# Measuring UK Crime Gangs: A Social Network Problem

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**Abstract** This paper describes the output of a study to tackle the problem of gang-related crime in the UK; we present the intelligence and routinely-gathered data available to a UK regional police force, and describe an initial social network analysis of gangs in the Greater Manchester area of the UK between 2000-2006.

By applying social network analysis techniques, we attempt to detect the birth of two new gangs based on local features (modularity, cliques) and global features (clustering coefficients). Thus for the future, identifying the changes in these can help us identify the possible birth of new gangs (sub-networks) in the social system.

Furthermore, we study the dynamics of these networks globally and locally, and have identified the global characteristics that tell us that they are not random graphs – they are small world graphs – implying that the formation of gangs is not a random event. However, we are not yet able to conclude anything significant about scale-free characteristics due to insufficient sample size. A final analysis looks at gang roles and develops further insight into the nature of the different link types, referring to Klerks' 'third generation' analysis, as well as a brief discussion of the potential UK policy applications of this work.

**Keywords** Gangs · Gun crime · Scale-free networks · Small-world networks · Social distance · Communities · Crime policy

This article is a substantially extended and revised version of the authors' ASONAM 2014 papers (Oatley and Crick, 2014b,c), with an updated research and policy context, literature review and methodology, along with new data and analysis.

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## 1 Introduction

There have been numerous studies of criminal networks and gangs; as highlighted in Hughes (2005), the popularity of qualitative studies of gang-related issues soared during the 1980s and 1990s, following renewed media and public interest, statistical advances, and increased government funding. Qualitative studies have taken three major forms: (a) surveys of law enforcement officials (and at times other agency personnel) regarding gangs in their jurisdictions and actions taken to control them, (b) analyses of data compiled by law enforcement agencies and/or court officials, and (c) self-reports of samples of youth and/or young adults. There have been calls for research evidence to be drawn into police practice, but development of such an agenda has been hampered by a range of factors (Bullock and Tilley, 2009). Research into youth gangs, especially the age at which youths join gangs and the early precursors, has been conducted in the USA and Canada (Hill et al, 2001), China (Webb et al, 2011) and Hong Kong (Lo, 2011), as well as the link between gun ownership and gang membership (Bjerregaard and Lizotte, 1995; Bricknell, 2008).

However, the UK has been slow in carrying out research into gang crime especially into what actions work best at controlling it (Hallsworth and Silverstone, 2009; Pitts, 2007), even with an increased policy focus (Golding and McClory, 2008; Hales et al, 2006). In Greater Manchester, a region in the north of the UK that has had a significant gun crime problem related to gang activity, primarily due to acute social deprivation in the area (BBC News, 2003, 2004; Hales et al, 2006), recent police initiatives have started to address this problem (BBC News, 2010).

Social network analysis has been applied across a wide number of domains, providing a unifying language to describe disparate systems ranging from social interactions to power grids. There is also a growing body of literature applied to crime analysis (for example: (Baron and Tindall, 1993; Calvó-Armengol and Zenou, 2004; Hansen, 2005; Hutchins and Benham-Hutchins, 1995; Klerks, 2001; Oatley et al, 2005, 2006a)). Related work (Calvó-Armengol et al, 2007; Patacchini and Zenou, 2008) on analysing the strength of weak ties in crime through steady state equilibria modelling has also been successful. Identifying structural holes, betweenness and social capital reinforces the value of using social network analysis for gang research (Papachristos, 2006).

We present the dynamics of a social network study of these gangs and their associates, using the intelligence gathered by police observations of known gang members and associated criminals. We develop the statistical analysis of network dynamics, combining well-known global topological measures, local motifs and modules (Costa et al, 2007; Jackson, 2008; Newman, 2003). Network motifs are subgraphs that appear more frequently in a real network than could be statistically expected. At a global level, if these networks of associations exhibit clustering behaviour this indicates the presence of gangs. At a local level, any defined sub-structures will provide us information about the gang structure. We are interested in modelling the dynamics of the gangs, their development and fragmentation into new gangs, and we hope that the study of the dynamics in such modules will provide information on the structural changes within gangs that lead to birth of new gangs, and predictors of other gang-related behaviour.

Furthermore, we investigate if the networks have scale-free, small-world or other characteristics (Albert and Barabási, 2002; Newman, 2003; Watts, 2003); small-world networks are characterised by a diameter that grows logarithmically with their size. One important characteristic of the small-world phenomenon is that each pair of nodes are connected through a relatively small number of steps to a huge network size defined by the total number of nodes. Scale-free structures consists of many nodes with low degrees and a few hubs with high degrees (Albert et al, 2004; Costa et al, 2007; Jackson, 2008). If the offender networks can be classified into either (or both) of these categories (or other known network types), then this provides not only insight into the dynamics of the gang network, but also operational uses; for instance, network disruption/destruction strategies, nodes/offenders to monitor, and so on.

## 2 Problem description and data

Gun crime in Manchester first gained media attention in 1988 after concern over eight shootings and a gun-related murder, at a time when gun crime was considered rare in the UK. Nevertheless, gun crime in Manchester appears to have begun in the late 1970s at a time of rising unemployment and poverty in the area.

Numerous shootings – both fatal and non-fatal – have taken place over the years as the Pepperhill, Gooch, Doddington and Longsight Crew gangs (see Table 1) have clashed over drug territories and other disputes. Many of these gun fire exchanges were on public streets, some were planned acts and some were spontaneous events.

| Gang label | Gang Name | Formation |
|---|---|---|
| A | Gooch | 1990s |
| B | Doddington/Pepperhill | 1990s |
| C | Longsight Crew | c.2001 |
| D | Rusholme Crew Gangsters | c.2004 |

**Table 1** Gang names and approximate dates of formation.

In 2001, a new approach to tackling gun crime began to develop with police working more closely with the local community and other agencies. The Manchester Multi-Agency Gang Strategy (MMAGS), a multi-agency approach to tackling gun crime and deterring young people from entering into a gang/gun culture was initiated as a result of a UK Home Office report (Bullock and Tilley, 2002). The report concludes:

- About 60 per cent of shootings are thought to gang-related.
- Violence in general, gun violence and fatal shootings in particular are concentrated in specific small areas of South Manchester.
- Gangs in South Manchester are loosely turf-based.
- Alliances are sometimes formed between South Manchester gangs, but conflict is endemic and easily triggered.
- Gang-related criminal behaviour includes drug-related offences, but only as one element of a patchwork of violent and non-violent crime.
- Gang membership is not just about criminality; for some young males it incorporates a credible lifestyle choice.
- Gang membership comprises a mix of same-age local friendship groups, blood relatives and recruits.
- The carrying of firearms by gang members is part protective, and part symbolic, though they are also sometimes used in the commission of violent crime.

- The majority of perpetrators of serious gun violence and victims in South Manchester have crimi-nal records.
- Those who have been victims of shootings are at increased risk of being a victim again.

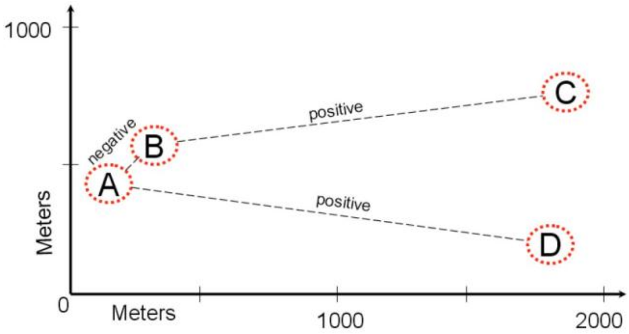


**Fig. 1** Gang geographical locations. *positive* indicates a positive alignment between the gangs, *negative* indicates negative alignment.

The geographical proximity of the gang locations and hub of all these activities can be seen in Figure 2, where the distance between Gangs A and B is hundreds of meters, literally a few streets away from each other. Gangs A and B show a negative attitude towards each other, often resulting in 'tit-for-tat' gun crimes. The alignment between Gangs A and D is possibly because of a mutual rivalry with B, while the positive alignment of B with C is because A has encroached on C's 'territory' for drug sales. The gang locations are overlaid on the locations of all serious crimes (murder, attempted murder, manslaughter, kidnapping, serious wounding, and firearms offences) recorded in the data available to the consortium for the period 1980-2007. Agreeing strongly with the 2002 UK Home Office report (Bullock and Tilley, 2002) we find: 38% (n=162) of all serious crimes occurring within 1 km radius (of gang locations) and 63% of all serious crimes occur within 2 km, and 53% (n=9) of murders are within 3 km; 38% (n=34) of attempted murders are within 1 km and 63% within 2 km; and, 33% (n=17) of serious woundings are within 1 km and 48% are within 2 km.

## 3 Police databases

The database used for this analysis included the list of associates for each gang member, with fields such as unique identifiers for each offender, date of birth, relationship between the offenders, ethnic origin, reason reported and date of occurrence.

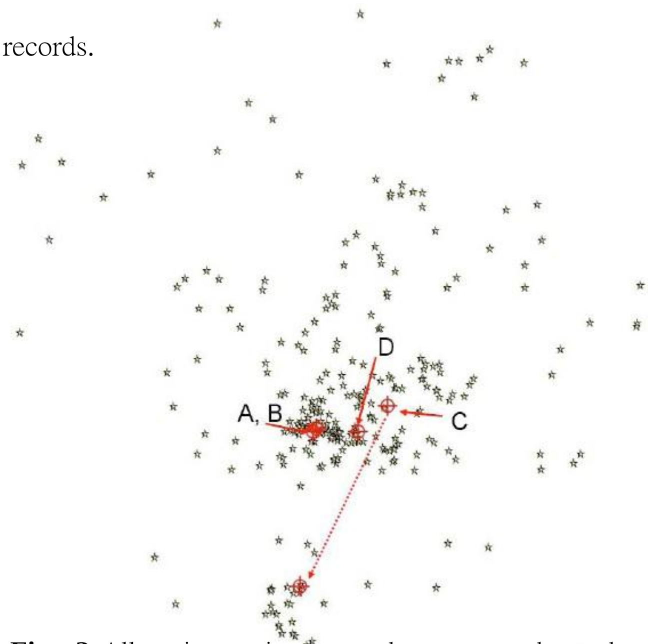


**Fig. 2** All serious crimes: murder, attempted murder, manslaughter, kidnapping, serious wounding, firearms offences. Gang C has moved into an additional location with drug selling. Gang geographical locations. *positive* indicates a positive alignment between the gangs, *negative* indicates negative alignment.

### 3.1 Link types

The network links available are quite different to other existing work with networks of burglars or retail fraudsters (Oatley and Crick, 2014a; Oatley et al, 2005, 2006b)). Examples of the data (link types) from which the networks of offenders are developed can be found in Table 2. These link types are: *Accomplice*; *Brother-Brother*; *Boyfriend*; *Brother*; *Sister*; *Charged with*; *Child*; *Co-habitant*; *Foster child*; *Foster parent*; *Friend*; *Girlfriend*; *Guardian*; *Other*; *Parent*; *Relative*; *Spouse*; *Sister-Sister*; *Ward*; *Gay Boyfriend*; and *Gay Girlfriend*.

An explanation of the dataset from Table 2 follows, and it is clear that it is a rich source of information. However, there are also many inconsistencies, and if this data is to be used to its full potential it will require a great deal of pre-processing, using natural language processing, matching with regular expressions, information extraction, and so on. As part of this pre-processing and data cleansing, further categorisation should be applied, as 50% of the data is classified of type *Other*.

### 3.2 Observations and inconsistencies in the dataset

The following indices refer to rows in Table 2, for instance *1-i* refers to *1. Accomplice* from the *Relationship*

| Magnet Category | Relationship | Frequency/Percentage | Reason Reported Examples |
|---|---|---|---|
| Crime related | 1. Accomplice | 502, 10.7% | (i.) Arrested Together<br>(ii.) Believed To Be Dealing Drugs Together<br>(iii.) X' s Sister Is Y' s Girlfriend |
| | 2. Charged with | 45, 1.0% | (i.) Charged Together Murder<br>(ii.) Arrested Together |
| Familial | 3. Brother | 65, 1.4% | (i.) Believed To Be Half-Brothers |
| | 4. Child | 23, 0.5% | (i.) Father & Son<br>(ii.) Admitted Above Named Is His Dad |
| | 5. Parent | 20, 0.4% | (i.) Mother & Son |
| | 6. Relative | 173, 3.7% | (i.) Cousins<br>(ii.) X States Y Is His Uncle |
| | 7. Sister | 18, 0.4% | (i.) Brother And Sister<br>(ii.) Stated They Are Brothers |
| | 8. Spouse | 2, 0.0% | (i.) Arrested Together Handling |
| Friendships | 9. Cohabitant | 5, 0.1% | (i.) Possibly Living Together At Anon Street |
| | 10. Friend | 1409, 30.0% | (i.) Stop Checked Together In car<br>(ii.) Attended Club Together<br>(iii.) Seen Together |
| | 11. Girlfriend | 61, 1.3% | (i.) Have Child Together |
| | 12. Boyfriend | 10, 0.2% | (i.) Girlfriend/Boyfriend |
| Other | 13. Other | 2364, 50.3% | (i.) Ex-Boyfriend Of The Above Named<br>(ii.) R Claimed E Stabbed Him<br>(iii.) C Intends Killing A/N Re Murder Of Bros<br>(iv.) Tog At Nightclub, Oldham<br>(v.) Seen Together<br>(vi.) Attended Murder Trial<br>(vii.) Arrested Together In Anon<br>(viii.) D' s Number In C' s Mobile<br>(ix.) Seen Together At Moss Side Festival |

**Table 2** Examples of the 'associates' data. This data is used to create the social networks. Gang membership comprises a mix of same-age local friendship groups, blood relatives and recruits: UK Home Office report Bullock and Tilley (2002).

column, and *(i.) Arrested Together* from the *Reason Reported Examples* column.

- *1-i* and *2-ii* indicate that the data is not rigidly recorded or categorised
- *1-iii* is incorrectly categorised
- *3-i*, *6-ii* and *9-i* illustrate that the intelligence is fallible, and is often based upon beliefs, and also that the link types are not all of equivalent strength, for instance the strength of a *Belief* link (possibly false) versus a *Charged Together* link (definitely true)
- *4-i* and *5-i* illustrate how the same information can be described, often in different forms, in separate fields
- *7-ii* shows an obvious mistake with *Brothers* recorded in the *Sisters* category
- *8-i* contains not only information about cohabitation, but also intelligence about handling stolen goods
- *11-i* illustrates again that links can be stronger or weaker, for instance the child may mean that there is a stronger bond/link between the offenders
- *10-i-iii* could all be placed in the *Other* category
- *13-ii,iii* contain a lot of intelligence
- *13-v* is a weak form of link, and should really indicate whether it was on good or bad terms
- *13-vii* should be in either the *Accomplice* or *Charged With* categories
- *13-viii* is noteworthy as it is a very specific link, a mobile phone link

## 3.3 Limitations of the data

In preparing our data for analysis, we faced the typical data quality issues referenced by Xu and Chen (2005), specifically that a criminal network is a special kind of social network with emphasis on both secrecy and efficiency. Such networks are intentionally structured to ensure efficient communication among members without being detected (Ferrara et al, 2014). The data problems therefore are: incompleteness, as criminal networks are covert networks that operate in secrecy and stealth, with missing nodes and links in networks; incorrectness, unintentional data entry errors or intentional deception by criminals; and, inconsistency, with many records of same person from difference contacts or sources.

Overall, it is concerning that this data is used as a gang database, but without explicit qualifications. Furthermore, it is generally not purged, but membership would not necessarily have an effect on sentencing. Comparing to gang criteria by states in the USA, *'Identified by reliable source (police)'*, and *'associates with members'* would secure membership in Florida (Barrows and Huff, 2009). Criticism of gang databases ranges from the position of being 'unconstitutional' if they are not correctly maintained, for instance, not regularly purged of citizens who have left the gang world (Jacobs, 2009), to including inaccuracies:

> *"In sum, gang databases appear to be riddled with factual inaccuracies, administrative errors, lack of compliance with departmental guidelines, and lack of oversight. But this is not the worst of it. The root of the problem may be that even if properly applied, application of the subjective criteria would not produce useful results."*
> Wright (2005)

It is important to be critical of information about gangs that come from the police or from journalists, which is often based on impressions and not on thorough research. For instance 'intelligence' that describes that there are leaders in gangs who are responsible for 'recruitment' is at odds with our findings, that our network data does not find any obvious leadership (which is in line with many criminological studies on gangs). Various network outcomes contradict current stereotypes of gang behaviour, for example the existence of many links and intermediaries between different and sometimes conflicting gangs.

Finally, there are recognised methodological issues with current evidence on girls and gangs in the UK (Batchelor, 2009), partly related to the difficulties associated with defining what constitutes a 'gang' or being a 'gang member'.

## 4 Identifying community structure

A key part of the analysis is concerned with identifying communities and community structure. While this is an important property of complex networks, an accurate definition of a community remains an open problem (Liu et al, 2014). In Orman et al (2011a), a community roughly corresponds to a group of nodes more densely interconnected, relatively to the rest of the network. In Orman et al (2011b), they use normalised mutual information (NMI) measure to assess the quality of the discovered community structure from 11 models. Similarly Yan and Gregory (2012) present a discussion of existing community detection algorithms – RFT, CNM, Infomap, COPRA and the Louvain method – compared against their method of edge detection integrated into community detection. It is not easy to determine which is best, and generally a measure is used that estimates the quality of community structures such as modularity (which measures internal consistency of identified communities with reference to a randomised null model with the same degree distribution). Their results had Infomap as the leading algorithm, followed by Walkrap, SpinGlass and Louvain. Infomap was used for the initial investigation of our network data, with Pajek also used for centrality and clustering coefficients (discussed in section 5). Infomap also gives the option to not force every node to be assigned to a single community. This is valuable as real world networks can have several overlapping communities, for example, a person may have family relationship circles, job circles, friend circles, hobby circles and so on. Contrast this with methods designed to work with homogenous data (Ferrara et al, 2014).

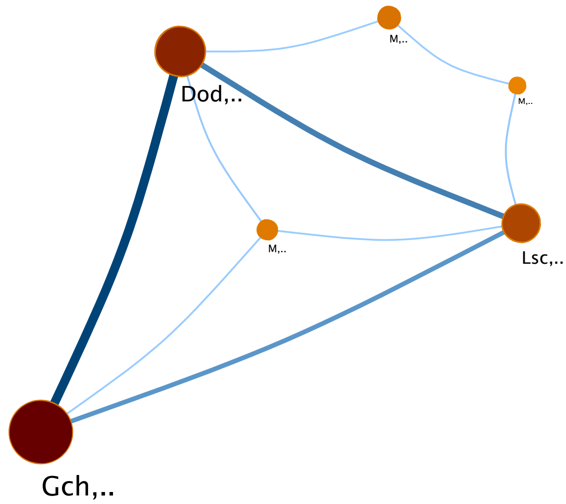


**Fig. 3** Infomap analysis of all data, including non-gang affiliated murders

As expected, looking at Table 3, familial and friendship links are strong within individual gangs (AA, BB, CC, DD), and also gangs with affinity (AD, BC). Accomplices are high within individual gangs and gangs with affinity (AA, BB, CC, DD, AD), although the high rate of accomplices for BD is surprising, perhaps accounted for by the relative and friendship links.

Looking at Table 4, it is unsurprising that we find greater numbers of links to members of single gangs (*a**, *b**, and *c**) than multiple gangs (*ab**, *bc**, *ac** and *abc**). The relative proportions of relationships re-

| Relationship | Gang Membership Relationships | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | AA | BB | CC | DD | AB | AC | AD | BC | BD | CD |
| Accomplice | 26 | 24 | 7 | 18 | 2 | 0 | 10 | 0 | 7 | 2 |
| Charged with | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Brother | 14 | 2 | 0 | 4 | 0 | 0 | 2 | 0 | 1 | 0 |
| Child | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Parent | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Relative | 4 | 0 | 4 | 10 | 0 | 0 | 4 | 0 | 1 | 0 |
| Sister | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Spouse | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Cohabitant | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Friend | 70 | 96 | 29 | 30 | 2 | 0 | 28 | 12 | 5 | 0 |
| Girlfriend | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Boyfriend | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Other | 162 | 74 | 36 | 71 | 22 | 2 | 65 | 4 | 14 | 5 |
| Total | 276 | 198 | 78 | 133 | 26 | 2 | 109 | 16 | 28 | 7 |

**Table 3** Link types between gang members. AA, BB, CC refers to all those gang members who have links only to Gang A, B and C respectively. AB refers to links between Gangs A and B

| Relationship | Gang Membership Relationships | | | | | | |
|---|---|---|---|---|---|---|---|
| | *a** | *b** | *c** | *ab** | *bc** | *ac** | *abc** |
| Accomplice | 139 | 83 | 46 | 26 | 13 | 11 | 4 |
| Charged with | 5 | 10 | 6 | 1 | 1 | 2 | 0 |
| Brother | 13 | 10 | 5 | 0 | 0 | 0 | 3 |
| Child | 8 | 6 | 3 | 0 | 0 | 0 | 0 |
| Parent | 15 | 0 | 2 | 1 | 0 | 0 | 0 |
| Relative | 72 | 41 | 9 | 10 | 1 | 2 | 4 |
| Sister | 6 | 8 | 1 | 2 | 0 | 0 | 0 |
| Spouse | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Cohabitant | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| Friend | 394 | 265 | 92 | 112 | 65 | 26 | 14 |
| Girlfriend | 16 | 25 | 7 | 2 | 0 | 1 | 0 |
| Boyfriend | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Other | 814 | 346 | 261 | 204 | 78 | 44 | 22 |

**Table 4** Link types between non-gang members and gang members. *a** refers to all those non-gang members who have links to Gang A, and only Gang A; *ab** refers to all those non-gang members who have links to Gang A and Gang B, but to no other gang; *abc** refers to all those non-gang members who have links to Gang A, Gang B, and Gang C, but to no other gang.

main constant, when normalised by count of crimes for that class, with the exception of the *abc** categories of 'Brother' and 'Relative'. These are above the norm, and could explain their placement in the category of abc*, likely because of the familial links.

In order to investigate community structure we removed any nodes with less than six connections (i.e. degree 6); Figure 4 shows data from 2002, with the well-established Gangs A and B, and also the newly formed Gang C (in 2001). The Gangs A, B, and C are highly interconnected, with Figure 4 also showing the 'go-betweens', labelled as *ab** and *bc**. Individuals who are only connected to one gang, and who are highly connected within themselves, are labelled *a** and *b**. In this way it is easier to see the communities.

Reviewing the *abc** non-gang members with the highest degree centrality, we can identify interesting patterns of relations. For instance, the following members: *#107023*, *#165035*, *#177519* and *#18170*. When it comes to friendship, *#107023* and *#165035* have friends amongst rival gangs. When it comes to commit- ting crimes together, presumably the opposite is true, only working with members of a preferred gang – see *#177519* and *#18170*.

#107023:
Friend: b,a,a,b,a,a
Other: a,a,a,a,d,d,d,d,d
Relative: a

#165035:
Friend: a, a
Other: a,a,a,a,a,a,a,a,a,a,a,a,a,b,b,d,d,d,d

#177519:
Accomplice: a,a,a,d,d,d,d
Other: a,a,a,a,a,a,a,a,a

#18170:
Accomplice: b,b,b

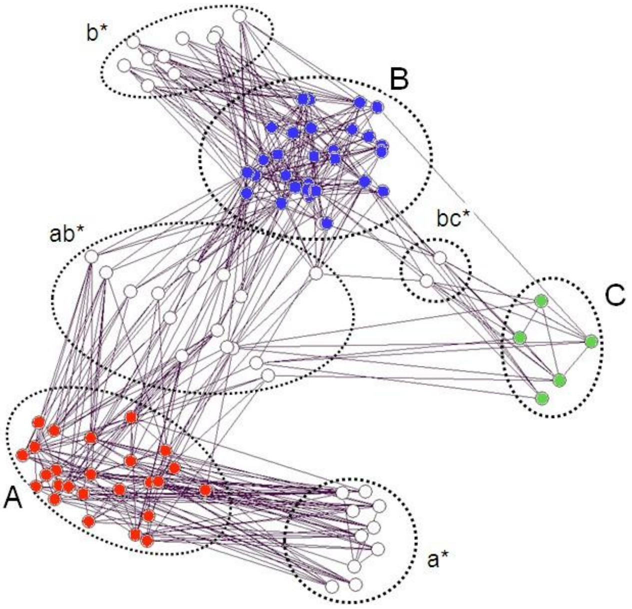


**Fig. 4** Link reduction, showing Gangs A and B and emergence of Gang C (for 2002). This also illustrates the large amount of non-gang members who are associated with individual gangs (*a**, *b**) or who are intermediaries (*ab**, *bc**).

Friend: b,b,b,b,b,b,b
Other: b,b,b,d

Therefore to investigate this more thoroughly, we looked at the familial links. While it is hard it determine, it appears that non-gang links have a significant number of family links. The complete database of links (1980-2007) is plotted in Figure 5, with each of the four main gangs represented by a different colour. The affiliations or 'alignments' of the gangs was presented in Figure 1, where positively aligned Gangs A and D are coloured red and yellow respectively, and the positively aligned Gangs B and C are coloured blue and green. Offenders who have committed murders are presented as black nodes, and non-gang members as white nodes. We limit ourselves in this paper to a visual examination of the complete network, plus additional networks for relatives (Figure 7) and relationships (Figure 8) and collapsed gang networks with murder nodes.

We are not always as interested in how a systems network structure was formed as in how a networks extant structure influences the systems behaviour (Rosvall et al, 2010). Flow, using the map equation, is an alternative to modularity, depending on the network type and desired analysis which we plan to investigate.

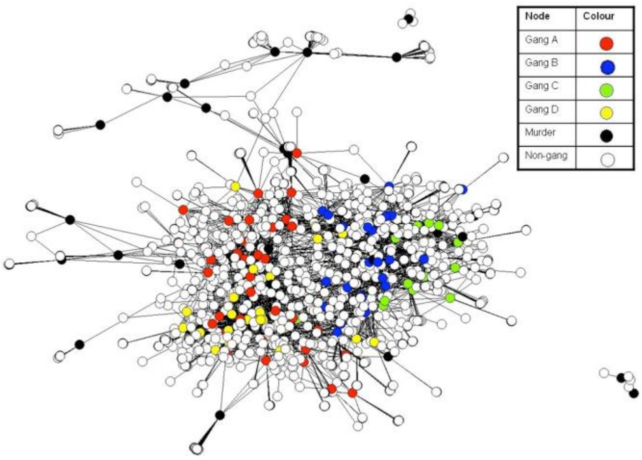


**Fig. 5** Gangs A, B, C, D labelled, showing affinities between Gangs A and D and Gangs B and C (for 2006).

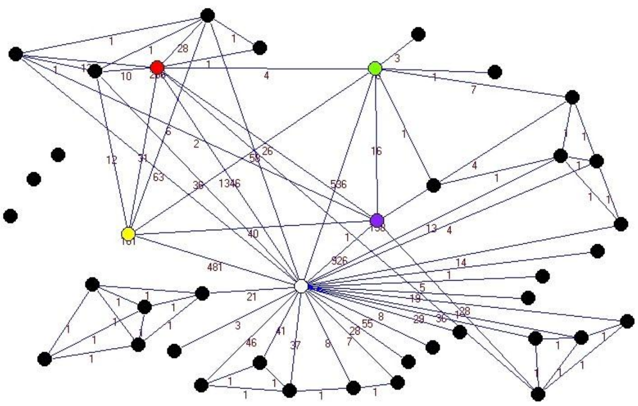

**Fig. 6** Gangs A, B, C, D and murder.

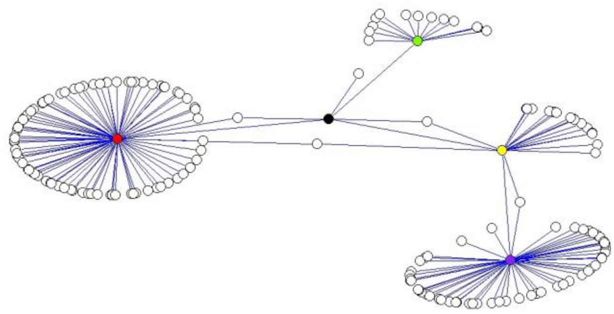

**Fig. 7** Relatives and gangs.

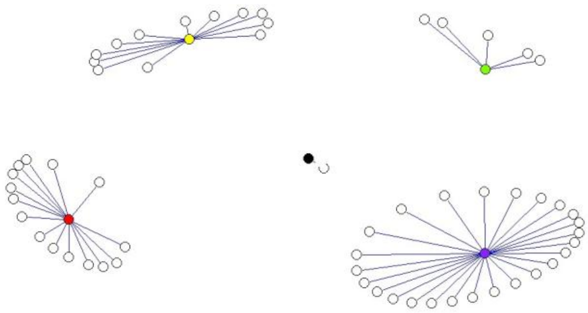

**Fig. 8** Girlfriend/boyfriend and gangs.

## 5 Network characterisation

A series of experiments were carried out to determine how the gang networks compare with well-known networks, for example scale-free and small-world networks.

### 5.1 Small-world networks

Table 5 presents the clustering coefficients (CC) (Watts and Strogatz, 1998) for each individual year, alongside the node and edge counts and various other measures to describe the network. For any simple connected graph $G$ with at least two vertices, the clustering coefficient (1-neighbourhood) measures the extent to which vertices linked to any given vertex $v$ are also linked to each other (Watts and Strogatz, 1998). Or in other words, are the friends of my friends also my friends? This is 1-neighbourhood clustering. The clustering coefficient 2-neighbourhood is a less stringent condition, and states: of the friends of my friends, are they linked to me by other friends?

The links presented in Table 5 are cumulative; that is, the links and nodes for 2002 include not only the new links and nodes for 2002, but also those for 2001 and 2000. Table 6 shows the same network measures, but this time the data has been sliced into the members of the Gangs A, B, C and D.

| Measure | A | B | C | D |
|---|---|---|---|---|
| Number of nodes (n) | 859 | 617 | 431 | 513 |
| 1/n | 0.00116 | 0.00162 | 0.00232 | 0.00195 |
| 4/n | 0.00466 | 0.00648 | 0.00928 | 0.00780 |
| log(n) | 6.76 | 6.42 | 6.07 | 6.24 |
| log(log(n)) | 1.91 | 1.86 | 1.80 | 1.83 |
| Number of links | 844 | 1047 | 602 | 707 |
| Total possible links | 368511 | 190036 | 92665 | 249571 |
| Diameter | 7 | 5 | 6 | 7 |
| Average path length | 3.61 | 3.38 | 3.37 | 4.11 |
| Density | 0.00396 | 0.00550 | 0.00648 | 0.00537 |
| Closeness | 0.302 | 0.298 | 0.393 | 0.305 |
| Betweenness | 0.185 | 0.179 | 0.350 | 0.239 |
| CC | 0.16 | 0.19 | 0.15 | 0.12 |

**Table 6** Network measures for Gangs A, B, C, D. CC is the average clustering coefficient from Watts and Strogatz (1998), considering only 1-neighbourhood.

A small-world network has both local connectivity and global reach (Watts and Strogatz, 1998), and is a simple connected graph $G$ exhibiting two properties:

1. Small characteristic path length: the presence of short-cut connections between some vertices results in a small characteristic path length $L(G)$.
2. Large clustering coefficient: each vertex of $G$ is linked to a relatively well-connected set of neighbouring vertices, resulting in a large value for the clustering coefficient $C(G)$.

To determine whether our network is a random one or is small-world, we can test whether or not it has exponential $k$-connectivity distribution. We do not observe this in the data, however, we do see large clustering coefficients, and the average path lengths are always less than $log(n)$. Based upon these two criteria we can still conclude that our networks have small-world characteristics.

### 5.2 Scale-free networks

This section also refers to the preceding tables, where we find a mixture of evidence for and against the case for scale-free networks. Plotting the clustering coefficient as a function of the number of nodes $n$, should follow the power-law distribution for scale-free networks (see later experiments), with the clustering coefficient being roughly four times larger than random networks (Albert et al, 2004). The value of the clustering coefficient for a random networks will be $1/n$. In this way we are able to compare the values of $4/n$ against CC in Tables 5 and 6. As the cumulative links increase from 2000 to 2006, the value of CC generally increases (with the number of nodes n) and is always significantly higher than the values of $4/n$. Each of the gang values for CC are also significantly higher than would be expected in a random network.

The diameter of the network (longest path length) should be approximately $log(log(n))$ for scale-free networks. In both cases (for the gangs and the years) the real values are significantly higher than would be expected for a scale-free network. The average path length should be approximately $log(n)$ for scale-free networks. For both the 'years' and 'gangs' data it was actually smaller than $log(n)$, indicating scale-free networks.

The statistics on degree centrality were low, indicating that there is no group leader. As we know when Gangs C and D are formed (2001 and 2004 respectively), it is interesting to note that the characteristic of the networks at this time are that the betweenness centralisation reaches 0.2. It is necessary to compare the closeness and betweenness averages for each gang against the value for the overall network.

### 5.3 Power law investigation

This section examines whether the data would follow the power-law distribution for scale-free networks, and therefore we plotted the clustering coefficient as a function of the number of nodes $n$.

| Measure | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 |
|---|---|---|---|---|---|---|---|
| Number of nodes (n) | 1095 | 1295 | 1487 | 1752 | 2090 | 2229 | 2408 |
| 1/n | 0.00091 | 0.00077 | 0.00067 | 0.00057 | 0.00048 | 0.00045 | 0.00042 |
| 4/n | 0.00365 | 0.00309 | 0.00269 | 0.00228 | 0.00191 | 0.00180 | 0.00166 |
| log(n) | 6.999 | 7.166 | 7.305 | 7.469 | 7.645 | 7.709 | 7.787 |
| log(log(n)) | 1.95 | 1.97 | 1.99 | 2.01 | 2.03 | 2.04 | 2.05 |
| Number of links | 1565 | 1903 | 2295 | 2844 | 3540 | 3872 | 4265 |
| Total possible links | 598965 | 837865 | 1104841 | 1533876 | 2183005 | 2483106 | 2898028 |
| Diameter | 12 | 14 | 11 | 11 | 14 | 12 | 13 |
| Average path length | 4.85 | 4.82 | 4.68 | 4.57 | 4.86 | 4.78 | 4.70 |
| Density | 0.00261 | 0.00227 | 0.00208 | 0.00185 | 0.00162 | 0.00156 | 0.00147 |
| Betweenness | 0.107 | 0.117 | 0.172 | 0.205 | 0.146 | 0.102 | 0.100 |
| CC (cumulative) | 0.47 | 0.48 | 0.47 | 0.46 | 0.49 | 0.55 | 0.56 |
| CC (per year) | 0.24 | 0.57 | 0.34 | 0.15 | 0.62 | 0.25 | 0.30 |

**Table 5** Network measures for 2000-2006. Clustering coefficients are always greater than 4/n. Average path lengths are always less than log(n).

**Definition 1** A quantity $x$ obeys a power law if it is

where $\alpha$ is a constant parameter of the distribution drawn from a probability distribution:

$$P(x) \propto x^{\alpha}$$

known as the exponent or scaling parameter. The scaling parameter typically lies in the range $2 < \alpha < 3$.

Our initial power law investigations used a log-log plot and $R^2$ values, and these all produced $\alpha$ values within this typical range (between 2 and 2.5). However being roughly straight on a log-log plot is a necessary but not sufficient condition for power-law behaviour (Clauset et al, 2009), and that there are problems (bias and inaccuracy) with fitting to the power-law distribution using graphical methods based on linear fit on the log-log scale.

We therefore proceeded to use maximum likelihood estimation (MLE), which is a far more robust method for estimating the scaling exponent (Clauset et al, 2009; Goldstein et al, 2004). We report the maximum likelihood estimate of the scaling exponent ($\alpha$), the estimate of the lower bound of the power-law ($xmin$).

By optimising the Kolmogorov-Smirnov goodness-of-fit statistic, we can use a *goodness of fit* to estimate where the empirically-best scaling region begins (Clauset et al, 2009). Given an observed data set and a hypothesised power-law distribution from which the data are drawn, we can then test whether our hypothesis is a plausible one using the goodness-of-fit test (the Kolmogorov-Smirnov statistic), given the data, and generate a p-value that quantifies the plausibility of the hypothesis.

Employing the Kolmogorov-Smirnov test we are able to choose among the hypotheses that:

- $H0$: the data follow a specified distribution;
- $Ha$: the data do not follow the specified distribution.

We did not use Vuong' s test to check for alternative distributions (non-power-law distributions) which could have produced the data. Instead, because our sample sizes are small (i.e., $<$ 100), we explicitly used an experimental finite-size correction, as recommended by Clauset et al (2009).

Figure 9 shows our results for our network between 2000-2006. In all cases the exponent $\alpha$ is less than 2. Only when the power-law exponent is in the range 2 − 3 do the hubs tend to connect to form a single cohesive hierarchy (Andamic et al, 2003). The goodness-of-fit (gof) and p-values however are significant. Even though the p-values are above 0.1 (arbitrary threshold level), we err on the side of caution because of the low $\alpha$ value and the small sample size. When $n$ is small, meaning $n \leq 100$, we cannot rule out the power-law hypothesis (Clauset et al, 2009). It is possible, for small values of $n$, that the empirical distribution will follow a power law closely, and hence that the p-value will be large, even when the power law is the wrong model for the data (Clauset et al, 2009). However, what we can say is that certainly the tail is heavy.

Table 7 shows our results for the power law exponent for the different gangs against years. The case is similar in that there are significant gof and p-values, however in nearly all cases the exponent is less than 2, and again we did not test for alternate explanatory distributions, satisfied (operationally) that the the tail was heavy in all cases, indicating the presence of very well connected offenders.

| Gang | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 |
|---|---|---|---|---|---|---|---|---|---|
| A | **2.65** | 1.47 | 1.00 | **1.91** | 1.07 | 0.10 | 0.94 | 0.77 | 0.74 |
| B | **2.95** | 1.44 | **3.64** | **1.88** | 1.36 | 0.09 | 0.97 | 0.63 | 0.51 |
| C | 0.27 | 0.24 | 0.17 | 0.32 | 0.38 | 0.02 | 0.46 | 0.36 | 0.32 |
| D | 1.26 | 0.76 | 0.56 | 0.69 | 1.14 | 0.03 | 1.21 | 0.81 | 0.65 |

**Table 7** Power law exponents for gangs, against years. Significant results are shown in bold-face.

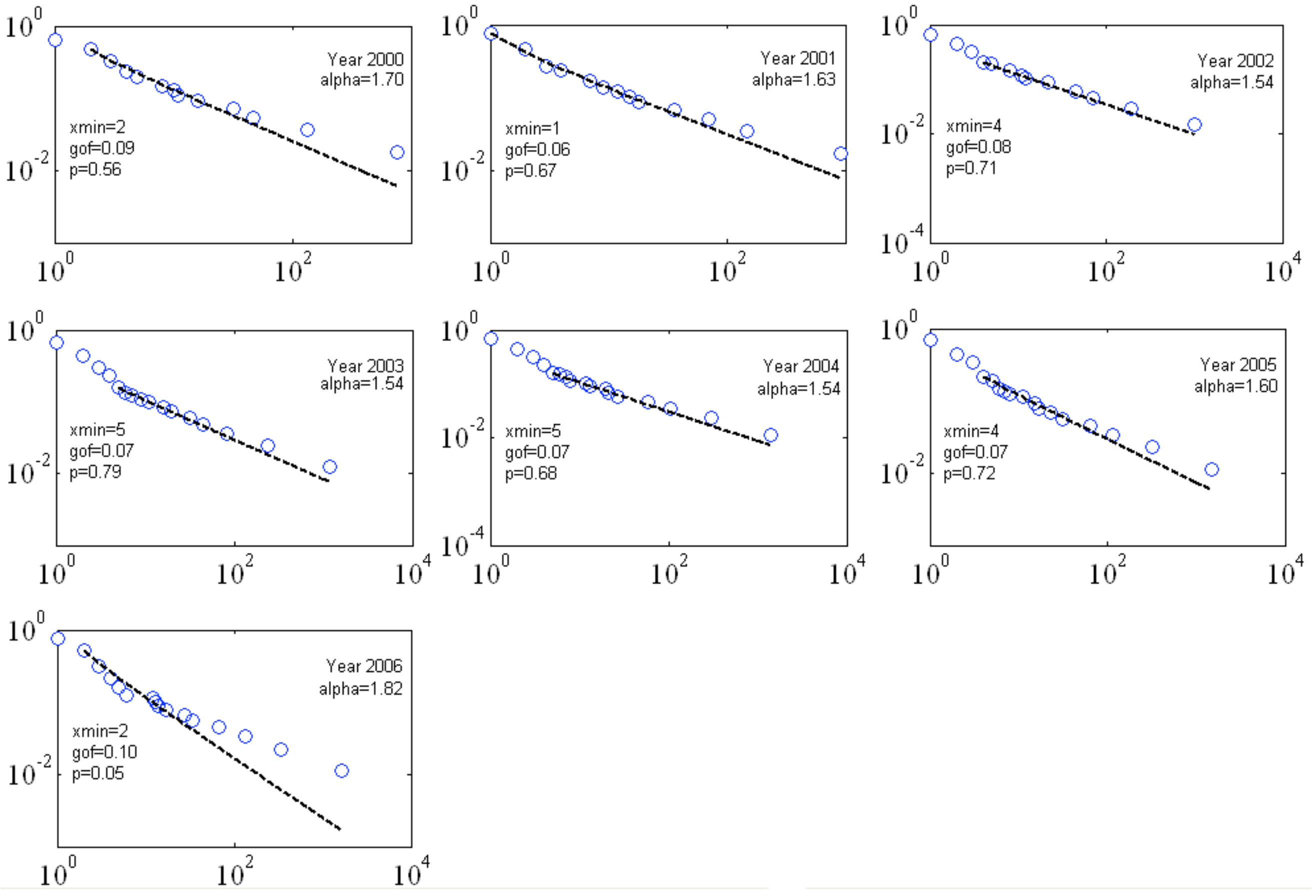


**Fig. 9** Power law investigations. A power law is fitted to each years data and various statistics calculated: the exponent alpha, xmin, goodness-of-fit (gof) and p-value.

Based on these experiments we are therefore unable to comment whether the networks possessing scale-free characteristics, however we can conclude that we have small-world networks, since consistently there are larger clustering coefficients and shorter path lengths compared to a random network with same number of gang members. This means two things for our system:

- The smaller path length means that the criminal activity (contagion) spreads more easily in this network than in a random network.
- Larger clustering coefficient means that contacts of contacts are treated as contacts as well.

### 5.4 Emergence of gangs

We might see changes in the path length and clustering coefficients from 2000 to 2005, indications of how the gangs have become more closely knit or are splitting apart. By examining annual links for 2001 and 2004, we might predict that the cumulative links decrease and the annual links increase, just before/as a gang forms, then both values increase afterwards as everyone becomes linked together. This is not the case, and neither are we able to see any meaningful behaviour in these data.

Figures 10 and 11 show the clustering coefficients for each gang and against years, and is also a pictorial view of the new links per year. In Table 11 the CC value of each gang dips at 2004. What this may indicate is clustering due to non-gang members (from Figure 4, offenders who are connected to gang members: ***a****, ***b****, ***bc**** and ***ab****) and less clustering that previous years between members of gangs themselves. There is also a significant peak in clustering during 2001 for Gang B, whereas all other gangs suffer a decrease in clustering.

## 6 Third-generation analysis

The previous analyses can be considered quantitative, contrasted with a more qualitative analysis presented in this section. Here we are interested in examining the specific nodes and links of the network. We look at specific offenders' histories' (in terms of crimes commit-

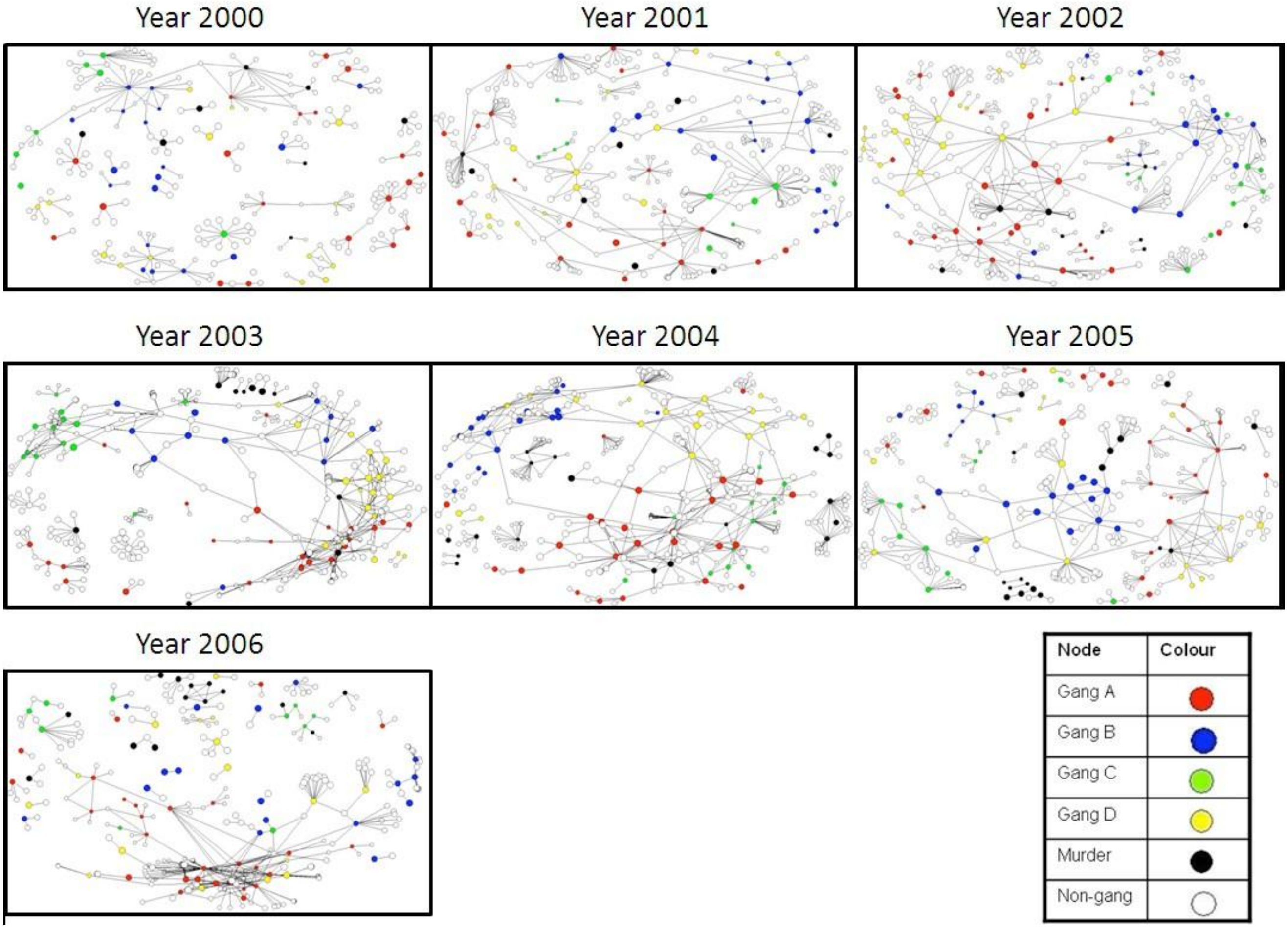


**Fig. 10** Annual links formation. Only nodes directly connected to a gang member are included. The network measures for each of these networks can be found in Table 6.

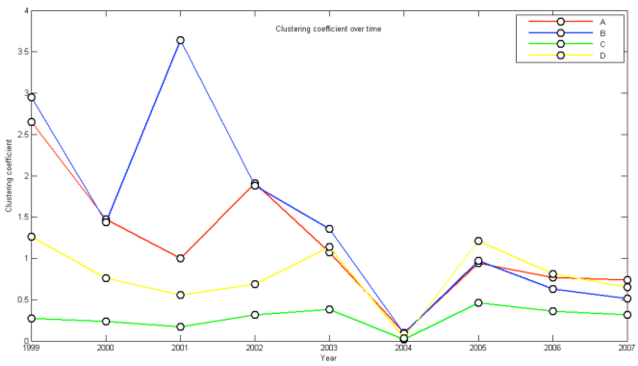


**Fig. 11** Per year clustering coefficients for each gang. Gang C was formed in 2001, Gang D in 2004.

ted), investigating who are the most hardcore offenders, and what if anything characterises the members with direct links to those who commit murder or use firearms. We consider the role of 'trust' relationships such as partnerships, family ties, and are interested in comparing these ties with those based on co-arrest data.

Recalling the definition presented earlier, 'third-generation' social network analysis focuses much more intensely on the content of the contacts, on the social context, and on the interpretation of such information. We are particularly interested in what constitutes the bonding mechanisms that tie people together in different constellations: greed, ethnic or tribal ties, family relations, common geographical (neighbourhood) or institutional (prison) (Klerks, 2001).

## 6.1 Specific gang roles or node analysis

There are many definitions of gangs; for instance Pitts (2007) reviews a plethora of definitions and typologies, eventually developing their own six-point typology for their particular study. Aldridge et al (2008) recognise the messiness and looseness of the social networks referred to as gangs, as well as their permeable and fluctuating boundaries. In contrast, Pitts (2008) claims, arguably without providing much evidence for it, that we are witnessing the development of new articulated 'supergangs' with long histories of involvement in organised crime, clear subgroups, role differentiation, established territories and neighbourhood control, vertical links into higher echelon organised crime, and organised drug dealing activity.

The ***degree*** values from our analysis of the gangs suggested that there are no obvious single leaders, however intelligence suggests that South Manchester gangs in the UK do appear to have a basic system of hierarchy. Gang's A and B members store firearms at the home addresses of younger affiliates of the gang, who are eager to prove themselves to 'superior' members of the gang. The roles within the gangs include the following:

- *Leader:* responsible for recruiting new members. Sanctions the enforcers to carry out 'missions' on their behalf and authorises who carries the firearm.
- *Provider:* an individual either internal or external to the gang able to supply firearms and/or ammunition.
- *Enforcers/riders:* nominated individuals who are active gunmen for the gang. 'Riders' are used as support to the gunmen with three or four riders to one gunman. They surround the gunmen on bikes until the target is in sight, also acting as decoys should the group attract police attention. They ensure that the gunman will get away whilst they are stopped and questioned.
- *Runners/dealers:* members of the gang who distribute and supply drugs, usually on the leaders behalf, usually the younger element of the group.

It is important to note that these defined roles give the impression of organisation within the group however the lifestyle of gang members is often disorganised and unplanned. Detailed qualitative/ethnographic descriptions tend to portray gangs as loosely-structured groups that lack clear role expectations and stable leadership (Hughes, 2005). Firearms incidents between gangs are sporadic in their nature and often have the hallmarks of chance encounters with members of opposing gangs, which makes them difficult to anticipate.

Table 8 shows the sequence of accused crimes for three members of the Gooch gang. Column one shows the first gang member with a 'profile' strongly related to robbery, in contrast to the second and third gang members with 'profiles' involving gun crime and serious crimes. It is clear from studying these data that not all gang members are gun users.

## 6.2 Link analysis

Duijn et al (2014) describe disruption techniques, and the notion of social capital of individuals in networks, often calculated by some measure of centrality. For instance the strength of weak ties lies in the offering of new opportunities in an otherwise redundant fully connected network. They follow research suggesting that identifying the actors fulfilling the most specialised tasks offer great opportunities for destabilising the criminal network. Their ideas around human capital, substitutability, criminal value chains and the crime scripting method will be incorporated into future work.

We thus require a better analysis of link types, for instance in the study by Patacchini and Zenou (2008) of whether weak ties play an important role in explaining criminal activities. They developed a model where individuals learn about crime opportunities by interacting with other peers. The theoretical predictions of the model are confirmed by the empirical analysis since they find that weak ties, as measured by friends of friends, have a positive impact on criminal activities.

To give a better idea of the interconnectedness of the gangs, the following Figures 12 and 13) demonstrate ***cycles*** in the data, passing from one gang to another via intermediaries. These examples have been chosen from the 2001 and 2004 data when the new gangs emerged. Plotted in this way we can see the complex relationships between (rival and sympathetic) offenders in this geographically small region. Furthermore, for 2001 and 2004, it would be interesting to examine the kinds of links within each gang which emerged.

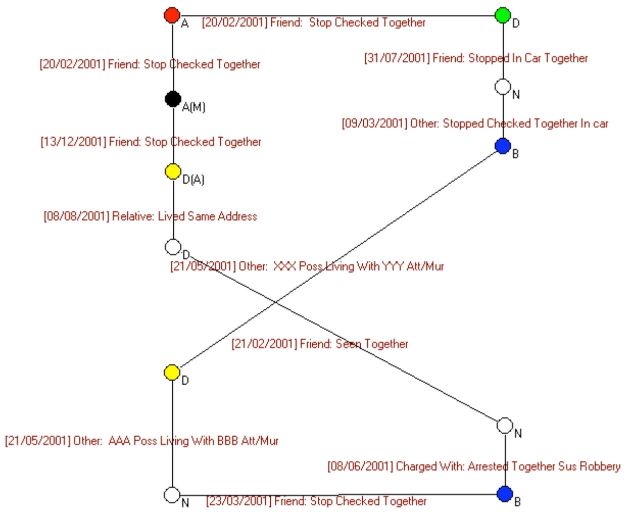


**Fig. 12** Cycle (2001). The tension is between Gangs A (red), B (blue), C (green) and D (yellow). A(M) is a member of the Gooch gang (Gang A), however they are coloured black to represent the crime of murder.

| **Gooch 1** | **Gooch 2** | **Gooch 3** |
| --- | --- | --- |
| ROBBERY - PERSONAL | ROBBERY | DAMAGE OTHER |
| S.5 PUBLIC ORDER ACT | ROBBERY | OFFENSIVE WEAPON |
| THEFT/TAKE PEDAL CYCLE | ASSAULT S. 47 | ROBBERY - BUSINESS |
| THEFT OF MOTOR VEHICLE | THEFT FROM THE PERSON | POSSESS CANNABIS |
| GOING EQUIPPED | ASSAULT S. 47 | TAKING A MOTOR VEHICLE |
| ROBBERY - BUSINESS | ASSAULT S.18 | ARSON |
| THEFT OF MOTOR VEHICLE | RACIAL COMMON ASSAULT | BURGLARY DWELL OTHER |
| MAKE OFF W/O PAYMENT | DAMAGE OTHER | ATTEMPTED MURDER |
| ROBBERY - BUSINESS | POSSESS HEROIN | ATTEMPTED MURDER |
| ROBBERY - PERSONAL | THEFT IN DWELLING | ATTEMPTED MURDER |
| BREACH: ANTI-SOC. ORDER | ASSAULT S. 47 | ROBBERY - PERSONAL |
| THEFT FROM MV | POSSESS UNSPEC. DRUG | ROBBERY - PERSONAL |
| VIOLENT DISORDER | COMMON ASSAULT | ATTEMPTED MURDER |
| ROBBERY - PERSONAL | ASSAULT S. 47 | POSSESS FIREARM ETC. |
| BURGLARY OTD OTHER | WITNESS INTIMIDATION | FIREARMS ACT OFFENCES |
| ROBBERY - BUSINESS | ASSAULT S. 47 | ATTEMPTED MURDER |
| ROBBERY - BUSINESS | ASSAULT S. 47 | ATTEMPTED MURDER |
| ROBBERY - BUSINESS | RECEIVING STOLEN GOODS | POSSESS FIREARM ETC. |
| ROBBERY - BUSINESS | S.5 PUBLIC ORDER ACT | FIREARMS ACT OFFENCES |
| ROBBERY - BUSINESS | DAMAGE (MOTOR VEHICLE) | POSSESS CANNABIS |
| ROBBERY - BUSINESS | ASSAULT S. 47 | POSSESS FIREARM ETC. |
| ROBBERY - BUSINESS | BREACH: ANTI-SOC. ORDER | FIREARMS ACT OFFENCES |
| ROBBERY - BUSINESS | MURDER (OVER 1 YEAR) | FIREARMS ACT OFFENCES |
| BURGLARY DWELL OTHER | POSSESS CANNABIS | RAPE OF FEMALE UNDER 16 |
| ROBBERY - BUSINESS | POSSESS CANNABIS W/I | ROBBERY - PERSONAL |
| ROBBERY - PERSONAL | ASSAULT S.18 | ATTEMPTED MURDER |
| ROBBERY - BUSINESS | ASSAULT S.18 | DANGEROUS DRIVING |
| ROBBERY - BUSINESS | BREACH: ANTI-SOC. ORDER | SUPPLY/OFFER CANNABIS |
| ROBBERY - BUSINESS | BREACH: ANTI-SOC. ORDER | POSSESS CANNABIS |
| MAKE OFF W/O PAYMENT | ROBBERY - PERSONAL | POSSESS CLASS A W/I |
| ROBBERY - BUSINESS | BREACH: ANTI-SOC. ORDER | KIDNAPPING |
| BURGLARY OTD | BREACH: ANTI-SOC. ORDER | THEFT OF MOTOR VEHICLE |
| ROBBERY - BUSINESS | | POSSESS CANNABIS |
| ROBBERY - BUSINESS | | ASSAULT POLICE |
| ROBBERY - BUSINESS | | ASSAULT POLICE |
| ROBBERY - BUSINESS | | ASSAULT POLICE |
| ROBBERY - BUSINESS | | POSSESS CANNABIS |
| ROBBERY - BUSINESS | | THEFT OF MOTOR VEHICLE |
| ROBBERY - PERSONAL | | MANSLAUGHTER |
| | | POSSESS CANNABIS |
| | | S.5 PUBLIC ORDER ACT |
| | | ABSCOND LAWFUL CUSTODY |
| | | BURGLARY OTD OTHER |
| | | KIDNAPPING |
| | | ROBBERY - PERSONAL |
| | | ROBBERY - BUSINESS |
| | | MURDER (OVER 1 YEAR) |
| | | MURDER (OVER 1 YEAR) |

**Table 8** Example offender histories in chronological order; all three offenders belong to the Gooch gang (Gang A).

This data presentation shows many things about the gang structure, for instance that the offenders who commit murders are not necessarily the most connected individuals (highest degree), in fact they are quite often peripheral nodes. Secondly, it is clear that there are a significant number of common connections between rival gangs. It would be useful to investigate intermediate-scale features, neither at node level nor network level, known as core-periphery structure, which entails identifying densely-connected core nodes and

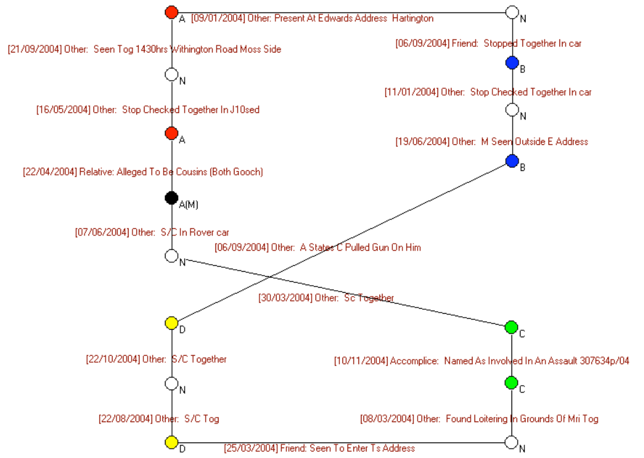


**Fig. 13** 2004 cycle; the tension is between Gangs A (red), D (yellow) and B (blue), C (green).

sparsely-connected periphery nodes. In contrast to communities, the nodes in a core are also reasonably well-connected to those in the periphery (Rombach et al, 2014).

One way is using the continuous scoring devised by Borgatti and Everett (2000), generalised recently by Rombach et al (2014) to an approach that gives nodes values (i.e., core scores) along a continuous spectrum between nodes that lie most deeply in a network core or at the far reaches of a network periphery.

We should also be careful when looking at data and creating networks from it. However, Klerks (2001) cites the case of the 'conspiracies' and mega-hierarchies that police had identified in the past among Dutch and Turkish organised crime which were in fact strings of interlinked smaller groups that lacked a central leader but that coordinated their activities along logistic trails and through bonds of friendship.

## 7 Discussion

The model of two rival sets of gangs is potentially a misrepresentation of the much more complex sets of smaller cliques and fluid changes within the larger gang structures. However, the four gangs discussed do exist, and are the main gangs; what is not possible is a high degree of exactitude.

### 7.1 External and internal factors

It is difficult to determine through the gathered data what is happening in the networks. We have little recorded evidence of gang formation, even knowing when these events 'allegedly' occurred, similarly with the alleged 'melt-down' following the death of prominent gang leader Raymond Pitt in 1995 (Walsh, 2005). The links are based upon observations by police officers – do we expect that these complex social situations can be reflected in the reported links? Can we detect these events, and did they really happen as they have been passed down to us? We are in the difficult situation of using intelligence instead of concrete facts, and this intelligence is often a poor reflection of what is happening in the chaotic social world of gang culture.

We require a much better analysis of link types, developed a model where individuals learn about crime opportunities by interacting with other peers; for instance whether weak ties play an important role in explaining criminal activities (Patacchini and Zenou, 2008), especially gang homicide (Papachristos, 2009).

The theoretical predictions of the model are confirmed by the empirical analysis since they find that weak ties, as measured by friends of friends, have a positive impact on criminal activities. Furthermore, for 2001 and 2004, it would be interesting to examine the kinds of links within each gang which split apart.

### 7.2 Covert links

Data collection is very partial and certainly biased, since not every actor is exposed to an equal extent and therefore some of those observed (perhaps the 'usual suspects') contribute far more to the dataset than others. Our earlier observation of a decrease in clustering as the network temporarily fragments, before an increase in clustering as everyone becomes linked together (as commented upon in section 5.4) finds equal explanation through the police having intelligence on the formation of a new gang and actively seeking observations on this event.

## 8 Conclusions

The work presented in this paper contains our initial findings about the offender/gang networks in Manchester in the UK, using network analysis, significantly extending previous work (Oatley and Crick, 2014b,c). The police crime recording database is routinely gathered and available for analysis; in this instance it has been gathered about a six year time period (2000-2006), allowing substantive analysis of gang formation, development and interaction. The additional databases of histories and associates of gang offenders are routinely gathered by the UK's National Crime Agency [1], who

[1] http://www.nationalcrimeagency.gov.uk/

investigate gang and gun-related crimes. These data are potential rich sources of information for data science and analytical technologies to deliver crime prevention and detection decision support systems. Criminal behaviour (modus operandi and offence profiling) is to be incorporated into social network analysis. This approach uses retrospective methodologies, appropriate given the time scale and the pilot nature of most work. Future work, such as looking at family and friends networks, crimes histories, progression of crimes, using GIS viewsheds to aid social network analysis (Oatley et al, 2015) and mapping against large social media datasets (Burnap et al, 2014; Procter et al, 2013), must be given the resources in order to increase the validity of decisions concerning their contribution, as well as develop wider positive socio-cultural outcomes.

The uses of this technology in an operational context are thus significant. As highlighted in Golding and McClory (2008), poor intelligence and information sharing between schools and police is a pervasive problem throughout England and Wales, along with un-coordinated approaches to outreach work leading to missed opportunities for intervention. With gangs taking over territory, creating virtual "no-go" areas (where residents may fear for their safety), alongside unclear domestic legislation regarding firearms and other offensive weapons over the study period, there is a significant opportunity for police to utilise the techniques we have described for widespread operational benefits. Even using the networks merely as visual representations of otherwise cognitively unmanageable data contained in spreadsheets and databases is operationally useful, for knowledge sharing and training, and identifying key offenders. With further pre-processing, the quality of the data collection process and analysis is improved, with significant future applications (especially in a policy context) available.

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