of OCGs. The number of co-offending incidents and intelligence associations indicated surprising levels of cooperation between OCGs. This is an opportunity to be exploited by law enforcement as it changes the perspective of OCGs working in isolation, to one of a large scale organised crime ecosystem. By targeting groups with high aggregated NHI scores it should be possible to disrupt not only the targeted OCG, but also any others that rely on that OCG for information or resources. For this reason, it may be beneficial for law enforcement agencies to have a more holistic and networked strategy for the allocation of resources to disrupt OCGs.

One further unexpected finding was in relation to Fraud recording. Research has shown that Fraud cases are underreported and only 17% come to the attention of the police or Action Fraud (ONS, 2017). Where Action Fraud is the first point of contact, solvability factors are taken into account before cases are disseminated to the police (HMICFRS, 2015). Furthermore, police forces are ill equipped and underfunded to deal with fraud, resulting in some setting thresholds to limit the number to be investigated (HMICFRS, 2015). The results show that only 12 Fraud OCGs of 126 (10%) were being targeted operationally during the data period. The Tracker puts 5 OCGs into the power few whereas the CHI puts 3 OCGs into the power few. The CHI provides a score for Fraud by Abuse of Position of 252, so Fraud OCG members only need be recorded as suspects on 3 of these offences to qualify for the CHI Power Few. The NHI only places 1 Fraud OCG into the power few due to low co-offending rates and intelligence links. Recording practises need to include Fraud offences and intelligence in their entirety rather than selectively due to a lack of evidence or resources. Fraud is now the country's most experienced offence (ONS, 2017) and policing practices and skills need to catch up.

5.5 Limitations

The limitations identified are well known in organised crime research, namely the lack of an adequate crime and intelligence recording system, non-standardised data, and a secretive police culture (Tusikov, 2011). One of the most influential factors that differentiates the Tracker measuring conditions from the NHI is access to intelligence or crime that has not been recorded on local systems. The Tracker utilises data that has been obtained from other jurisdictions. For the Network Harm Indexing to be more accurate, this information needs to be included into the data set. Changing recording practices for sources of external data should be implemented to ensure that future objective methods can capitalise on these assets and make sure that any decision-making processes can be held to account.

Another hurdle for objective processes is how law enforcement agencies balance information availability with information security. Many police forces silo intelligence when it is deemed too sensitive or when it is to laborious to input. Serious and Organised Crime Operations gather a lot of intelligence which is never made available to a wider audience. This has both positive and negative effects. The positive is reduced confirmation bias regarding which offenders should be targeted for future disruption. The negative is that intelligence may be over-sequestered, resulting in a vacuum of information to the detriment of the analysis. This means that the NHI would not have the data normally gathered on offenders, which reduces its capability. Police forces should endeavour to centrally record all intelligence but implement suitable security permission levels so that sensitive information can made accessible by to those who require it.

The research included proactive operations as no accurate method could be used to exclude them from the data search. This is a problem for interpreting the results, as focussed disruption activity will inevitably lead to greater detections. Many of the convictions obtained through proactive operations would have occurred after the OCG active date, meaning that they would have been excluded from the analysis, however some will have slipped through due to continued OCG monitoring and some arrests would have been made during the operation. Over a prolonged and repeated analysis, the inclusion of these offences can lead to confirmation bias, where the analysis identifies priority targets as a result of proactive work, which then go onto be prioritised again during any further targeting. To ensure that this effect does not occur, policing systems should include a means to record when a subject's involvement in crime resulted from proactive policing so that these offences can be excluded from the data searches.

5.6 Policy Implications

By using the CHI and Social Network Analysis measures, this research has demonstrated a new way of objectively identifying and ranking OCGs using a simple data set of crime and intelligence. The research used data in its purest form, without considering other data points such as system flags or group intelligence entities. This means that Network Harm Indexing can be a flexible tool when applied to other jurisdictions with varying computer software architecture.

The ability to identify the majority of known OCG members from an area with a population of nearly 180,000 (ONS, 2016) is testament to the technique's effectiveness. Furthermore, previously unknown offenders who were not being operationally monitored by the Serious and Organised Crime Unit, were shown to be actively involved in the orchestration of organised criminality. By taking a large scale, data focussed approach to identifying organised crime, the research has been able to analyse more intelligence and crime data than any policing team could hope to achieve using traditional methods.

The research has also shown that OCGs do not work in isolation, but are to some degree interdependent on each other for the purposes of committing crime. This big picture approach will present new opportunities for disruption by targeting groups that will have a cascading detrimental effect to other OCGs with whom they cooperate.

Crime is becoming more complex and law enforcement is starting to capitalise on technological approaches which improve targeting and detection whilst decreasing demand. By taking an objective approach to various aspects of policing, it will be possible to explore ways of automating tasks that use considerable human resources which increases costs. Thames Valley Police currently employs one OCGM Coordinator and one Researcher to conduct OCGM assessments, however the process is laboriously administrative. Police forces across the UK then submit this data to the National Crime Agency (NCA), who then collate all the data to obtain a national picture. Towards the end of 2016, there was an estimated 5,866 OCGs operating in England and Wales, consisting of 39,414 individuals (NCA, 2017). Analysis on this scale requires significant investment in human resources, which could be alleviated using and automated form of Network Harm Indexing.

Limitations do exist, mainly due to police force information management, where sources of external data are used for decision making but are not recorded onto local police systems. The same issue arises for data that is siloed across the force with examples including highly sensitive or complex data. Policing are taking an increasingly scientific and technological approach to crime detection, and solutions must be implemented that can overcome these limitations. By improving information management and conducting further tests on the accuracy of Network Harm Indexing, there is the potential to radically improve upon the current organised crime assessment process.

5.7 Further Study

This research has studied known OCGs across the Thames Valley Police Force and analysed data from the Wycombe area. Further research in other jurisdictions will be required to confirm the validity of the findings. As Network Harm Indexing uses data in its simplistic form, the process should be available to any law enforcement agency.

The next step from this research in Thames Valley would be to increase intelligence gathering on the individuals identified in by the NHI as belonging to a particular OCG, that were not being monitored in the Tracker or being monitored as part of another group. This would provide greater context on whether the NHI and Community Detection analysis are an improvement upon current methods.

Although this research has shown success in identifying OCGs, there are gaps where improvements can be made. This is especially true for the detection of low activity offenders. Further research could broaden the data sets in use, to allow more precise prioritisation of offenders who are orchestrating crime but are more hands-off. This could include algorithms to detect organised crime predictors in intelligence reports, the use of flags on reports, links to OCG entities created on the system, and even current imprisonment status. Iterative improvements on this process would increase its effectiveness to the point where it could be used as the primary detection and prioritisation method. Until such time, Network Harm Indexing would need to be used a supplementary tool for organised crime investigators.

The research has shown some interesting interdependencies between OCGs which could be explored in further research. By increasing the understanding of these interdependencies, it will be possible to formulate new disruption techniques that will allow for better proactive policing of organised crime.

There is also the possibility of adapting Network Harm Indexing for other purposes. This technique is useful for identifying offenders, but the same process can also be applied to the identification of high harm repeat victims. Individuals that suffer high harm from a number of offenders should be one of the police's highest priorities. By looking at the CHI scores for offences where individuals are in a victim capacity rather than an offender capacity, it should be possible to identify and rank the most vulnerable people for proactive policing support. Arguments have been made that harm suffered by victims of organised crime is more relevant than harm perpetrated by organised criminal (Tusikov, 2011). If both functions could be built into a software solution that interfaces with current crime and intelligence recording systems, this would be big step towards offering more protection to the public and society’s most vulnerable victims.

6. Conclusion

The first part of the research was to see of the combination of CHI and SNA could produce an objective method to rank known OCGs. The results showed the NHI and Tracker agreed on 5 out 29 OCGs identified in the power few of each measure. Analysis of the crime types showed that the NHI prioritised Drug Supply and Exploitation OCGs whereas the Tracker prioritised OCGs specialising in Fraud. This highlights the differences in the data available to each method, as there appears to be a lack of Fraud offences recorded on local systems, indicating that external data is being used in the Tracker which is not available to the NHI.

The second part of the research aimed to identify OCG members from a larger data set and then use Community Detection to form them into groups. The CHI was used successfully as an objective way to measure the harm perpetrated by OCGs and OCG Members. A power few of 474 (3%) were shown to be perpetrating the most harm in the Wycombe LPA, 24 of which were OCG members in the Tracker. The NHI identified a power few of 103 (0.57%), and 30 of those were OCG members recorded in the Tracker, meaning that Degree Centrality measures had improved the targeting performance supporting the findings of Bichler et al. (2017). Individuals not identified by the NHI had engaged in very little crime during the data period and new methods need to be explored outside the scope of this thesis. Community Detection formed groups which almost perfectly matched those recorded in the Tracker, which provides an excellent basis ongoing identification of potential OCG members for operational activity.

In the absence of any better comparison for organised crime, the Tracker has been used as a baseline for performance in this study, but is not infallible. In fact, risk assessment methodology has been criticised quite extensively in literature to date (Innes et al., 2005; Zoutendijk, 2010). It may be possible that law enforcement have resorted to using clinical judgment on the decisions regarding which individuals were targeted for operational activity, supporting observations by Varese, (2010). This leaves room for bias, in that there is a tendency to focus on individuals of interest, to the detriment of others (Rostami, 2015).

There were 73 individuals identified in the NHI power few that were not being monitored in the Tracker. An intelligence review revealed that 21 of these showed characteristics of organised criminality according to the definition set out in the Methods. This could be for two reasons. Either the individuals were not identified as potential OCG members by investigators, or they were deliberately omitted for unknown reasons. If they were missed, then it supports the argument by Innes et al. (2005) that law enforcement lacks an objective methodology for their identification of OCG members. If they were omitted, this supports the observation by Innes et al. (2005) that police risk assessment methodology is "plastic" and that processes simply reflect law enforcement interests. It may be that individuals were not targeted for fair reason, such as resourcing shortages or OCG member imprisonment, however this does not mean that the individual should be removed entirely from the Tracker.

Consistently through the stages of analysis, it was shown that individuals with a high crime degree were not likely to also have a high intelligence degree. This corroborates Rostami's (2015) assertion that combining multiple data sources such as crime and intelligence increases the reliability of the network analysis. However, individuals responsible for orchestrating organised crime, but whom did not engage in crime directly, where difficult to detect despite the inclusion of intelligence. Tayebi & Glasser (2012) argue that intelligence should make up for a lack of recorded criminal involvement. This research has found that whilst this is the case, individuals with very low co-offending rates did not make it into the NHI power few, suggesting further research needs to address this issue.

The literature is very clear that for network analysis to be reliable, data sets need to be complete as possible (Rostami, 2017; Bichler et al., 2017). The results show that Fraud recording practises have had a negative effect on the ability of the NHI to capture the co-offending between members of Fraud OCGs. This has also had an impact on the CHI to attribute a score, meaning that Fraud OCGs score far lower than they should. This highlights that the IT infrastructure and information management environments need to record crime in its entirety to ensure suitability for an objective method.

The CHI reflected concentrations seen in other research (Bland and Ariel, 2014; Dudfield et al., 2017; Sherman et al., 2016; Weinborn, 2017), even within a pool of serious offenders. This adds to existing findings that harm is concentrated in just a small number of offenders. The average CHI score was nearly 8 times higher higher among OCG members (1248) compared to non OCG members (152), corroborating evidence from Hallworth (2016) and Jeffery (2012 cited Crocker et al., 2016), that OCG members tend to commit high harm offences. Degree centralities were considerably higher in OCG members for both co-offending (71) and intelligence associations (160) compared to non-member co-offending (2) and intelligence associations (2), providing strong support for the findings of Campana and Varese (2013) and Morselli (2009).

Hobbs, (1997) has asserted that UK OCGs consist of a series of temporary social arrangements between a constantly changing group of individuals. Findings shared by Tayebi & Glasser (2012) and by Sarnecki (2001), show that collaborations do not persist over long periods of time. Tayebi & Glasser (2012) showed that about 14% of offender groups survived and only 1% of groups merged and split over the 4 year data period. This research did not study groups through time, rather a 3 year snapshot, however Community Detection accurately partitioned offenders into the pre-existing OCG formations except for OCG74, which had a high level of collaboration with other groups. This suggests, that in Thames Valley at least, members collaborate but tend to stay loyal to existing groups.

The research concludes that Network Harm Indexing can be an excellent method to identify OCGs and OCG members, and with better information management, the technique could also provide a viable means for prioritisation. It is hoped that this study presents a methodological foundation for the design of new practices and systems, which can deliver valuable insights and the opportunity to develop cost effective proactive and preventative strategies.

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8. Appendices

Appendix 1: OCG Correlations

		TotalMembers	IntelCount	CrimeCount	IntelDegree	CrimeDegree	TotalCHI	NHI	AveTracker
TotalMembers	Pearson Correlation	1	.638**	.192*	.423**	.399**	.556**	.692**	.257**
	Sig. (2-tailed)		0.000	0.031	0.000	0.000	0.000	0.000	0.004
	N	126	126	126	126	126	126	126	126
IntelCount	Pearson Correlation	.638**	1	.247**	.760**	0.107	.318**	.612**	.208*
	Sig. (2-tailed)	0.000		0.005	0.000	0.231	0.000	0.000	0.019
	N	126	126	126	126	126	126	126	126
CrimeCount	Pearson Correlation	.192*	.247**	1	0.145	.323**	0.089	.262**	-0.048
	Sig. (2-tailed)	0.031	0.005		0.105	0.000	0.323	0.003	0.596
	N	126	126	126	126	126	126	126	126
IntelDegree	Pearson Correlation	.423**	.760**	0.145	1	0.119	.227*	.691**	.238**
	Sig. (2-tailed)	0.000	0.000	0.105		0.184	0.011	0.000	0.007
	N	126	126	126	126	126	126	126	126
CrimeDegree	Pearson Correlation	.399**	0.107	.323**	0.119	1	0.154	.576**	0.150
	Sig. (2-tailed)	0.000	0.231	0.000	0.184		0.085	0.000	0.094
	N	126	126	126	126	126	126	126	126
TotalCHI	Pearson Correlation	.556**	.318**	0.089	.227*	0.154	1	.727**	0.152
	Sig. (2-tailed)	0.000	0.000	0.323	0.011	0.085		0.000	0.088
	N	126	126	126	126	126	126	126	126
NHI	Pearson Correlation	.692**	.612**	.262**	.691**	.576**	.727**	1	.270**
	Sig. (2-tailed)	0.000	0.000	0.003	0.000	0.000	0.000		0.002
	N	126	126	126	126	126	126	126	126
AveTracker	Pearson Correlation	.257**	.208*	-0.048	.238**	0.150	0.152	.270**	1
	Sig. (2-tailed)	0.004	0.019	0.596	0.007	0.094	0.088	0.002	
	N	126	126	126	126	126	126	126	126

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix 2: OCG Member Correlations

		IntelCount	CrimeCount	IntelDegree	CrimeDegree	TotalCHI	NHI	AveTracker
IntelCount	Pearson Correlation	1	.169**	.622**	0.009	.225**	.395**	0.041
	Sig. (2-tailed)		0.000	0.000	0.812	0.000	0.000	0.261
	N	760	760	760	760	760	760	760
CrimeCount	Pearson Correlation	.169**	1	.078*	.173**	.093*	.162**	-.100**
	Sig. (2-tailed)	0.000		0.032	0.000	0.011	0.000	0.006
	N	760	760	760	760	760	760	760
IntelDegree	Pearson Correlation	.622**	.078*	1	0.060	.282**	.611**	.254**
	Sig. (2-tailed)	0.000	0.032		0.097	0.000	0.000	0.000
	N	760	760	760	760	760	760	760
CrimeDegree	Pearson Correlation	0.009	.173**	0.060	1	.295**	.632**	0.052
	Sig. (2-tailed)	0.812	0.000	0.097		0.000	0.000	0.151
	N	760	760	760	760	760	760	760
TotalCHI	Pearson Correlation	.225**	.093*	.282**	.295**	1	.816**	.132**
	Sig. (2-tailed)	0.000	0.011	0.000	0.000		0.000	0.000
	N	760	760	760	760	760	760	760
NHI	Pearson Correlation	.395**	.162**	.611**	.632**	.816**	1	.205**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000		0.000
	N	760	760	760	760	760	760	760
AveTracker	Pearson Correlation	0.041	-.100**	.254**	0.052	.132**	.205**	1
	Sig. (2-tailed)	0.261	0.006	0.000	0.151	0.000	0.000	
	N	760	760	760	760	760	760	760

**. Correlation is significant at the 0.01 level (2-tailed).

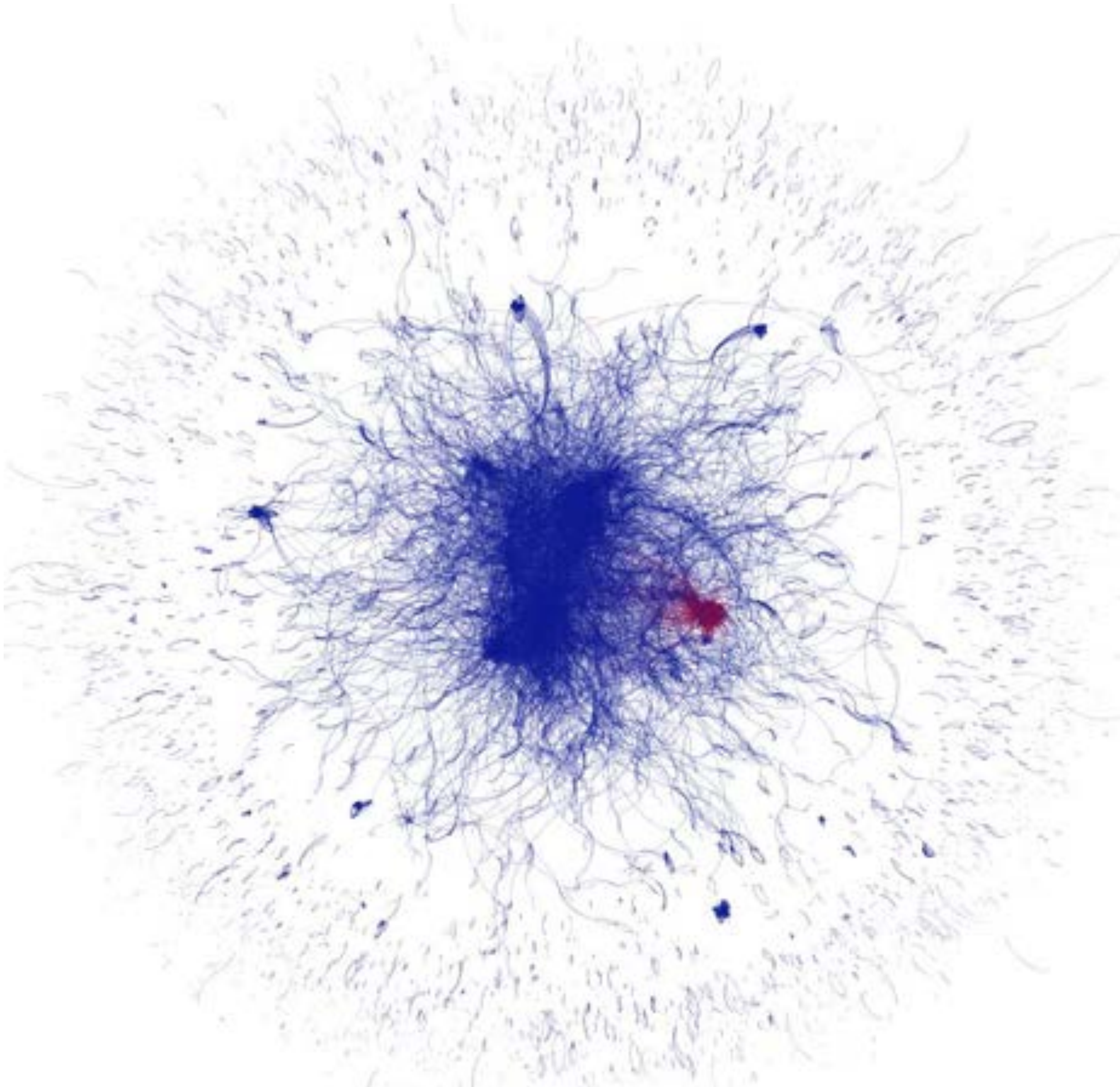
*. Correlation is significant at the 0.05 level (2-tailed).

Appendix 3: Comparison of Community Detection and Known OCG Formations

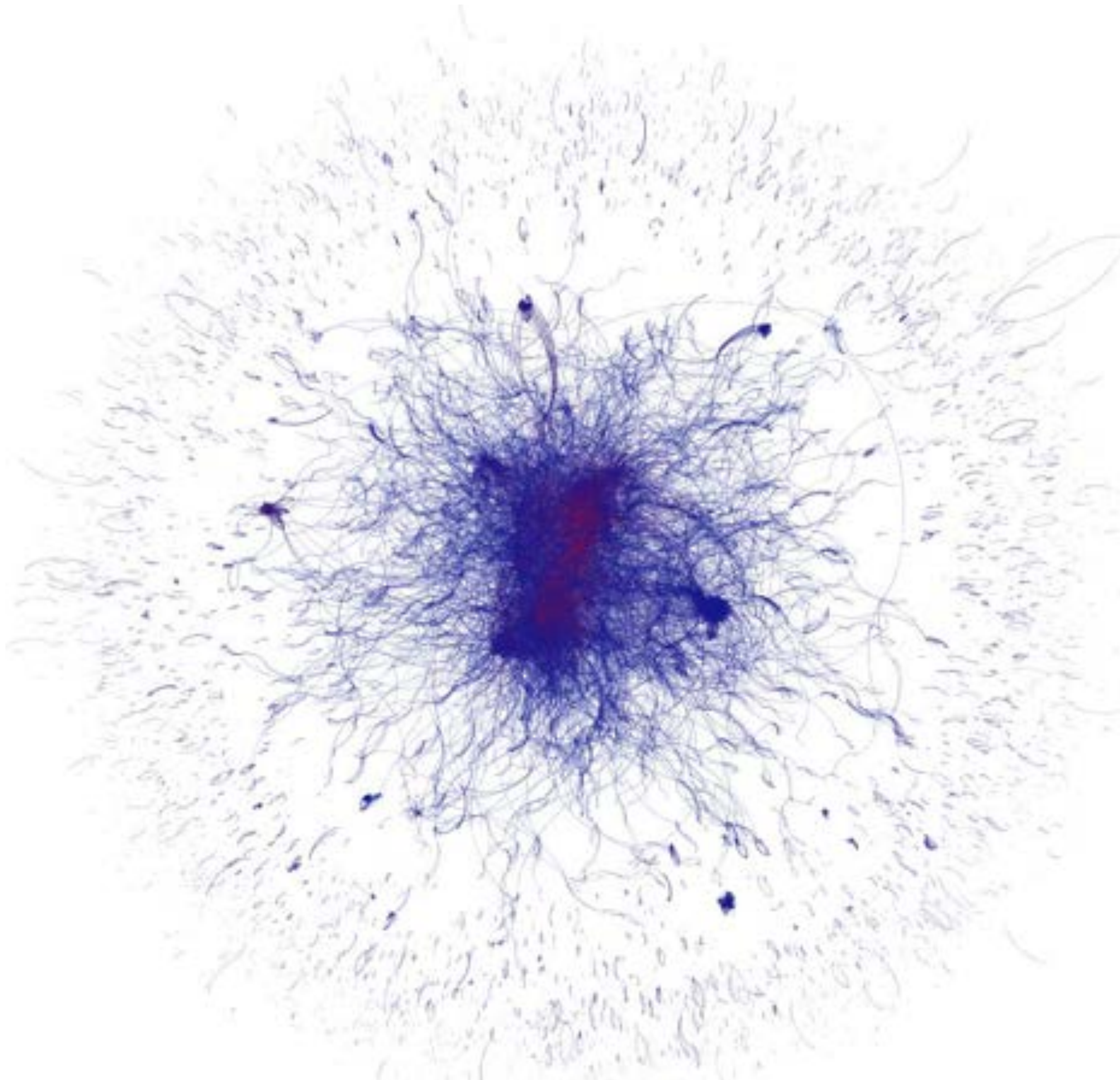
Individuals Grouped via Community Detection

Individuals Grouped via Established OCG ID in the Tracker

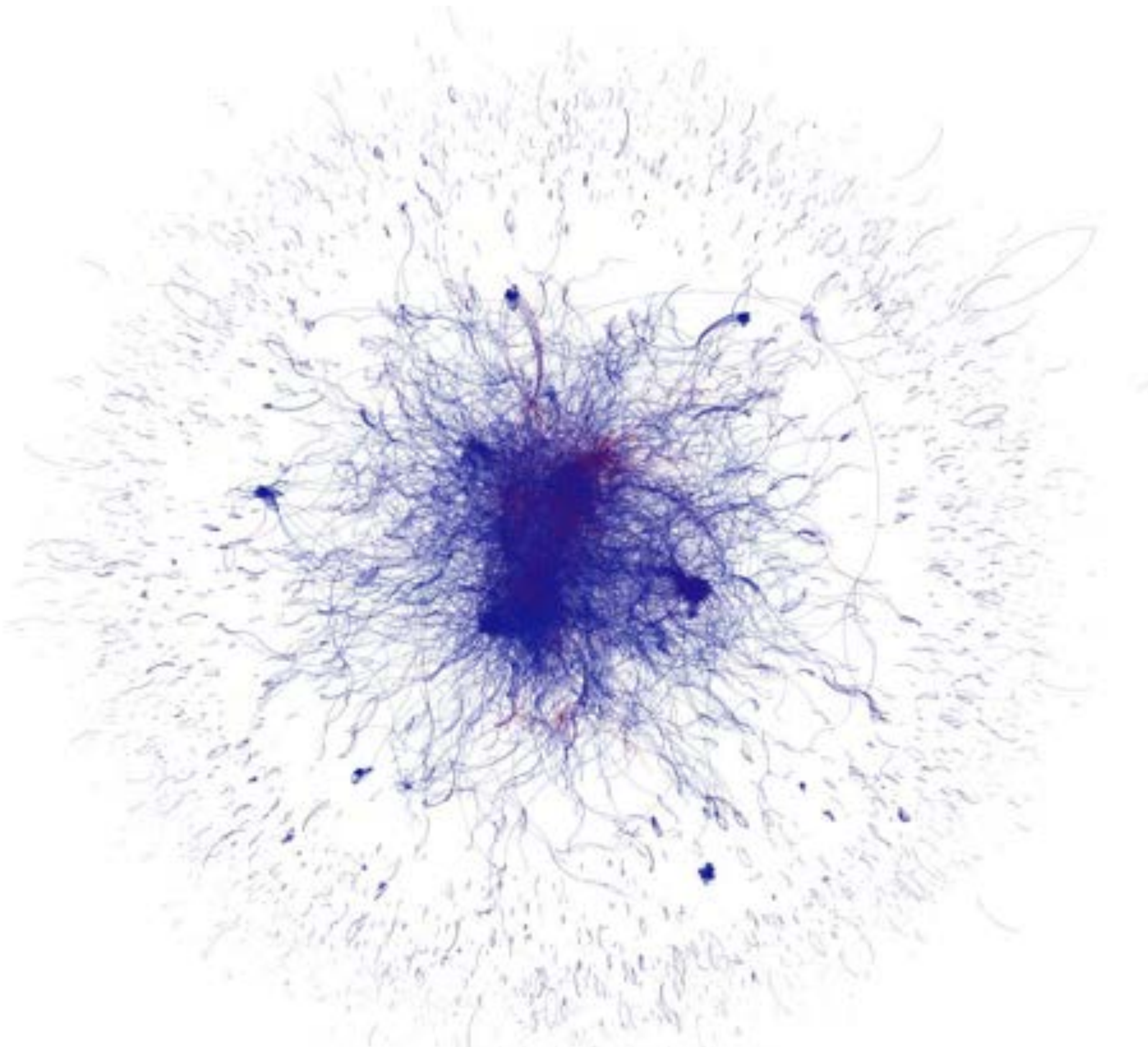
Appendix 4: Network Visualisation of Crime Degree for Wycombe LPA



Appendix 5: Network Visualisation of Intel Degree for Wycombe LPA



Appendix 6: Network Visualisation of CHI Scores for Wycombe LPA



Appendix 7: Wycombe Offender Correlations

		IntelCount	CrimeCount	IntelDegree	CrimeDegree	TotalCHI	NHI
IntelCount	Pearson Correlation	1	.227**	.660**	.148**	.236**	.561**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000
	N	17938	17938	17938	17938	17938	17938
CrimeCount	Pearson Correlation	.227**	1	.146**	.927**	.150**	.500**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000
	N	17938	17938	17938	17938	17938	17938
IntelDegree	Pearson Correlation	.660**	.146**	1	.086**	.232**	.729**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000
	N	17938	17938	17938	17938	17938	17938
CrimeDegree	Pearson Correlation	.148**	.927**	.086**	1	.096**	.462**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000
	N	17938	17938	17938	17938	17938	17938
TotalCHI	Pearson Correlation	.236**	.150**	.232**	.096**	1	.738**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000
	N	17938	17938	17938	17938	17938	17938
NHI	Pearson Correlation	.561**	.500**	.729**	.462**	.738**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	
	N	17938	17938	17938	17938	17938	17938

**. Correlation is significant at the 0.01 level (2-tailed).