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ORIGINAL PAPER

Investigating the Dynamics of Outlaw Motorcycle Gang Co-Offending Networks: The Utility of Relational Hyper Event Models

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Abstract

Objectives Approaches to the study of Outlaw Motorcycle Gangs OMCGs tend to focus on offending at the individual level, with limited focus on the nature and extent of co-offending among these affiliates. We aim to examine co-offending by using relational hyper event models (RHEM) to determine what additional insights can be discerned on co-offending above and beyond more traditional network approaches.

Methods Using de-identified police recorded incident data for affiliates of OMCGs in New South Wales, Australia, including their rank and club affiliation, we examined the positioning of OMCG affiliates in co-offending network structures. The data comprised 2,364 nodes and 12,564 arrest events. We argue that Relational Hyperevent Models (RHEM) are the optimal analytical strategy for co-offending data as it overcomes some of the limitations of traditional co-offending analyses.

Results We conducted RHEM modelling and found that co-offending networks were stable over time, whereby actors tended to repeatedly co-offend with the same partners. Lower ranked members were more likely to engage in co-offending compared with office bearers.

Conclusions Results provide some support for the scenario in which OMCGs operate as criminal organisations, but also the protection and distance from offending that is afforded to office bearers. We review implications of the results for law enforcement policy and practice and for the scholarship of OMCGs.

Keywords Co-offending · OMCG · Relational hyperevent models · Networks · Outlaw motorcycle gangs

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Introduction

In many countries, including the United States and Australia, outlaw motorcycle gangs (OMCGs) are implicated in a range of criminal activities including the production and distribution of illicit drugs, firearms trafficking, serious violent crime, tax evasion and money laundering (e.g., Morgan et al. 2020; Quinn and Forsyth 2009; Quinn and Koch 2003). While the last few years have seen a notable increase in research on the criminal activities of those affiliated with OMCGs (e.g., Blokland et al. 2017, 2019; Morgan et al. 2020), little is known about co-offending among OMCG affiliates. This includes the extent of co-offending within and between OMCGs, which may involve collaborating or competing for stakes in illicit markets, and the role of those who occupy leadership positions in clubs (known as 'office bearers') in such co-offending. This paper presents an exploratory study to examine co-offending across different ranks within and between OMCG groups in the Australian state of New South Wales (NSW). Differing from prior research, we aim to examine co-offending by using relational hyper event models (RHEM) to determine what additional insights can be discerned on co-offending above and beyond more traditional network approaches. However, our approach is not atheoretical: we derive a set of research questions based on existing theory and research, and we conduct empirical tests using RHEM as an illustration for other researchers who might consider applying RHEM for studies on co-offending networks. This innovative approach to the analysis of co-offending data can serve as a model for future research on co-offending networks across a range of contexts (e.g., juveniles, types of offending).

First, we provide an overview of the state of knowledge on OMCGs and on co-offending. Second, we discuss the current study, applying RHEM to sequences of co-arrest events, and how it contributes to our understanding of OMCGs specifically, and co-offending networks generally. Third, we provide an overview of results and discuss them in the context of existing literature on offending and co-offending among OMCG members. Fourth, we briefly compare RHEM with two alternative (and more established) approaches to the analyses of co-offending data: relational event models (REM) for dyadic interaction events and temporal exponential random graph models (TERGM). Finally, we conclude the paper and offer some implications for theory and practice.

Outlaw Motorcycle Gangs

Much of the research on criminality among OMCG affiliates analyses individual-level information on recorded offending (e.g., Blokland et al. 2019, 2020; Klement 2016a; 2016b; Morgan et al. 2020). This research has found that most OMCG members have histories of offending. Much of the criminal activity of affiliates is a by-product of their everyday lives within the outlaw 'barbarian' cultures of OMCGs, including fighting, traffic violations, drug possession and disorderly conduct (von Lampe and Blokland 2020). However, empirical studies have shown that involvement in more serious violent and organised crime is also common. Unfortunately, research on individual-level criminality does not address the question of how OMCG affiliates collaborate in crime, or of the role that club structures and hierarchies play in these collaborations. OMCGs are highly structured, with formal hierarchies consisting of various executive office bearing roles such as presidents, vice presidents and sergeants-at-arms, along with regular members and prospective members at the bottom. Office bearers oversee the semi-independent regional chapters of

OMCGs, while club-level office-bearers manage clubs at a national and international level. These governance mechanisms have been assumed by governments and police forces to play a significant role in the crimes of OMCG affiliates, and significant effort has gone into disrupting the structures and hierarchies of OMCGs (Bartels et al. 2021). However, there is ongoing debate in the literature as to the importance of these structures and hierarchies to the offending of OMCG affiliates (von Lampe and Blokland 2020).

Von Lampe and Blokland (2020) suggest three possible ideal scenarios regarding the nature of criminal collaboration within OMCGs, and its relationship with club structures and hierarchies: (1) the ‘rotten apples’ scenario in which individual members act alone or in collaboration with other members or non-members to commit crime, outside of club structures and hierarchies; (2) the ‘club within a club’ scenario where there is some overlap between the organizational structure of the group and criminal activity networks. In this case, authority within the criminal networks is driven by network position rather than formal hierarchical position; and (3) the ‘club as criminal organization’ in which the club is organized for the purpose of committing crime and office bearers authorize and direct criminal activity. These three scenarios are not mutually exclusive and hybrid versions of the three scenarios may exist within any one club, or shifts may be observed between the scenarios across time. The same OMCG club may show evidence of one, two or all of the scenarios depending on the specific context and the manner in which criminal activities are undertaken in that club (see also van Deuren et al. 2022). In their systematic review of the literature, Bright and Deegan (2021) suggest that when OMCG members engage in crime, they tend to operate in small networks that may include other OMCG members. Von Lampe and Blokland (2020) also note that the structures and formal hierarchies of OMCGs are not well adapted to maintaining the secrecy and security necessary for organized crime and may explain why small informal networks are utilized by OMCG members instead of OMCGs operating as criminal organizations.

Some studies have drawn attention to the role of OMCGs as facilitators of crime, with membership being found to increase the risk of offending (Klement 2016a, 2016b, 2019; van Deuren et al. 2021), and offending by affiliates being more prevalent, frequent and serious than that of other motorcycle owners (Blokland et al. 2019). These findings hint at some level of criminal collaboration within OMCGs, and at the role of club structures and hierarchies in enabling or directing it. However, in their in-depth analysis of OMCGs in the Australian state of Queensland, Lauchs and Staines (2019) found that twelve out of sixteen members in leadership positions were not involved in organized criminal activities, although four had significant involvement in the manufacturing and trafficking of illicit drugs in collaboration with other members. They concluded that individuals in office bearer positions appeared to operate criminally within small networks or cliques. In another study, Lauchs (2019) examined one specific chapter of an OMCG in Queensland and found that only eleven out of 44 patched members had serious illicit drug-related convictions, suggesting that these members operated alone or in small groups. Two of the individuals involved in drug trafficking were office bearers, although no evidence was uncovered that the office bearers directed or controlled the activities. Eighty-three percent of members were not involved in organized criminal activities.

Blokland et al. (2017), adopting a novel approach to address these questions, used official convictions data to examine the relative proportion of office bearing and non-office bearing members with criminal histories in 12 Dutch OMCGs. Most (8 clubs) had a high proportion of both office bearing and non-office bearing members with a criminal history. Replicating this analysis, but limiting it to organised crime-type offending, Morgan et al. (2020) found eight of 28 Australian clubs had more than ten percent of office bearing and non-office bearing members with a recent recorded history of this offending. The assumption underpinning these analyses is that, where high proportions of both office bearing and non-office bearing members within a club are engaged in crime, that club is likely to be operating as a criminal organization, as defined by von Lampe and Blokland (2020). While not unreasonable, this approach is incomplete in its absence of any direct examination of criminal collaboration, or of the importance of office bearers to these collaborations.

A Network Approach to Understanding Co-Offending

A growing amount of criminological research is taking a network approach to study crime and better capture the structure and dynamics of co-offending relationships. This approach emphasizes and facilitates analysis of the relational elements of co-offending that are often missed in more individually-focused methods. The methodological underpinning of this approach has been social network analysis (SNA), which is a family of methods for measuring and graphically depicting complex sets of relationships between multiple individuals, or actors. Analyses of co-offending networks can investigate theoretically relevant assumptions about social processes and structural relationships that affect crime occurrence in ways that move beyond analyses assuming offender independence. Co-offending network studies can also examine social structure and processes in the context of actor attributes such as age and gender (see Bright et al. 2022b, c) and across crime types (e.g., Morselli et al. 2015). In the case of OMCGs, additional attributes of particular relevance include gang rank and co-offending across different gangs. The current study seeks to advance the literature on both co-offending and OMCGs by examining these aspects in an OMCG co-offending network disaggregated by crime type, OMCG ranks, and offending within and between different OMCG groups.

Research on co-offending networks has tended to rely on the same methodological and analytical approach (e.g., Sarnecki 2001; Carrington 2009; Morselli et al. 2015; Bright et al. 2022c). In this approach, a two-mode network is first constructed from data (e.g., arrest data) in which actors / offenders are tied to co-offending events (e.g., arrest events). Next, the two-mode network is transposed to a one-mode network in which all offenders who are connected to the same crime event are considered to be co-offenders. This one-mode projection of the two mode network results in only dyadic connections between co-offenders who have been involved in the same crime event. In other words, if actors *a*, *b*, and *c* were all arrested in event A, once a one-mode projection is undertaken, we have dyadic connections between *a-b*, *b-c*, and *a-c*.

Only a handful of previous studies have adopted a network approach to examine the structure of co-offending among OMCG affiliates. In their analysis of co-offending within a Canadian OMCG, McNally and Alston (2006) found that centrality metrics, measuring the number of direct connections actors have to other actors, did not mirror the formal hierarchy of the club. For example, while the vice president and president were among actors with high degree centrality, other members of the leadership group did not have high degree centrality scores. A later analysis of the Hells Angels Motorcycle Club in Canada, and particularly its Nomad chapter, by Morselli (2009) found that most actors with high degree centrality scores held an official rank with the group. Higher ranking Nomad members however more commonly had high scores on betweenness centrality, a measure of indirect as opposed to direct connections, indicating that they were in strategic brokerage positions. Morselli (2009) concluded that the network only partially mirrored the formal hierarchical organization of the OMCG. Rostami and Mondani (2019) examined the co-offending networks of three Swedish OMCGs. In one group, when members co-offended with other members, they tended to do so with members of the same local chapter, while two other groups collaborated with members from chapters located across the country (Sweden). One club (Hells Angels) showed 15% of co-offending ties were to members of the same group, compared with 9% and 5% in the other two groups. Rostami and Mondani (2019) suggest that this may explain why the Hells Angels were involved in more sophisticated crime types. They suggested that having a higher proportion of in-house co-offending ties may enhance security and reduce the potential for detection and apprehension. Coutinho et al (2020) found that members of OMCG clubs are more likely to collaborate across clubs when illicit markets in which they are involved overlap, suggesting that clubs have advanced capacity to coordinate criminal activity. In a more recent paper Mondani and Rostami (2022) examined co-offending networks of Swedish OMCG members and found that individuals who were members of multiple OMCG clubs had higher centrality scores and showed greater clustering within the network compared with individuals who were members of a single club only. They concluded that individuals with multiple OMCG club memberships tended to co-offend with members of different clubs.

In concluding this section, we note that some studies focus on a single criminal case often using observational and wiretap data related that specific case. In contrast, studies covering multiple years and many different cases usually describe a combined network that covers multiple, most likely substantively different, criminal events. Given the different data sources and time windows, conclusions drawn from single case studies do not readily translate to studies covering multiple cases. For further discussion of these issues related to network data and analysis, the reader is directed to Bright et al., (2022a).

Advances in the Analysis of Co-Offending Networks

Scholars have pointed out that this one-mode projection of a two-mode network leads to a loss of information, and alternative approaches have been put forward (Broccatelli et al. 2016; see also Borgatti and Everett 1997; Opsahl 2013; Hollway and Koskinen 2016). Relational hyperevent models (RHEM) can analyse data on co-offending events without projection to a one-mode network and without the need to aggregate events over (typically arbitrary) time intervals (Lerner et al. 2021; Lerner and Lomi 2022; see also Relational Event Models e.g., Butts 2008). In a nutshell, RHEM can specify and estimate for every set of actors and every point in time a separate *event rate* (also known as *hazard rate* or *intensity*) based on exogenous or endogenous covariates. For instance, the propensity of a set of actors *{a, b, c}* to co-offend at a given point in time might depend on actor-level characteristics (e.g., average seniority of *a*, *b*, and *c*, difference in seniority of *a*, *b*, and *c*, or whether or not *a*, *b*, and *c* are members of the same group or gang) as well as on their (co-)offending history (e.g., average number of previous offenses, average number of previous co-offenses, pattern of previous co-offenses with yet other actors different from *a*, *b*, and *c*, and so on). RHEM build on hypergraphs – an extension of graphs in which multiple actors can be connected with a single event, or *hyperedge* (see Fig. 1). One aim of this study was to examine the potential application of RHEMs to the analysis of co-offending networks. We compare RHEM to other social network models that analyze derived dyadic co-arrest networks, namely Relational Event Models (REM) and temporal exponential random graph models (TERGM). In a dyadic co-offending (or co-arrest) network, whenever {*a*, *b*, *c*}

$$
\begin{aligned}
e_1 &= (t_1, \{a, b, c\}) \\
e_2 &= (t_2, \{c, d, e\}) \\
e_3 &= (t_3, \{b, d\})
\end{aligned}
$$

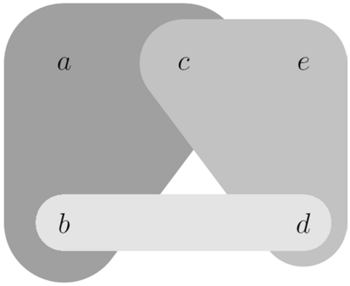

Fig. 1 A hypergraph as a sequence of hyperevents. A sequence of three hyperevents. At time*t1* actors *a*, *b*, and *c* are co-arrested. At time *t2* actors *c*, *d*, and *e* are co-arrested. At time *t3*, *b* and *d* are co-arrested. The third event would indicate a closure effect in which actors *b* and *d*, having co-offended with a common third actor *c*, become co-offense partners

get arrested in the same event, this generates three dyadic ties: *ab*, *ac*, and *bc*. These dyadic networks could also be referred to as a "one-mode projection" (of a hypergraph or of a two-mode actor-event network).

We argue that REM or RHEM are more appropriate for analyses of co-offending networks compared with social network models such as Exponential Random Graph Models (ERGM; Lusher et al. 2013) or Stochastic Actor Oriented Models (SAOM; Koskinen and Snijders 2022) since the data has fine-grained time stamps and is about *relational events* (i.e., offences or arrests) rather than relational states. In this paper we will compare results of analyses using RHEM with results revealed using REM and TERGM. The advantages of RHEM over dyadic REM, meanwhile, include, but are not limited to, the following: (1) the ability to include single-actor arrests in the same analysis (note that these events do not generate any dyadic events); (2) avoiding the potentially invalid inflation of observations (i.e., many dyadic events derived from the same multi-actor event); (3) avoiding the potentially invalid assumption that dyadic events derived from the same multi-actor event (three or more actors) are independent; and (4) avoiding structural artefacts such as an over-representation of closed triangles that stem from arrests that include three or more actors. Indeed, a recent study by Nieto et al (2022) demonstrated that the traditional approach of using one-mode projections for co-offending data can produce inflated transitivity values and clustering coefficients. We note that (T)ERGM and SAOM are for networks of relational states (like “being friends”, “having esteem for”, etc.), whereas we argue that REM and RHEM are optimised for analyses using relational events (e.g., co-offending at a given point in time). Moreover, REM, ERGM, TERGM and SAOM all require the transformation of hyperevents into pairwise events (or pairwise edges).

Given ongoing research and policy interest in the extent to which OMCG co-offending networks overlap with the formal structures and hierarchies of clubs, the research was guided by the following questions: (1) Are office bearers more likely than lower ranked offenders to engage in co-offending, overall and across different offence types?; (2) Does co-offending tend to occur across or within member ranks, overall and across different offence types?; (3) Does co-offending tend to occur within or between members of different OMCG gangs, overall and across different offence types?; (4) Does co-offending between OMCG members show evidence of network closure, that is, a tendency for co-offenders of one OMCG member to become co-offending partners, overall and across different offence types?

Method

Sample and Data

De-identified data for this research was provided by the New South Wales (NSW) Police Force, and was linked with data from the NSW Bureau of Crime Statistics and Research (BOCSAR), and NSW Corrective Services. The de-identified data obtained from the NSW Police Force described offences in which police had apprehended and proceeded against (through some form of legal action) an individual who had some affiliation with an OMCG. This was linked with data from the BOCSAR and NSW Corrective Services on custodial episodes of OMCG affiliates. The data included the following: (1) alphanumeric person identifiers (anonymized) denoting affiliates; (2) event reference numbers (anonymized) denoting crime events (i.e. arrests); (3) the date of the incident and legal action for each offence; (4) crime type, coded using Australian and New Zealand Standard Offence Classification divisions (Australian Bureau of Statistics 2018); (5) club affiliation at the time of data extraction, denoted with a unique numeric club identifier; and (6) affiliate status/rank. The dataset contained information on 93,623 unique crime events attributed to 5513 individuals.

Coding and Analysis

Although data was available from 1995 to 2020, we included only data from 2015 to 2020. In other words, we used only the most recent data to enhance the validity of club membership and rank information. The data used a static measure of rank, obtained at the time of data extraction (20th of May 2020). Event reference numbers, allocated by Police at the time events (typically the date when an offender was proceeded against), were recorded against person identifiers and used to match individuals to offences. When an event reference number was recorded against two or more individuals, they were treated as co-offenders. The most serious charge within each event was used as an attribute for ties between all individuals within that event. We classified 'seriousness' using the Standard Offence Index published by the Australian Bureau of Statistics (2018) which ranks the seriousness of all offences. The method therefore allows for the translation of event-person links into an undirected co-offending network. The network is undirected because the links between individuals indicate only that they have co-offended together and therefore have no direction.

All offences were classified into five offence categories (see Table 1) consistent with previous research on OMCGs (e.g., Barker 2014; Voce et al. 2021). This categorization facilitated analyses of collaboration networks by crime types. Of particular interest were the offences of violence and intimidation and ongoing criminal enterprise as these offences are most commonly associated with organized criminal activities and violence by OMCGs (Quinn and Koch 2003).

Ranks of OMCG affiliates were classified according to information recorded in intelligence files. The following ranks were included in our analyses:

Table 1 The five offence categories

Offence category	Description	Crime events for each category (n)
Violence and intimidation	Crimes against the person (e.g., assault, murder, attempted murder, kidnapping and threatening behavior)	1106
Short-term instrumental acts	Crimes committed for short-term material gain (e.g., robbery, burglary, theft, minor fraud and non-commercial drug dealing)	1654
Ongoing criminal enterprise	Crimes committed within illicit markets (e.g., commercial supply of drugs and firearms, serious fraudulent activity and serious regulatory offences)	713
Public order and regulatory offences	Offences against public safety and regulations (e.g., possess/use illicit drugs, trespass)	8750
Other offences against the person	Crimes against the person not classified under 'violence and intimidation '(e.g., stalking, child pornography offences)	341

- Office bearer: A current fully patched member of an OMCG who occupies an executive role in their club (e.g., president, vice-present, sergeant-at-arms)
- Member: A current fully patched member of a club who is not in an office bearing role
- Nominee: Someone who is undertaking a probationary period seeking full membership of a club.
- Associate: An individual who is an associate of a club but not a nominee or member. These individuals may be seeking to undertake a period as nominee.

In the analysis, we coded these ranks numerically where the office bearer was coded as 4, member as 3, nominee as 2, and associate as 1. Since we were also interested in focusing on the office bearers, for the office bearers' analysis, we created a dummy variable where we coded the office bearers as 1 and the lower ranks as 0.

Finally, each individual was allocated to one of 26 de-identified clubs that were active across the observation period, based on data provided by police. These clubs were anonymized but refer to an umbrella name of a particular club (e.g., Hells Angels, Finks, Comancheros).

We therefore have data on a set of actors A (OMCG affiliates), $n = |A| = 2364$, over a period of five years, from 2015 to 2020. This set of actors does not change over time and actors were attributed to only one club or only one rank over the five-year window. Additionally, we employ time-invariant actor-level attributes: *rank* (ordered nominal with four levels) and *club* (a categorical attribute inducing a partition of the set of actors into 26 discrete clubs). These attributes were validated at the time of data extraction.

Models

The observation of central interest is a list of arrest events $E = e\_1, e\_2, \ldots, e\_N$ (number of arrest events = N = 12,564, where each event $e = (t\_e, h\_e, x\_e)$ is a triple comprising the time of the arrest t_e (given by the day), the set of participants h_e of the arrest (each h_e is a subset of the entire set of actors A consisting of any number of OMCG members, from 1 to n, who are co-arrested in the event), and x_e is the type of the event (which is the type of the offense/crime). The same actors can be arrested several times during the five-year observation period. Each set of co-arrested OMCG affiliates h_e gives rise to a hyperedge in the hypergraph whose nodes are the actors A. Hyperedges in a hypergraph generalize edges in graphs: while an edge always connects exactly two actors at a time, a hyperedge can connect any number of actors, from 1 to $n = |A|$. In the following we give the mathematical description of RHEM for arrest events of any type, that is, ignoring the event type x_e. Transferring these definitions to arrest events of any given specific type x is straightforward by removing events of all other types from E. The statistical framework underlying RHEM and dyadic REM (point-process models or survival models and in particular the Cox proportional hazard model, "CoxPH") is covered exhaustively in Aalen et al (2008). The specifics of RHEM are given in Lerner et al (2021) and are repeated here for clarity.

Relational Hyper Event Models (RHEM)

For a point in time *t*, let *E[<t]* denote those events *e* in *E*, whose event time is strictly before *t*, that is, *t_e<t*. For each subset *h* of *A*, that is, each possible list of event participants, let the hazard rate (also event rate or intensity) of the counting process

$$N_t(h) = \left|\left\{e \in E[<t] \, : \, h_e = h\right\}\right|$$

be denoted by *lambda(t,h)*, compare Aalen et al (2008). The hazard rate is defined by:

$$\lambda(t,h) = \lim_{dt \to 0} \frac{N_{t+dt}(h) - N_t(h)}{dt}$$

Intuitively, for small *dt*, the product *dt*lambda(t,h)* is the expected number of events *e* in the time interval *[t, t+dt]* whose set of participants is equal to *h*. Following the approach of the Cox proportional hazard model (CoxPH) the hazard is decomposed into a global *baseline hazard lambda_0(t)* (intuitively: average hazard over all hyperedges) and a parametric *relative hazard rate lambda_1(t,h)* – the factor by which the hazard on the given hyperedge *h* is higher or lower than the baseline.

$$\lambda(t,h) = \lambda_0(t) \cdot \lambda_1(t,h)$$

Although the baseline hazard could be estimated by non-parametric means, this is of little interest in our study. The baseline hazard is an incredibly small number due to the huge number of all subsets of A. In our study we are interested in why some sets of actors co-offend at a higher or lower rate than others – which is conveyed by the relative hazard.

The relative hazard is specified in parametric form as follows.

$$\lambda_1(t,h) = \exp\left(\sum_{j=1}^{k} \theta_j \cdot s_j(t,h)\right)$$

In the formula above, *s_j(t,h), j=1,…,k* is a vector of explanatory variables (or *hyperedge statistics*) quantifying characteristics that might explain why members of *h* co-offend at a higher or lower rate. These statistics can be functions of actor-level characteristics (such as the average rank of members in *h*, the ratio of office bearers in *h*, or the ratio of pairs in *h* that are in different gangs). Importantly, hyperedge statistics *s_j(t,h)* can also be functions of the event history *E[<t]*. Examples of the latter include the average number of previous arrests in which members of h were involved, the average number of previous co-arrests in which pairs of members of h were involved, and so on (see definitions below). The parameters *theta_j, j=1,…,k* indicate whether and how these hyperedge statistics affect the event rate. More quantitatively, if *s_j(t,h)=s_j(t,h')+1*, that is, if hyperedge *h* assumes a value in *s_j* that is by one unit higher than that of hyperedge *h'* – and if these two hyperedges assume the same values in all other statistics – then *lambda_1(t,h)=exp(theta_j)*lambda_1(t,h')*. If *theta_j* is positive, then *exp(theta_j)>1*, so that the rate on *h* is higher, if *theta_j* is negative then *exp(theta_j)<1*, so that the rate on *h* is lower, and if *theta_j* is approximately zero, then the value of *s_j* has no effect on event rates. Thus, *exp(theta_j)* is the hazard ratio (or relative risk factor) implied by statistic *s_j*.

The parameters theta can be estimated from the data E by maximizing the following partial likelihood; compare Aalen et al (2008) for general results about the CoxPH model and Lerner et al (2021) for the special case of RHEM.

$$L(\theta) = \prod_{e \in E} \frac{\lambda_1(t_e, h_e)}{\sum_{h \in R_e} \lambda_1(t_e, h)}$$

The so-called risk set *R_e* in the formula above is the set of hyperedges h to be compared with the event hyperedge *h_e*. Since the set of all subsets of *A* grows exponentially in |*A*|, we resort to case–control sampling, which is a well-established technique for estimating CoxPH models (Langholz and Borgan 1997; Aalen et al 2008) and has been applied for estimating dyadic REM on large networks (Vu et al 2015; Lerner and Lomi 2020) and for estimating RHEM (Lerner et al 2021). Specifically, following the method suggested by Lerner et al (2021), the risk set *R_e* contains the event hyperedge *h_e* (the "case") plus *m* alternative hyperedges ("controls") *{h_1, ..., h_m}*, sampled uniformly at random from the set of all subsets of *A* that have the same size as *h_e*. (In our empirical study we set m to 1000) The function *L* is called a *partial* likelihood since it explains only part of the data: it cannot explain the average rate of arrest events over all sets of actors (the baseline rate)—that is, it cannot explain whether co-offense frequency goes up or down in the entire population—but it can explain the hazard ratio by which a given set of actors is more or less likely to co-offend than another.

Below we list explanatory variables (hyperedge statistics) s(t,h) included in our models. See Lerner et al (2021) for precise mathematical definitions and further graphical illustration.

1. *avg.#.arrests(t, h)* is the average number of previous arrests (that is, arrest events before time *t*) over the members of *h*. For instance, if *h = {a, b, c}* is the set of actors *a*, *b*, and *c* and before time *t*, actor *a* has been arrested three times, *b* has been arrested once, and *c* has never been arrested before, then *avg.#.arrests(t, {a, b, c}) = 4/3*. Note that for *avg.#.arrests* it does not matter whether the previous arrest events involve just a single actor (*a*, *b*, or *c*, respectively) or whether these actors have been co-arrested with others within or outside of the set *h*. The statistic *avg.#.arrests* models variation in the "arrest-activity" of actors. A positive parameter of this statistic would reveal that actors who have been arrested more often than others in the past are also more likely to be arrested in the future and would lead to a skewed distribution of arrest-activity. In contrast, a negative parameter associated with this statistic would lead to a more evenly distributed activity.
2. *Avg.previous.joint.arrests(t, h)* is the average number of previous arrest events in which pairs of members of *h* has been co-arrested. For instance, if *h = {a, b, c}* is the set of actors *a*, *b*, and *c* and before time *t*, actors *a* and *b* have been co-arrested once (that is, *a* and *b* are participants of the same previous arrest event, possibly with other actors outside of the set *h*) and *c* has never been co-arrested either with *a* or with *b* (that is, actor *c* might have been arrested before, but not with other members of *h*), then *avg.previous.joint.arrests (t, {a, b, c}) = 1/3*. Note that for *Avg.previous.joint.arrests* it matters whether the previous arrest events involve two or more actors from the set *h*. The statistic *Avg.previous.joint.arrests* models varying "closeness" in the space of actors. A positive parameter of this statistic would reveal that actors who have been co-arrested before are "close" to each other and thus are more likely to be co-arrested in the future. This would point to a latent clustering in the space of actors into subsets of actors that are more likely to be co-arrested (and could be described as a "dense groups of actors"). Note that the statistics average rank difference and average gang difference explicitly model "closeness" of actors as a function of exogenous actor-level attributes. In our

analyses, if prior shared activity has a positive effect on top of these attribute-based statistics, it implies that the clustering in the space of actors is not just a function of rank and/or membership of a particular club.

3. *closure(t, h)* is a statistic measuring to what extent members of *h* have previously been co-arrested with the same "third" actors. For instance, if *h* = *{a, b, c}* is the set of actors *a*, *b*, and *c* and before time *t*, there was an arrest event e_1 = (t_1, {a, d}) in which actor *a* has been co-arrested with the third actor *d* and there was another arrest event e_2 = (t_2, {b, d}) in which actor *b* has been co-arrested with the same third actor *d*, then it is *closure(t, {a, b, c})* = *1/3*. Note that the "third" actor *d* does not have to be a member of the focal hyperedge *{a, b, c}*. The closure statistic has to be understood together with prior shared activity. In the given example, actors *a* and *d* would be considered as close to each other (due to their prior shared event) and actors *b* and *d* would be considered as close to each other. Thus, actors *a* and *d* would be members of a dense group and actors *b* and *d* would be members of a potentially different dense group that overlaps with the first group in the common actor *d*. The parameter of the closure statistic explains whether such overlapping dense groups have a tendency to merge over time or remain separate: if closure has a positive parameter is implies that a and b have an increased probability to be co-arrested in the future, which would induce the two dense groups to merge. In contrast, if closure has a negative parameter then actors *a* and *b*, which are both connected to the same third actor *d* but have no history of prior joint arrests would also "stay apart" in the future. From another perspective, actor *d* would maintain a "broker" position spanning structural holes. See Lerner et al (2021) for further explanation.[1]
4. *average rank:* measures whether higher ranks are more likely to offend of co-offend (positive parameter); a negative parameter indicates that lower ranked affiliates are more likely to offend or co-offend. We convert the four ranks to numeric code: office-bearer = 4, patched member = 3, nominee = 2, associate = 1. For any given set of actors, the average rank is the average of the ranks of the members of the set. We chose this numerical coding procedure as the hierarchy of clubs (from a social organisational perspective, not a criminal organisation perspective) puts associates lower than nominees who are lower than patched members who are lower than office bearers.
5. *ratio of office bearers*: If the office bearer rank is indicated by a 0/1 variable, then the average over this variable is the ratio of office bearers to lower ranked affiliates within a co-offending event. In the case of a negative coefficient, the ratio of office bearers in those sets of actors that are (co-)arrested is lower than the ratio in the overall population/sample of actors. For example, if 10% in the sample of all actors are office bearers and arrests involve on average 5% office bearers, then this would lead to a negative coefficient; if, on the other hand, arrests involved on average 15% office bearers, this would lead to a positive coefficient, since office bearers would be over-represented in arrest events, compared to their ratio in our sample. Note that in all cases (for all effects) we compare sets of actors that are (co-)arrested with random sets of actors sampled uniformly from the entire sample of actors.

[1] Note that some models did not include closure effects. Where closure is not included in the models, this is because model parameters were unstable (swung between positive to negative or vice versa). This might be due to an insufficient number of configurations (open two-paths) that are preconditions to closure events. With a small number of observations that show variation in the closure statistic, estimation of the respective parameter becomes unstable.

6. *rank heterophily:* measures whether co-offending involved affiliates of different rank (positive parameter) or the same rank (negative parameter); see also point 4 above. Rank homophily is the average absolute difference in ranks taken over all pairs of co-offending actors. For example, if an arrest involves three members, having ranks 1, 2, and 4, respectively, then the rank heterophily is $(1+2+3)/3$. That is, the absolute difference between ranks 1 and 2 equals 1, between ranks 2 and 4 equals 2 and between ranks 1 and 4 equals 3.
7. *club heterophily* measures whether co-offending involved affiliates from different clubs (positive parameter) or the same clubs (negative parameter). This variable gives the fraction of pairs of co-offending actors who are in different gangs.
8. *rank heterophily office bearer:* is similar to "rank heterophily" (see point 6 above) but applied to a binary variable (1 for office bearer and 0 if not an office bearer). It is the ratio of "mixed" dyads within a hyperedge: pairs i,j such that i is an office bearer and j not, so that the difference can just be zero or one. A positive parameter would reveal that office bearers tend to be co-arrested with non-office bearers. A negative parameter would reveal that office bearers tend to be co-arrested with other office bearers and non-office bearers tend to be co-arrested with other non-office bearers.

Results

We now present the results for analyses of all crime types taken as an aggregate, and results for each of the five different crime types: (1) violence and intimidation, (2) public order, (3) criminal enterprise, (4) short term instrumental acts and (5) other offences against the person. For each crime type, we only look at crime events for that specific crime type and do not include crime events from the other four crime types. We report results separately for co-offending events involving OMCG affiliates, as well as results for co-offending events with a focus on office bearers. The focus on office bearers is especially relevant in trying to determine the extent to which OMCG co-offending networks demonstrate overlap with the formal hierarchical structure of OMCG clubs. In the scenario whereby OMCGs are operating as criminal organizations, office bearer members would be more likely to co-offend with the same partners, with members of their own club, and with non-office bearers, consistent with the notion of the involvement of club leaders in criminal activity in collaboration with lower ranking members of the same club.

All Crime Types

Figure 2 shows the complete network of OMCG affiliates connected to crime events (blue nodes represent people, red nodes represent events). In total, there were 2364 OMCG affiliates and 12,564 arrest events for the period of 2015–2020. Figure 3 illustrates the number of re-arrests for OMCG affiliates in the sample. From the graph, we can see that the majority of OMCG affiliates were arrested more than once.

Table 2 provides the results of all models for all OMCG affiliates. Table 3 gives results for all models focused on office bearers (as a binary variable). Table 2 (all OMCG affiliates included) shows that OMCG affiliates who were arrested more often in the past tended to be arrested more often in the future (i.e., they were repeat offenders) and, if they had previously co-offended, the repeat arrest tended to be with the same co-offending partners.

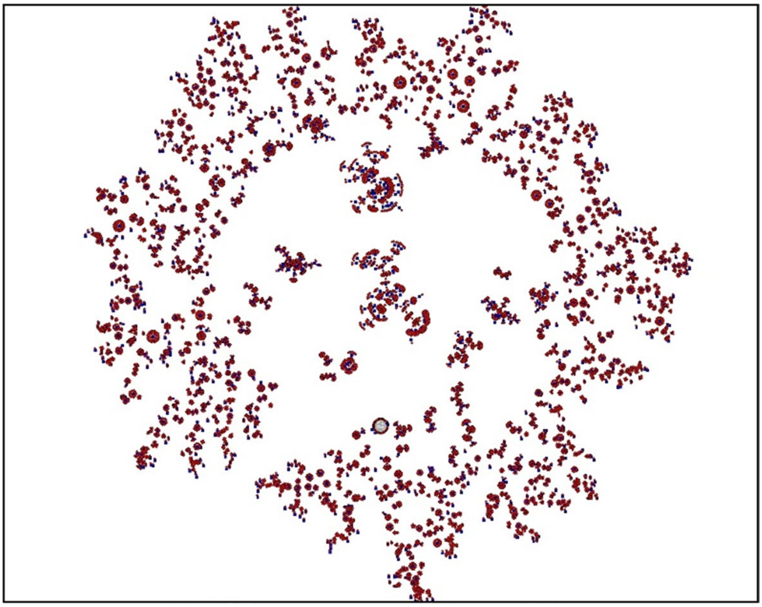

Fig. 2 Network map of complete co-offending network

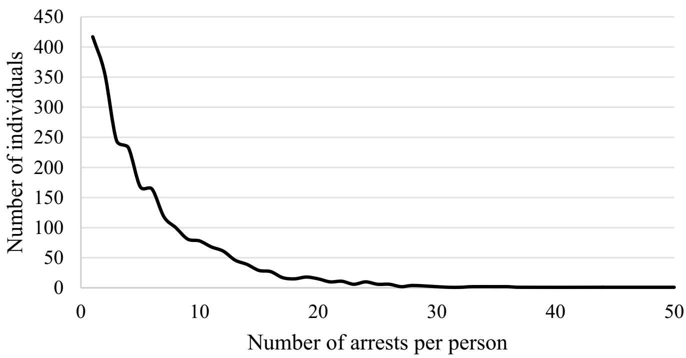

Fig. 3 Distribution of number of arrests per OMCG member

Table 2 RHEM model results for all co-offending involving all OMCG members

Model	Coeff(se)			
	All	VI	PO	OOAP
avg#arrests	0.10(0.00)***	0.35(0.02)***	0.13(0.00)***	0.80(0.07)***
avg.previous.joint.arrests	2.24(0.04)***	7.39(0.32)***	3.03(0.11)***	
closure		− 1.21(0.20)***	1.15(0.19)***	
average.rank	− 0.10(0.01)***	− 0.14(0.03)***	− 0.10(0.01)***	− 0.08(0.05)
rank.heterophily	− 0.22(0.03)***	0.03(0.06)	− 0.20(0.04)***	− 0.02(0.12)
club.heterophily	− 0.89(0.04)***	− 0.29(0.13)*	− 0.68(0.07)***	0.20(0.30)

Table 3 RHEM model results for co-offending involving office bearers

Model	Coeff(se)			
	All	VI	PO	OOAP
avg#arrests	0.10(0.00)***	0.24(0.00)***	0.13(0.00)***	0.82(0.07)***
avg.previous.joint.arrests	2.48(0.04)***	5.76(0.33)***	3.46(0.10)***	
closure	−0.19(0.06)**			
ratio.officebearer	−0.05(0.03)	−0.01(0.08)	−0.09(0.04)*	−0.14(0.19)
club.heterophily	−1.10(0.04)***	−0.26(0.13)*	−0.85(0.06)***	0.04(0.30)
rank.heterophily.officebearer	−0.63(0.10)***	−0.10(0.30)	−0.69(0.17)***	−1.10(0.36)**
ratio of officebearer:club heterophily	0.94(0.18)***	0.17(0.56)	0.76(0.30)*	2.07(0.49)***

Lower ranked OMCG members tended to be arrested more often and the arrests tended to involve co-offenders of similar rank and from the same club.

According to the results displayed in Table 3 (focus on officer bearers as binary variable), OMCG affiliates who were arrested in the past tended to be arrested again in the future (i.e. they were repeat offenders) and, if they had previously co-offended, the repeat arrest tended to be with the same co-offending partners. There was a tendency against closure which means that overlapping, dense groups of co-offenders tended not to merge over time. This finding suggests the presence of brokers who span structural holes in the network. Co-offending tended to occur between OMCG affiliates who belonged to the same club. Office bearers were less likely to be arrested compared to other ranks but were more likely to be arrested with fellow office bearers, and with affiliates from different clubs.

Violence and Intimidation Offences

In total, there were 945 OMCG affiliates charged with violence and intimidation offences, and 1106 arrest events for the period of 2015–2020. Table 2 shows that OMCG affiliates who were arrested for violent crimes in the past tended to be repeat offenders and if they have had a co-offending partner, the repeat arrest tended to be with the same partners. There was also a tendency against closure which means that the overlapping, dense groups tend not to merge over time, again suggesting the presence of brokers in this network. Lower ranked affiliates tended to be arrested more often and the co-offending partner(s) tended to be from the same club.

Table 3 shows that OMCG affiliates who were arrested for violent crime in the past tended to be repeat offenders and if they have had a co-offending partner, the repeat arrest tended to be with the same partner. The arrest partner(s) tend to be from the same club. There were no significant results regarding office bearers.

Public Order Offences

In total, there were 2123 OMCG affiliates charged with Public Order offences and 8750 arrest events for the period of 2015–2020. According to the results displayed in Table 2, OMCG affiliates who were arrested for Public Order offences in the past tended to be repeat offenders and if they have had a co-offending partner, the repeat arrest tended to be with the same partners. In contrast to other crime types, in public order offenses, there was

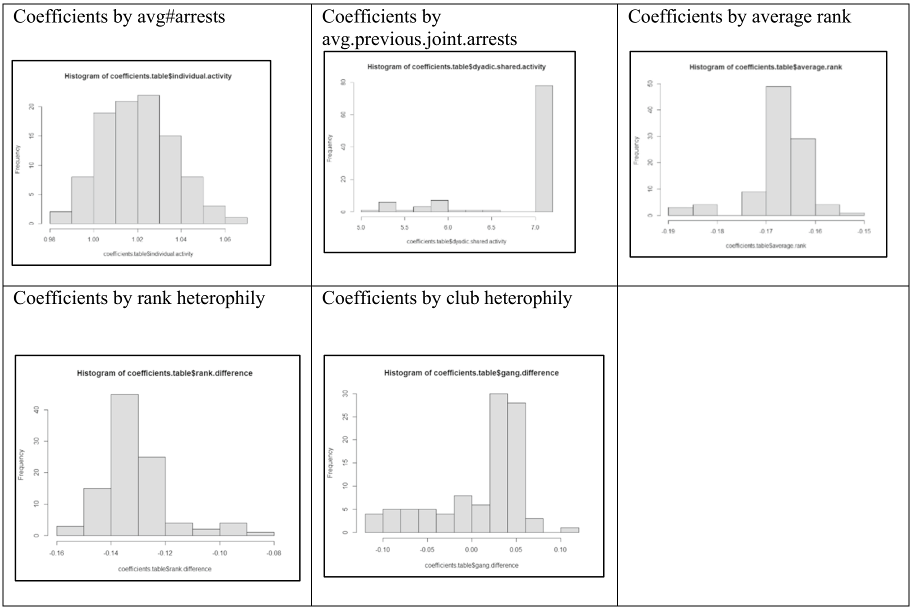

Fig. 4 Histograms for ongoing criminal enterprise

a tendency for closure which means that the overlapping, dense group merged over time. In this case, brokers' partners are likely to become co-arrested themselves – which implies a tendency to close structural holes. Lower ranked affiliates tended to be arrested more often and the arrest partner(s) tended to be from the same club and be of the same rank.

Results displayed in Table 3 reveal that OMCG affiliates who were arrested for Public Order offences in the past tended to be repeat offenders and when they had a co-offending partner, the repeat arrests tended to be with the same partners. The arrest partner(s) tended to be from the same club. Office bearers were less likely to be arrested compared with other ranks but were more likely to be arrested with fellow office bearers, and with members from different clubs.

Ongoing Criminal Enterprise

In total, there were 674 OMCG affiliates charged with Criminal Enterprise offences and 713 arrest events for the period of 2015–2020. Due to the instability of some of the parameters, significance was determined by fitting the same models to 100 repeated samples (taking each time a different sample of non-events via case control sampling). A parameter was deemed significant if the majority (at least 97.5%) of parameters from these repeated samples have the same sign. We reported the distribution over all 100 parameter estimates for Ongoing Criminal Enterprise offences since for models for this type of crime, the variation across samples was much larger than for the other models. We therefore believe that just reporting a single point estimate of every parameter, together with an estimate of its standard error, could have been misleading. (For the other models, variation across samples was smaller and was well represented by the estimated standard error). See Fig. 4 for the histograms of the coefficients.

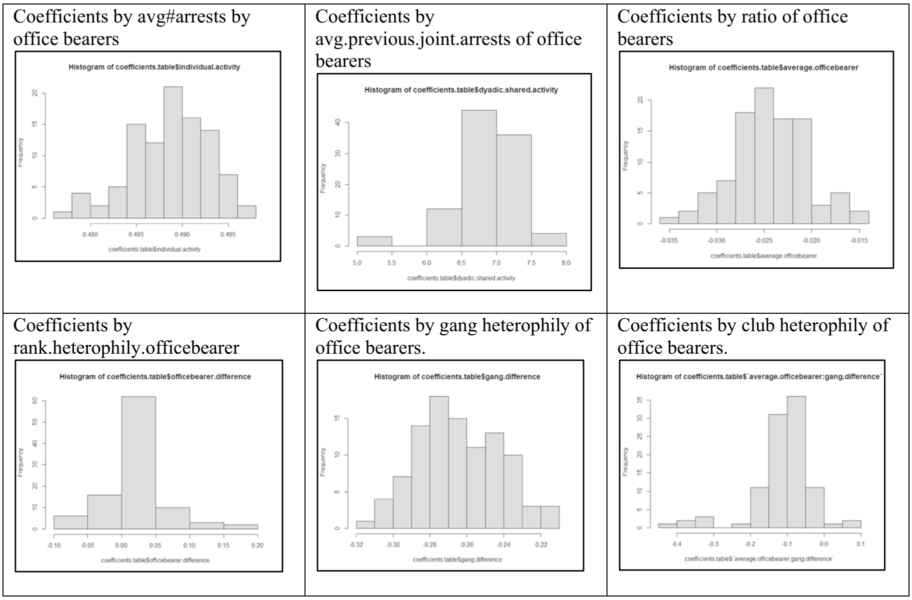

Fig. 5 Histograms for ongoing criminal enterprise including office-bearers

From the histograms, we can see that all coefficients for *avg#arrests* and *avg.previous.joint.arrests* were positively signed. Running significance test for the 100 results, we found that all results for these two parameters were significant. This means that there were tendencies for OMCG affiliates to have repeat arrests with the same partner(s). The average rank coefficients are all negatively signed and all were significant. This means that OMCG affiliates from the lower ranks tended to be arrested more often. The *rank heterophily* coefficients were all in the negative area as well, however they were not significant. This means that neither homophily nor diversity in ranks were observed among OMCG affiliates. *Club heterophily* coefficients results were divided between positive and negative suggesting that there is no observed homophily or diversity in club membership among the OMCG affiliates.

When the model was fitted for office bearers, the results were as follows (Fig. 5):

In the “Office Bearer” models, the only significant effects were for repeat arrests (‘avg.#.arrests’) and repeat arrests with the same partner(s) (‘avg.previous.joint.arrests’). The coefficients for those two parameters were positive which means that OMCG affiliates tended to be arrested multiple times and if they have co-offending partner(s), they tended to be arrested with the same partner.

Short Term Instrumental Acts

In total, there were 822 OMCG affiliates charged with Short Term Instrumental Acts offences and 1654 arrest events for the period of 2015–2020. The short-term instrumental acts category was also investigated by running the calculation 100 times (due to the instability of some of the parameters) and then comparing the results from the models. The results are as follows (see Fig. 6):

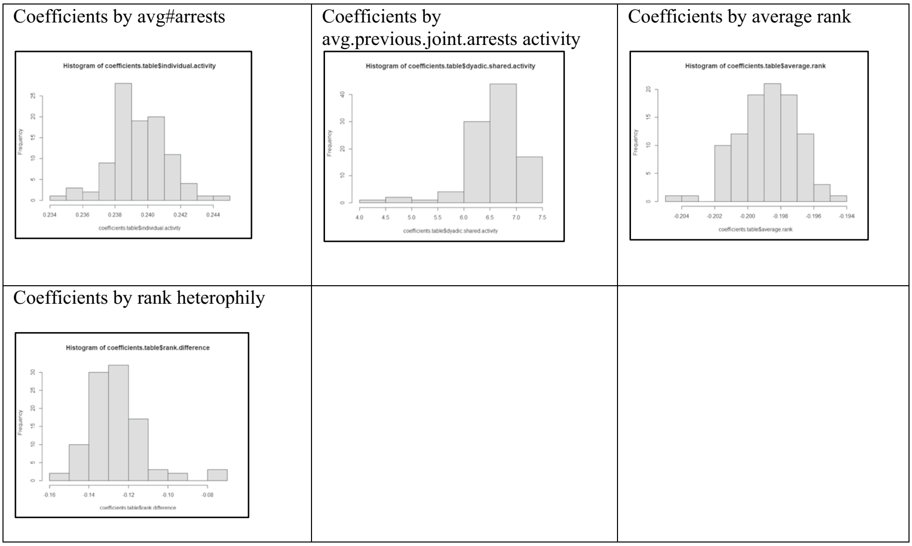

Fig. 6 Histograms for short term instrumental acts

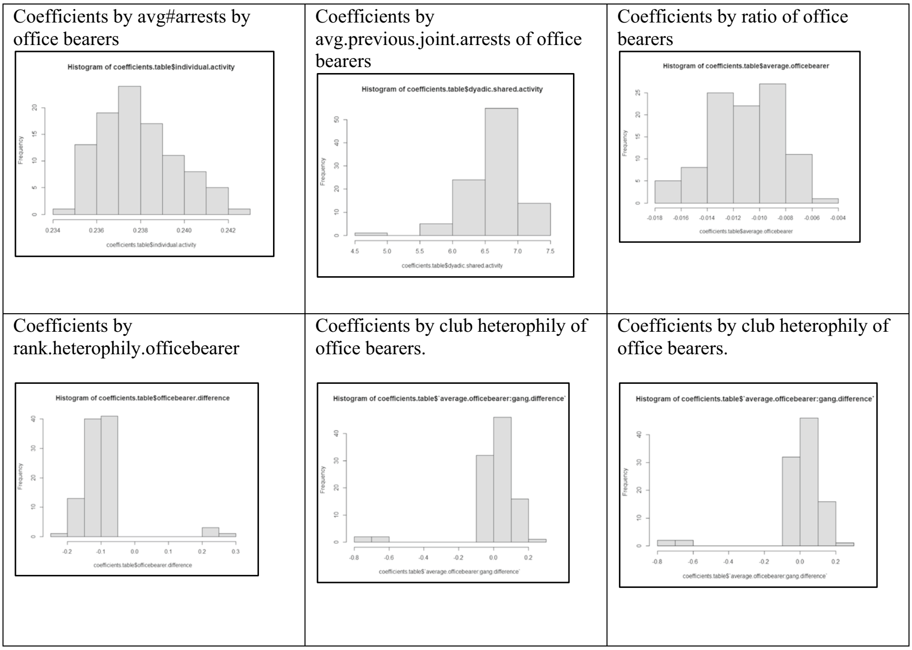

Fig. 7 Histograms for short term instrumental acts, including office bearers

From the histograms, we can see that all *'avg#arrests'* coefficients and *'avg.previous.joint.arrests'* coefficients are positively signed. Running the significance test for the 100 results, we also found that all results for these two parameters are significant. This means

Table 4 Summary of results for RHEM

Effects	All	VI	PO	OCE	STIA	OOAP
Rearrest	+	+	+	+	+	+
Repeat arrests, same partners	+	+	+	+	+	
Lower ranked, more likely	+	+	+	+	+	
Co-arrests, same rank	+		+			
Co-arrests, same gang	+	+	+			
Closure	–	–	+			
Office bearers, more likely	+		–			
Office bearers, more likely with other office bearers	+		+			+
Office bearers, more likely with different clubs	+		+			+

that there were tendencies for repeat arrests and repeat arrests with the same partner(s). The average rank coefficients are negatively signed and all of them were significant. This means affiliates from the lower ranks tended to be arrested more often. The *rank heterophily* coefficients were all in the negative area as well, however they were not significant. This means that neither homophily nor diversity in ranks were observed among OMCG affiliates. *Club heterophily* coefficient results were divided between positive and negative. This means that there was no observed homophily or diversity in club membership among OMCG affiliates.

When the model was fitted for office bearers, the results are as follows (see Fig. 7):

The only significant effects were for 'avg#arrests' and 'avg.previous.joint.arrests'. This means that OMCG affiliates tended to be arrested multiple times and if they have had a co-offending partner(s), there was a tendency for repeat arrests with the same partner(s).

Other Offences Against the Person

In total, there were 344 OMCG affiliates charged with 'other offences against the person' and 341 arrest events for the period of 2015–2020. Table 2 shows that for "other offences against the person", there was no significant pattern except an effect for OMCG affiliates being more likely to reoffend in the future if they had offended in the past. The *dyadic.shared.activity* and *closure* were excluded because of their instability in the model and in some instances they prevented the model from converging. When the model was fitted for office bearers (see Table 3), results.indicated that there was a tendency for OMCG affiliates to reoffend in future if they had offended in the past. Further, if office bearers were arrested, they tended to be arrested with other office bearers and their arrest partners were more likely to be members of a different club.

Table 4 provides a summarised overview of all RHEM results and allows for comparisons of results across crime categories. It shows the variation in the pattern of effects across crime types. For example, all crime types other than 'other offences against the person' showed positive effects for rearrests with the same co-offending partners and greater probability of co-offending for lower ranked affiliates. The closure effect was positive only for public order offences while it was negative for violent offences.

REM Results

Details regarding REM are provided in Appendix 1 and full results for REM are displayed in Appendix 2. As with the RHEM analyses, relational event models were developed for the complete network of actors and for each of the five offence types. In contrast to RHEM, all REM were created by removing all isolates (i.e., OMCG affiliates who were never arrested with co-offenders across the data window). We provide here the results for the complete network only, while results for the five different crime categories are presented in Appendix 2. Using REM, the results indicated that OMCG affiliates who were arrested together in the past tend to be arrested again in the future (positive *avg.previous.joint.arrests*). In contrast, those who did not have a history of being arrested together were less likely to be arrested together in future (negative *avg.#previous.dyadic.arrests*), unless they shared a common third co-offending partner. That is, where a partner of a partner was previously arrested together (evidence of positive closure). Co-offending partnerships tended to involve those of lower rank and were more common between individuals of the same rank and those from different clubs.

As compared with RHEM, in REM the negative *avg.#.previous.dyadic.arrests* and positive *avg.previous.joint.arrests* effects have to be interpreted differently (i.e., to *avg#arrests*) since in our REM models there is no possibility of being arrested alone (we only model dyadic arrests having removed all isolates). Assume that Actor A and Actor B have been co-arrested once in the past (possibly with yet others). Assume that Actor C has been co-arrested with some actors but not with Actor A or B. The past arrest on the dyad (A, B) increases their value in the individual activity statistics, which has a negative effect, but it also increases their value in the shared activity statistic which has a larger positive effect. Thus, the joint effect of the past arrest event on (A, B) is that a future co-arrest including both of them becomes more likely. Actors A and C have no past co-arrest with each other (but co-arrests with others). Thus, the dyad (A, C) has a positive value in the individual activity statistic, which has a negative effect on future event probability, and this dyad has a value of zero in shared activity (no positive effect). Thus, their past arrests with others, along with the lack of a joint arrest history, make it less likely that Actors A and C are co-arrested in the future. In general, a negative parameter of *avg#previous.dyadic.arrests* and a positive parameter of *avg.previous.joint.arrests* means that actors become more and more likely to experience common events with their "in-group" (former acquaintances, co-offenders) but less and less likely to experience common events with actors with whom they don't have a previous event history (see Lerner and Lomi 2022).

The main difference between the two analyses is that, as expected, REM supports triadic closure for all models (overall crime and all five crime categories) whereas RHEM find evidence of positive closure in one crime type (public order offences) and evidence against closure in overall crime and for violent crime. This result is consistent with our expectation that dyadic REM would result in over-estimation of triadic closure, due to the conversion of multi-actor events into cliques of dyadic events.

TERGM Results

Full results for TERGM are displayed in Appendix 3. In general, the TERGM results for the six different networks indicated that all networks were sparse and had significant formation of triadic closure over time. Overall, this result is consistent with our expectations that TERGM would result in over-estimation of triadic closure.

As for the covariates, the results were varied across different networks. Overall, OMCG affiliates of higher rank tend to form more co-offense ties over time compared with those affiliates of lower rank, but these ties tended not to persist over time. Office bearers tend to be co-arrested with other office bearers, but those ties also tended to not persist over time. Unlike in RHEM, homophily for affiliate rank and club were not found in TERGM results. For the *violent* crimes network, in the formation of ties, office bearers tended to have more co-offenders compared with non-office bearers. The TERGM result also diverged from results using RHEM as it did not detect homophily in gang. In the *public order* co-offense network, TERGM results indicated that people from higher rank tend to form more co-offense ties over time compared with those of lower rank. Again, in contrast to RHEM results, the TERGM result did not indicate that there was homophily for rank, gang, or office bearer. In the criminal enterprise and short-term instrumental act networks, TERGM did not find any significance for any of the covariate effects. This result was consistent with RHEM result in which no homophily effects were found. Finally, in the *other offences against the person* network, TERGM results indicated that office bearers tended to have more co-offenders and they tended to co-offend with other office bearers. This result was consistent with results using RHEM.

Discussion

The 'All Crime' Network

For the 'all crime' network we found that OMCG affiliates who had previously been arrested were more likely to be arrested in future. When repeat arrests occurred with other affiliates, those repeat arrests tended to be with the same affiliate. This suggests some consistency in co-offending partnerships over time, which is likely driven (at least partly) by shared membership of the same club or chapter. To reduce risks and enhance security, co-offending partners are likely to be drawn from an inner trusted network of affiliates (e.g., see Bright et al., 2022c), which, much of the time, comprises fellow club members. This explanation reflects co-offending between affiliates of the same club but not co-offending that relates to conflict either within or between clubs.

Affiliation with an OMCG may provide opportunities to co-offend with like-minded individuals, holding similar attitudes and beliefs, many of whom are known to have criminal backgrounds. This ongoing access to potential co-offenders who have already been vetted by the club reduces the 'search time' (and risks) involved in locating a motivated, willing accomplice. These advantages may develop over time as successful co-offending relationships are likely to be enduring, as we found in this study. Given that the co-offending tended to occur between affiliates from the same club, it would be reasonable to assume that the "pool" for co-offending partners tends to be the more easily accessible local pool of affiliates form the same club (i.e., the group who socialise together, meet for club events, and form co-offending relationships). However, this explanation relies on co-offending being an interaction between the individuals within the club, rather than organised by the club or occurring as a consequence of organised club activities. It is difficult to remove the findings of this analysis from the possibility that offences of this type were a component of organised offending on behalf of the club, with the intention of benefiting the club. Given the scale of co-offending, the findings of this paper support the notion that co-offending among OMCG members appears to be a function of organised criminal offending by the club.

Our interpretation of these findings holds similarities to prior research into co-offending. For example, Charette and Papachristos (2017) found that co-offenders who maintain an offending relationship over time show increased trust in one another. Moreover, having shared characteristics – in the current case, affiliation with an OMCG and similar attitudes—has been found to be germane for co-offending networks in building trust (see Charette and Papachristos 2017). Similarly, Grund and Morselli (2017) found that co-offenders tend to co-offend with the same partners over time, a finding the authors posit is based on trust within 'working relationships' formed and strengthened over time. This is especially relevant to OMCGs, which place great importance on notions of 'brotherhood' and require members to demonstrate strict loyalty to their club and fellow club members. Indeed, some offences may be conducted on behalf of the club, including where members are ordered to commit specific offences by senior members. In these instances, criminal collaborations would be formed to advance the interest of the club, as part of club business. These collaborations would, by virtue of their motivation and purpose, involve members of the same club.

Explanations of co-offending dynamics over time must also take account of criminal justice sanctions and the avoidance of such by offenders. For co-offenders in this sample to be co-arrested again, they must have either been successful in avoiding incarceration, or released from prison with time enough to co-offend within the five-year sample period. Where these co-arrests involved co-operation, it is likely that the prior experience of co-offending featured a degree of perceived success and / or the promotion of trust between individuals to the extent that they had opportunities to co-offend again. Alternatively, the result may reflect limited options for selection of co-offending partners, resulting in the observed consistency in co-offending partnerships. Given that the majority of co-offending (especially for violent offences) was observed within clubs, we believe that the majority of co-offending reflects cooperative criminal activity. Nonetheless, there may be occasions where co-offending involves competition or enmity. Where co-arrest involves some type of enmity, for example physical altercations between affiliates of two clubs, the result might indicate that such enmity persists over time resulting in the same OMCG affiliates being arrested together on multiple occasions.

Lower ranked members were more likely to engage in co-offending compared with office bearers. This could mean that office bearers are less likely to engage in offending / co-offending behaviour, or that they are less likely to be detected or arrested for this behaviour. Building on the first hypothesis, this finding may reflect age differences between ranks, and specifically that lower ranked affiliates tend to be younger than those of higher ranks (especially office bearers). The widely supported age-crime curve has shown that offending peaks in adolescence and early adulthood for a variety of age-related reasons (e.g., DeLisi 2015), and research has found a similarly higher prevalence and frequency of offending among younger organized crime offenders (Campedelli et al. 2021; Meneghini and Calderoni 2022) and OMCG affiliates (Cubitt and Morgan 2022; Morgan et al., in press). Relatedly, research has highlighted that recent generations of OMCG members have more extensive histories of (particularly violent) offending in adolescence and early adulthood than their older counterparts, pointing to a stronger propensity for crime and violence among younger members (Dowling et al. 2021; Voce et al 2021).

Regarding the second hypothesis, previous work has shown that office bearers prefer to indirectly control the criminal activity of lower ranked affiliates so that their 'hands are clean' and they are insulated from any potential legal consequences (e.g., Morselli 2009). It has been argued that younger members may be recruited as 'foot soldiers' into violent confrontations with rival clubs (e.g., Quinn and Forsyth 2009), or to undertake higher risk activities in ongoing criminal enterprises (Cubitt and Morgan 2022; Morgan et al., in press) under the direction of older and more senior members. Additionally, lower ranking affiliates may be more likely to engage in crime to prove their worth to the club, and secure full membership or higher office (e.g., Morselli 2009; Rostami and Mondani 2019). Initiation rituals and processes are fundamental to the recruitment of new members into OMCGs (see von Lampe and Blokland 2020), and these may include committing certain crimes, including violent crimes, that target other clubs. Taken together, these findings suggest that office bearers, rather than simply offending less, may play some role in directing or influencing the offending of other members from behind the scenes, while taking care not to become too directly involved in it and risk attracting the attention of law enforcement.

The RHEM model revealed that there was evidence against triadic closure for the overall co-offending network. This suggests that while affiliates *a-b* and *b-c* offend together, it is not likely that affiliates *a-c* will later co-offend despite their indirect connections to *b*. The likelihood of two individuals co-offending is reduced if they each co-offended with the same third actor in two separate events but have no previous co-offending history among themselves. In the example above, actor *b* occupies a broker position spanning a structural hole. Negative closure means that structural holes tend to remain open, that is, actors tend to keep their broker positions.

Significant results also emerged regarding a number of other variables. As mentioned, when OMCG affiliates engage in co-offending they are more likely to co-offend with other affiliates of the same rank. Co-offending was more likely among affiliates of the same OMCG, although office bearers exhibited a tendency to co-offend with affiliates of other clubs, and with other office bearers. The co-offending between office-bearers may reflect a type of homophily based on their rank and leadership position in the clubs. Office-bearers may place higher levels of (criminal) trust in other office-bearers given their privileged position within the club with their office-bearer status being indicative of higher loyalty and trustworthiness. The perceived benefits of co-offending between office bearers, may overcome the risks posed by criminal collaboration between clubs. If this is the case, these findings support the notion that offending by members of OMCGs occurs not only clubs, but potentially also between clubs under certain conditions. Of relevance here, Australian police have recently reported that OMCGs are increasingly turning to collaboration with rival clubs, and with other organised crime groups, to secure control of markets and enhance their profits (ABC News 2017; Pearson and Estcourt 2022). However, while these findings may represent collaboration (e.g., two office bearers from different clubs cooperate in a joint endeavour to traffic illicit drugs), they may also represent a conflict (e.g., two office-bearers from different clubs in a physical altercation). As an example of conflict that results in co-offending, we use the category of public order offences. There may be public order crime events in which members of two clubs meet (by design or by chance) and engage in some type of violent conflict, however it is more likely that these conflicts attract criminal collaboration between lower ranking OMCG members (Cubitt et al. 2022). We now turn to a closer examination of the results regarding each of these categories.

The Five Offence Types

As with the findings for all crime, across all of the five crime categories OMCG affiliates were likely to be re-arrested if they were previously arrested for offences within that specific crime category. Affiliates were also likely to maintain the same co-offending partners, and lower ranked affiliates were more likely than higher ranked affiliates to be arrested, for all offence categories except other offences against the person.

OMCG affiliates were likely to co-offend with members of the same rank for public order offences only. Public order offences include offences such as the possession and use illicit drugs, property damage and disorderly conduct – offences which tend to be of lower seriousness and are more representative of 'barbarian' type behaviour OMCG affiliates commonly engage in to show off their bravado and daring (von Lampe and Blokland 2020). These types of offences, often spontaneous and unplanned, may be undertaken by OMCG affiliates within sight of other OMCG affiliates as a way to demonstrate their commitment to the outlaw culture of their clubs. We note though that the result may also be a function of law enforcement activity. It is these large gatherings that may result in arrests of multiple members at once, usually for some type of public order offence such as affray. By virtue of the fact they outnumber office-bearers, most of those arrested will be lower ranked affiliates such as nominees and associates.

OMCG affiliates were likely to co-offend with members of the same club for violence/intimidation offences and public order offences, but the effect was not observed for ongoing criminal enterprise, short term instrumental acts or other offences against the person. As discussed previously, many offences categorised within the violent and public order categories probably reflect barbarian-type behaviour that affiliates commonly engage in with others in their clubs. Regarding violence/intimidation offences, these results could, to some degree, reflect conflicts with rival club members, and especially more planned and predatory attacks on the affiliates of rival cubs where police may only arrest the aggressors and treat the rival club members as victims. That affiliates were not found to be more likely to co-offend with others from their club in relation to short-term instrumental acts and ongoing criminal enterprise offending suggests that club loyalty may be less important when the primary motivation of criminal activity is financial profit.

Triadic closure was found to occur only for public order offences. Clustering of co-offenders may be more likely for these type of low risk, more opportunistic type offences, and is more in keeping with the hedonistic, barbarian culture of OMCGs as opposed to more planned instrumental offending and organised crime type offending. In contrast, we found evidence against triadic closure for violence and intimidation offences. Given the more easily detectable nature of these offences, and the risk that violence may spill-over and impact bystanders, attracting increased law enforcement attention, clubs are likely to actively avoid incidents in which groups of their affiliates may be arrested. It is therefore possible that this analysis has identified numerical thresholds for violent co-offending among OMCGs, in which an individual member is unlikely to commit violence on their own, but where violent offences are not typically engaged in by more than three or more members. Whether this was an intentional decision by affiliates, or a naturally occurring phenomena relating to opportunity, remains unclear.

Office bearers were less likely than lower ranked affiliates to be co-arrested for public order offences. This could, again, reflect the age differences between ranks within OMCGs. Office bearers, who are likely to be older on average, may be less inclined towards public order offending which, in the barbarian-style OMCG milieu, could often be centred on displays of youthful bravado, impulsivity and thrill-seeking. To the extent that public order offences are seen in this milieu as a way for lower-ranked members to prove their dedication to a club and their willingness to undertake criminal activities on its behalf, there would obviously be less reason for senior ranking office bearers to do the same. Alternatively, this finding could reflect selection bias. Police are typically aware of who the senior ranked affiliates in OMCGs are, and regularly subject them to greater scrutiny and enforcement activity. As a result, office bearers may refrain from lower-level offending that is highly visible or otherwise easily detectable by police. Office bearers may also be more experienced at evading law enforcement attention: they know they are more likely to be targeted by police and may therefore be less likely to engage in those behaviours.

The Three Scenarios

With respect to the three scenarios developed by von Lampe and Blokland (2020), our results support the notion that some OMCGs operate, at least at times, as organized criminal groups, especially where there is evidence that office bearers are involved in co-offending with other affiliates, and particularly when such offending involves organized crime type offences (e.g. drug trafficking). Although we are unable to determine whether office bearers direct or oversee such criminal activity, it should be remembered that, by virtue of their position in the club, they hold distinct power over lower ranked members. Therefore, it is also probable that office bearers hold some degree or control or influence over their criminal collaborations with lower ranking members as well, particularly when these co-offences feature a material benefit to the club (ie. Increases in territory, power or financial gain). Importantly, given our reliance on data concerning offences detected by police, any overlap of offending and club hierarchies is likely obscured to some extent by the insulation office-bearers regularly have from legal consequences (e.g. Morselli 2009), making the identification of clubs operating more as criminal organisations difficult.

When co-offending involved members of more than one club, the resulting criminal network may at times feature members of several clubs, such that the boundaries of discrete clubs are difficult to identify. It was also apparent that some clubs comprised of features consistent with the ‘club within a club’ scenario. In particular, our results highlight the presence of brokers as important members who connect different clubs within the broader co-offending network and facilitate a type of cross-club offending. Our findings mirror those of van Deuren et al. (2022), in that the extent to which Australian OMCGs adhere to each of the scenarios varies across the types of criminal activities in which they are involved. While the three scenarios provide a working framework for understanding OMCG offending, the reality is much more complex and suggests a hybrid type co-offending network that includes some clubs operating as both criminal organisations and ‘clubs within clubs’ interconnected by key brokers (who are often office bearers).

Having concluded our discussion of the implications of the results for OMCG offending and co-offending, we now turn to a brief discussion of the comparison of the two analytical models: REM and RHEM. We offer some tentative conclusions about the relative utility of RHEM for the analysis of co-offending networks.

Comparison of RHEM with REM and (T)ERGM

A subordinate focus of this study was to examine the potential benefits of using RHEM over other modelling approaches such as REM or TERGM to analyse complex network data, given the potential for traditional co-offending models to produce spurious findings relating to co-offending dynamics (Nieto et al. 2022). We found that the main difference between the two analyses is that, as expected, REM and TERGM find triadic closure for all models (the ‘all crime’ network in addition to all five crime categories) whereas RHEM find evidence of closure in one crime type (public order offences) and evidence against closure in overall crime and for violent crime. This is one concrete illustration of potentially invalid findings resulting from dyadic REM, or TERGM – in contrast to an analysis with RHEM. We observe that dyadic REM and TERGM suggested a *positive* closure effect for nearly all subsets of the data, while the RHEM analysis revealed *negative* closure for most crime types (the exception being public order offenses). It can be well explained why REM and TERGM are bound to yield positive closure: the one-mode projection of events with three or more participating actors, by construction, leads to a large number of closed triangles (the number of resulting triangles scales as the number of participating actors to the power of three). This structural artefact, which is caused by forcing hyperevents into dyadic events, is “explained” by dyadic REM with a positive closure effect. Indeed, in data with many large hyperevents, it is nearly impossible for dyadic REM to find negative closure, due to the abundance of generated closed triangles. In contrast, the analysis with RHEM painted a more differentiated picture: closure was found to be negative for most crime types – pointing to the existence of overlapping dense clusters, connected by brokers bridging structural holes. Only in the network of public order offenses did the RHEM analysis find positive closure. Similarly, triadic closure was overestimated for all six co-offending networks analysed in this study. We therefore argue that RHEM should be the preferred analytical approach to co-offending networks as one type of network within the class of ‘relational’ models. In particular, we note that negative closure is not inevitable whenever RHEM is applied, but it can reveal important differences between networks. We further point out that an analysis with (T)ERGM entails the additional disadvantage of having to aggregate co-offense events over typically arbitrary time intervals – a problem that does not occur for REM nor for RHEM. Since co-offense networks typically come in the form of time-stamped relational events – rather than stable relational states – models for relational events, REM or RHEM, are more appropriate than (T)ERGM. On the other hand, it is the polyadic (or hypergraph) nature of co-arrests that imply the preference of RHEM over REM.

We note that RHEM are implemented and made available in the open-source software eventnet (https://github.com/juergenlerner/eventnet) enabling other researchers to conduct a similar analysis.

Limitations

There are several limitations related to these data and analyses: (1) the dataset only includes offences that are detected by police so the data will underestimate criminal behaviour and co-offending by OMCG members; (2) the data includes only OMCG affiliates who were arrested by the police. There could be affiliates who were known by the police but were never arrested, and these people were not captured in the data; (3) arrests may be reflective of the strategic focus of police investigations and may therefore reflect this focus (see Bright et al. 2022a for a discussion of this and similar limitations in criminal networks research); (4) for the purposes of this project we operationalised co-offending as criminal collaboration (as most studies on co-offending do). But although being arrested at the same crime event usually indicates criminal collaboration, it may also capture individuals arrested at a similar event who are not collaborating and may even be antagonists (e.g. a fight between rival clubs). This is more likely for some offence types (e.g., public order offences) than others (e.g., short-term criminal acts); (5) the data include only those OMCG affiliates who are known to be members through police reports (so some actual members including office bearers may not be included); (6) the data does not include individuals who were not affiliated with OMCGs so we know nothing about co-offending and collaboration with non-members, including other criminal groups; (7) individuals may be less likely to remain in the pool of available offenders if they are arrested for a more severe/serious offence (e.g. murder), an example of a time-varying risk set; RHEM can deal with time-varying covariates (changing rank or group membership) and also with time-varying risk sets (who could participate in events at a given time); (8) We do not have the information whether individuals who were arrested were subsequently incarcerated, so we assumed that all arrestees had been released and had the opportunity to be re-arrested; and (9) as noted in the methodology section, while the data covered the period 2015–2020, we employed rank attribution from 2020. Therefore, ranks of individuals may have changed over the five period without being recorded in the data and analysis. Given the potential data limitations listed above, especially with respect to missing data, we conducted some robustness analyses using simulated missing data. Results of these simulations did not differ from our substantive results in any meaningful way (see appendix 4).

Implications

The results have implications for policy and practice in the investigation and disruption of OMCGs. Specifically, intelligence agencies and law enforcement agencies should collect data on co-offending within and across OMCG clubs and seek to disrupt connections between some of the key players such as office bearers, especially for more serious categories of crime such violence/intimidation and ongoing criminal enterprise. Our results further suggest that the focus of law enforcement should be on the co-offending networks involved in serious crime such as organised crime, rather than on specific clubs. Given the importance of collecting and analysing intelligence, these approaches could be incorporated into predictions models (e.g., Cubitt and Morgan 2022) to guide LEA in terms of targeting (based on whether it adds any predictive power, obviously, but this remains untested).

With respect to practical considerations, RHEM has already been applied to data comprising hundreds of thousands of actors and events (see Lerner and Hâncean 2023) by using case–control sampling. We therefore believe that RHEM could be applied with reasonable computational runtime to any currently available data on co-offending networks. Among the challenges, we note that the estimation of some RHEM effects become unstable if the network is very sparse, for instance, if most events have a single or only few participants (see Lerner and Lomi 2023). Ultimately, this can mean that some RHEM effects must be dropped from the models to ensure a convergent estimation (eg. in the empirical analysis in our paper we had to drop the 'closure' effect in several models). A possible way around this instability is to reduce the network to a core of actors that are sufficiently active in co-offending (thereby increasing the density). We further recommend that researchers and practitioners fit RHEM not just once but several times with different samples of non-events ('controls') to assess the uncertainty in parameter estimates that is caused by case–control sampling (we did this in our empirical analysis).

The stability of co-offending networks over time reaffirms the importance of focusing on smaller networks – meaning chapters – given the 'franchise' structure of OMCGs probably influences co-offending networks. The observed stability of co-offending networks suggests that prior arrests may have limited effect on long-term disruption of OMCG co-offending networks. This highlights the need for further research into the effects of law enforcement activity on co-offending, as part of the broader need for research into the impact of disruption strategies more generally.

Future Research

This research suggests that there may be benefit to analytic approaches using RHEM to analyse other co-offending data sets across contexts (e.g., gang offending, other country data). There may also be benefit to conducting network analyses using data collected on OMCG groups in different contexts (e.g. other states of Australia, other countries). Further, to further aid in interpretation and to establish context to administrative crime datasets, we strongly recommend combining results of SNA with ethnographic research such as interviews with ex-OMCG members. This type of approach may enable researchers to delve more deeply into the social dynamics that drive co-offending in OMCGs including the possibility that office bearers direct or oversee criminal activities with or without engaging in such activities. Finally, we suggest that future research should examine the "evolution" of crime in OMCG or other co-offending contexts (i.e., if one is co-offending with someone that previously was charged with a more serious crime than him, would he get an "upgrade" in the next crime).

Appendix 1: REM and ERGM

Dyadic REM for Modelling Co-Offending Data

In our empirical analysis presented in this paper, we compare results obtained by RHEM with results obtained by relational event models (REM) for dyadic data, which are a more established framework (Butts 2008). REM can also be specified within the CoxPH modelling framework – the difference to RHEM is that REM can model only dyadic events connecting exactly two nodes at a time (such as a telephone call linking one sender with one receiver). We outlined above the disadvantages of analysing co-offending networks with REM. Arrest events have to be converted to dyadic events which forces us to drop single-actor arrests. Moreover, converting arrests with three or more participants into pairwise dyadic co-arrests artificially increases the number of observations, violates the assumption of conditionally independent events, and creates structural artefacts, such as a high number of closed triangles. These points are further clarified by the more formal treatment below.

As with RHEM, the observation of central interest is a list of arrest events $E = e\_1, e\_2, \ldots, e\_N$, where each event $e = (t\_e, h\_e, x\_e)$ is a triple comprising the time of the arrest t_e (given by the day), the set of participants h_e of the arrest (each h_e is a subset of the entire set of actors A consisting of any number of OMCG members, from 1 to $n = |A|$, who are co-arrested in the event), and x_e is the type of the event (which is the type of the offense/crime). These events in which the number of participants |h_e| is a variable number between 1 and n have to be converted to a list of dyadic events E' = e'_1, …, e'_N' (note that the number of constructed dyadic events N' is typically different from the number of original events N) by the following steps.

1. All single-actor arrest events (|*h_e*| = *1*) are discarded.
2. All arrest events involving exactly two actors (|*h_e*| = *2*) are left unchanged.
3. All arrest events involving three or more actors (|*h_e*| > = *3*) get converted into undirected dyadic events: for each unordered set *{a,b}* of two different members of *h_e*, we add an event *e' = (t_e,{a,b},x_e)* to *E'*. After that, the multi-actor event gets discarded.

The first step could be problematic since – even in a study only concerned about *co*-offending – single-actor arrests could still trigger (or prevent) future co-arrests. Even more problematic is the creation of multiple dyadic co-arrest events from original co-arrests with three or more actors. The number of dyadic events resulting from a hyperedge *h_e* is |*h_e*|**(*|*h_e*|−*1)/2*. For instance, an arrest event involving three actors yields three dyadic events, an arrest event involving five actors already yields ten dyadic events. Thus, the conversion into dyadic events artificially increases the number of observations – which could result in invalid estimates. Moreover, the assumption that events occurring at the same time (on the same day in our study) are conditionally independent of each other gets violated. For instance, if actors *a*, *b*, and *c* are co-arrested at time t, then it is not even thinkable that the three resulting dyadic events, *{a,b}*, *{b,c}*, and *{a,c}* are independent (more to the point, the third one is even implied by the two former events – which is the strongest form of dependence). Last but not least, the conversion of arrests involving three or more actors into clusters of dyadic events creates structural artefacts, such as an abundance of closed triangles, since any subset of three members of *h_e* is mutually connected by construction.

After having constructed the list of dyadic events *E'* from *E* as detailed above, the specification of REM within the CoxPH framework follows the same steps as in the case of RHEM. In particular, the relative co-arrest rate on a dyad *{a,b}* (any combination of two actors from *A*) at time *t* is specified in parametric form as follows.

$$\lambda'_1(t,\{a,b\}) = \exp\left(\sum_{j=1}^{k} \theta'_j \cdot s'_j(t,\{a,b\})\right)$$

The difference here compared with RHEM is that the statistics *s'(t,{a,b})* are functions of exactly two nodes. The parameters *theta'* can be estimated by maximizing the following partial likelihood (we write {a_e,b_e} for the two actors of a dyadic co-arrest event e).

$$L'\left(\theta'\right) = \prod_{e\in E'} \frac{\lambda'_1\left(t_e,\left\{a_e,b_e\right\}\right)}{\sum_{\{a,b\}\in R'_e} \lambda'_1\left(t_e,\{a,b\}\right)}$$

The difference compared with RHEM is that the risk set R'_e is a set of unordered dyads, that is, sets of exactly two members of A. If A is large so that |A|^2 becomes computationally intractable, we resort to case–control sampling, as described above for the case of RHEM.

Exponential Random Graph Models (ERGM) for Modelling Co-Offending Data

Besides dyadic REM we also analyse our co-offending networks with exponential random graph models (ERGM) and compare results to those obtained with RHEM. Giving a formal introduction to ERGM is out of scope of this paper and we refer the reader to Lusher et al (2013). Briefly, ERGM specify the probability of a graph G = (A,E) – where A is the set of nodes (actors) and E is a set of undirected edges {a,b}, indicating which pairs of members of A are connected, for instance, have been co-arrested in a given time interval – by

$$P(G) = \frac{1}{Z} \exp\left(\sum_{j=1}^{k} \theta_j \cdot s_j(G) \right)$$

In the formula above, the s_j are graph statistics (such as the number of edges, edges connecting members from the same gang or rank, triangles, or 2-stars in G), theta_j are parameters and Z is a normalizing constant. A temporal version of ERMG, denoted as TERGM, models the conditional probability of a graph G_t in time step t, given the graph G_{t−1} from the previous time step, by a similar formula (Krivitsky and Handcock 2014). In our comparison study we estimate TERGM with a "formation" and a "persistence" component. The formation model explains which edges are newly formed (i.e., edges present at time t but not present at time t−1, that is, pairs of actors co-arrested at time t but not at t−1) and the persistence model explains which edges, among the edges at time t−1, are repeated at time t (that is, pairs of actors repeatedly co-arrested at two successive points in time), compare Krivitsky and Handcock (2014).

In order to analyse co-arrest data with ERGM or TERGM we first have to apply the same conversion from multi-actor arrests to derived dyadic co-arrest events as for REM – entailing the same problems. Additionally, we have to aggregate the entire observation period into one or several time-intervals (one in the case of ERGM, two or more in the case of TERGM) to convert event sequences into static graphs. In our case, since repeated arrests of the same person within short time are rare, we decided to connect two actors in graph G_t, if they have been co-arrested at least once within the associated time interval t. (ERGM variants for count data, which could model the number of dyadic co-arrests within intervals also exist but have not been applied in our comparison study.)

In summary, analysing co-arrest data with ERGM entails the same problems as REM analysis due to the conversion of multi-actor events to collections of dyadic events. Additionally, we have to decide on (typically arbitrary) sub-intervals of our observation period. If time intervals are chosen that are very short, the resulting graphs are very sparse and there is little stability from one timestep to the next. If time intervals are long, we lose the temporal ordering of arrest events within the same interval. Last but not least, the estimation of ERGM parameters is much more demanding from the computational point of view (compared to estimating REM or RHEM parameters) and ERGM can suffer from near-degeneracy in which almost all probability mass is centred on a small subset of (typically unrealistic) graphs, compare Lusher et al (2013). Indeed, it turned out that we could not estimate ERGM or TERGM parameters on our data by the standard MCMC-MLE algorithm with available computational means and had to resort to maximum pseudolikelihood estimation (MPLE) which entails the additional problem of violating (or blatantly ignoring) the complex dependency structure of ERGM, compare Lusher et al (2013), shedding additional doubts on estimated parameters.

Table 5 Co-offending involving all OMCG members

Model	Coeff(se)					
	All	VI	OCE	STIA	PO	OOAP
avg.#.previous.dyadic.arrests	−0.16(0.01)***	−0.03(0.02)	−0.20(0.07)**	1.91(0.07)***	−0.27(0.04)***	−0.31(0.05)***
avg.previous.joint.arrests	1.10(0.01)***	1.43(0.04)***	2.54(0.12)***	0.64(0.09)***	1.90(0.05)***	2.28(0.16)***
closure	0.37(0.01)***	0.09(0.02)***	1.54(0.16)***		0.68(0.07)***	0.26(0.10)**
average.rank	−0.11(0.02)***	−0.10(0.04)**	0.03(0.06)	−0.18(0.06)***	−0.08(0.04)*	0.15(0.09)
rank.heterophily	−0.04(0.02)*	−0.04(0.03)	0.00(0.05)	−0.07(0.04)	−0.05(0.03)	0.02(0.07)
club.heterophily	0.14(0.05)**	−0.23(0.08)**	−0.13(0.13)	0.12(0.13)	0.11(0.10)	0.75(0.25)**

Table 6 Co-offending involving office bearers

Model	Coeff(se)					
	All	VI	OCE	STIA	PO	OOAP
avg.#.previous.dyadic.arrests	−0.17(0.01)***	−0.01(0.02)	−0.19(0.07)**	−0.03(0.05)	−0.32(0.04)***	−0.41(0.03)***
avg.previous.joint.arrests	1.11(0.01)***	1.54(0.04)***	2.90(0.11)***	1.97(0.08)***	2.08(0.05)***	1.99(0.13)***
closure	0.38(0.01)***	0.31(0.02)***	0.55(0.10)***	0.66(0.09)***	0.72(0.06)***	
ratio.officebearer	0.63(0.22)**	0.12(0.42)	−0.61(0.75)	0.45(0.60)	0.67(0.41)	−1.77(1.23)
club.heterophily	0.07(0.06)	−0.11(0.09)	−0.23(0.14)	0.06(0.14)	0.13(0.11)	0.20(0.23)
rank.heterophily.officebearer	−0.38(0.07)***	−0.27(0.13)*	0.17(0.27)	−0.04(0.21)	−0.51(0.13)***	0.14(0.26)
ratio of officebearer:club heterophily	−0.34(0.22)	0.12(0.40)	0.19(0.63)	−0.55(.56)	−0.27(0.41)	1.67(1.15)

Below we report the results of a TERGM analysis where we split our observation period into 6 intervals.

Appendix 2: Results Using REM

As with the RHEM analyses, Relational Event Models were developed for the complete network of actors and for each of the five offence types. In contrast to RHEM, all Relational Event Models were created by removing all isolates (i.e., individuals who were never arrested with co-offenders across the data window).

Table 5 shows the results of all models across all crime categories including all OMCG ranks. Table 2 displays results from all models across all crime categories including models that focus on office bearers. Using REM, the result indicated that OMCG members who were arrested together in the past tend to be arrested again in the future (positive *avg.previous.joint.arrests*). If two actors A and B did not have a history of being arrested together, then their probability to be co-arrested in the future decreases with the number of previous dyadic arrests with “third actors”, different from A and B, (negative *avg#previous.dyadic.arrests*), unless they have been previously co-arrested with the same common third co-offending partner (positive closure). Co-offending partnerships tended to involve those of lower rank and were more common between individuals of the same rank and those from different clubs (Table 6).

As compared with RHEM, in REM the negative *avg.#.previous.dyadic.arrests* and positive *avg.previous.joint.arrests* effects have to be interpreted differently (to *avg#arrests*) since in our REM models there is no possibility of being arrested alone (we only model dyadic arrests having removed all isolates). Assume that Actor A and Actor B have been co-arrested once in the past (possibly with yet others). Assume that Actor C has been co-arrested with some actors but not with Actor A or B. The past arrest on the dyad (A, B) increases their value in the individual activity statistics, which has a negative effect, but it also increases their value in the shared activity statistic which has a larger positive effect. Thus, the joint effect of the past arrest event on (A, B) is that a future co-arrest including both of them becomes more likely. Actors A and C have no past co-arrest with each other (but co-arrests with others). Thus, the dyad (A, C) has a positive value in the individual activity statistic, which has a negative effect on future event probability, and this dyad has a value of zero in shared activity (no positive effect). Thus, their past arrests with others, along with the lack of a joint arrest history, make it less likely that Actors A and C are co-arrested in the future.

In general, a negative parameter of *avg#previous.dyadic.arrests* and a positive parameter of *avg.previous.joint.arrests* means that actors become more and more likely to experience common events with their “in-group” (former acquaintances, co-offenders) but less and less likely to experience common events with actors with whom they don’t have a previous event history (see Lerner and Lomi 2022). The result indicates that OMCG members who were arrested together in the past tend to be arrested again in the future (positive *avg.previous.joint.arrests*). However, those who did not have a prior history of co-offending together were less likely to be arrested together in the future (negative *avg.#.previous.dyadic.arrests*), except where they each have a common co-offending partner; that is, where a partner of a partner would be arrested together (positive *closure*). Office bearers tended to be arrested more often than lower ranked members and when they did, they were more likely to be arrested with another office bearer.

Violent Offences Network

The model indicated that individuals tend to be arrested with the same partner(s) and that partners of a partners tend to be arrested together (positive *closure*). Lower ranked members tended to be arrested more often and when they had co-offending partner(s), those partner(s) tended to be from the same club. The model indicated that individuals tend to be arrested with the same partner(s) and that partners of a partners tend to be arrested together. Office bearers tend to be arrested with other office bearers.

Criminal Enterprise Offences Network

The result indicated that OMCG members who were arrested together in the past tend to be arrested again in the future (positive *avg.previous.joint.arrests*). Again, those who had never been arrested together previously were less likely to be arrested together in the future (negative *avg.#.previous.dyadic.arrests*), unless they shared a common third co-offender (i.e., we found evidence of positive *closure*). The model indicated that individuals tend to be arrested with the same partner(s) and the partner of a partner tend to be arrested together. For this network, we found no specific effects for office bearers.

Short Term Instrumental Act Offences

In this networks, the results for *avg.#.previous.dyadic.arrests* had to be removed from the model because it was unstable. The model indicated that individuals tended to be arrested with the same partner(s) and the partner of a partner tend to be arrested together (positive closure). Actors of lower rank tend to be arrested more often than those of higher ranks. The model indicated that individuals tend to be arrested with the same partner(s) and the partner of a partner tend to be arrested together. There were no specific effects for office bearers.

Public Order Offences Network

The result indicated that OMCG members who were arrested together in the past tended to be arrested again in the future (positive *avg.previous.joint.arrests*). In contrast, those who did not have a history of being arrested together were less likely to be arrested together in the future (negative *avg.#.previous.dyadic.arrests*), unless they shared a common co-offending partner (i.e., positive closure). The *average.rank* effect could not be interpreted as it was unstable. The results indicated that OMCG members who were arrested together in the past tend to be arrested again in the future (positive *avg.previous.joint.arrests*). Actors who did not have a history of being arrested together were less likely to be arrested together in the future (negative *avg.#.previous.dyadic.arrests*), unless they shared a common co-offending partner in the past, where a partner of a partner were more likely to be arrested together (positive *closure*). As per previous results. office bearers tended to be arrested with other office bearers.

Other Offences Against the Person Network

The result indicated that OMCG members who were arrested together in the past tend to be arrested again in the future (positive *avg.previous.joint.arrests*). In contrast, those who did not have a history of being arrested together were less likely to be arrested together in the future (negative *avg.#.previous.dyadic.arrests*), except where they shared a co-offending partner in the past (positive *closure*). Co-arrests tended to comprise members from different clubs. The results indicated that OMCG members who were arrested together in the past tend to be arrested again in the future (positive *avg.previous.dyadic arrests*). In contrast, those who had never been arrested together were less likely to be arrested together in the future (negative *avg.#.previous.dyadic.arrests*).

Appendix 3: Results of TERGM

In the analysis below, we specify TERGM that have a formation and persistence component (compare Krivitsky and Handcock 2014) with effects taken from the following list of statistics. For some models we had to remove some statistics from the specification, since their inclusion resulted in non-convergence during MPLE estimation (see details below).

- "edges" controls for the density of the networks; a negative parameter points to sparsity of the networks (which is almost always the case in empirical social networks)
- "closure" (specified via the statistic "gwdegree(decay = 0.1, fixed = TRUE)") reveals whether there is an over-representation (if positive) or under-representation of closed triangles (if negative)
- "homophily gang" (specified via the statistic "nodematch("gang")", counting the number of edges {a,b} in which a and b are members of the same gang); a positive parameter reveals that actors have a tendency to be co-arrested with members of the same gang
- "edge rank" (specified via the statistic "nodecov("rank")", adding up the sum of the ranks of a and b over all edges {a,b}); a positive (negative) parameter reveals that actors of higher rank are typically co-arrested more (less) often
- "different rank" (specified via the statistic "absdiff("rank")", adding up the absolute difference of ranks of a and b over all edges {a,b}); a positive (negative) parameter reveals that actors of different rank are typically co-arrested more (less) often; thus, it is a measure of rank heterophily
- "edge office bearer" (specified via the statistic "nodecov("office.bearer")", adding up for each edge {a,b} the number of office bearers in it); a positive (negative) parameter reveals that office bearers are typically co-arrested more (less) often
- "different office bearer" (specified via the statistic "absdiff("office bearer")", counting the number of edges {a,b} in which exactly one of a or b, but not both, is an office bearer); a positive parameter reveals that office bearers are typically co-arrested with non-office bearers; a negative parameter reveals that office bearers are typically co-

Table 7 All network

	Estimate	Std.Error	z value	Pr(>|z|)	
Formation					
Edges	– 10.47	0.18	– 57.98	< 0.001	***
Closure	3.41	0.03	101.14	< 0.001	***
Homophily gang	– 0.09	0.11	– 0.80	0.43	
Edge rank	0.07	0.03	2.25	0.02	*
Different rank	0.01	0.04	0.12	0.91	
Edge office bearer	0.24	0.16	1.55	0.12	
Different office bearer	– 0.44	0.18	– 2.41	0.01	*
Persistence					
Edges	– 0.32	0.27	– 1.18	0.24	
Homophily gang	– 0.10	0.18	– 0.55	0.58	
Edge rank	– 0.13	0.05	– 2.52	0.01	*
Different rank	0.11	0.07	1.68	0.09	
Edge office bearer	– 0.00	0.21	– 0.02	0.99	
Different office bearer	– 0.55	0.25	– 2.20	0.03	*

Signif.: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

arrested with office bearers and non-office bearers are typically co-arrested with non-office bearers; thus, it is a measure of heterophily with respect to being an office bearer

Complete network

TERGM results for the complete network indicated that the network was sparse (negative parameter of the *edges* statistic) with a high positive closure effect. OMCG affiliates of higher rank tended to form more ties with co-offenders over time compared to those of lower rank, but these ties tend not to persist over time. Office bearers tend to be co-arrested with other office bearers, but those ties tended to not persist. The effect of closure for persistence had to be excluded from the model because the inclusion of the effect would cause the model not to converge.

Criminal Enterprise

The TERGM for Criminal Enterprise indicated that the network was sparse and had a high closure effect. Co-offending ties with OMCG affiliates of higher rank tended to persist over time compared with those affiliates of lower rank. The effects for closure, different rank, and office bearer persistence had to be excluded from the model because the inclusion of the effect would cause the model not to converge.

Table 8 Criminal enterprise

	Estimate	SE	z value	Pr(>|z|)	
Formation					
Edges	−8.69	0.47	−18.64	<0.001	***
Closure	4.17	0.14	28.85	<0.001	***
Homophily gang	0.37	0.24	1.52	0.13	
Edge rank	−0.14	0.09	−1.59	0.11	
Different rank	0.15	0.11	1.31	0.19	
Edge office bearer	−0.32	0.52	−0.62	0.54	
Different office bearer	0.17	0.56	0.30	0.76	
Persistence					
Edges	−7.76	2.39	−3.25	0.001	**
Homophily gang	−0.27	1.11	−0.24	0.81	
Edge rank	0.69	0.35	1.99	0.05	*
Edge office bearer	1.19	1.37	0.87	0.39	

Signif.: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

Table 9 Short term instrumental acts

	Estimate	Std.Error	z value	Pr(>|z|)	
Formation					
Edges	−9.53	0.39	−24.68	<0.001	***
Closure	4.02	0.14	28.48	<0.001	***
Homophily gang	−0.43	0.29	−1.50	0.13	
Edge rank	0.05	0.06	0.83	0.41	
Different rank	−0.09	0.09	−1.03	0.30	
Edge office bearer	0.25	0.32	0.79	0.43	
Different office bearer	−0.28	0.38	−0.73	0.46	
Persistence					
Edges	−2.91	1.51	−1.93	0.05	
Edge rank	−0.05	0.25	−0.21	0.83	
Different rank	−0.30	0.37	−0.81	0.42	
Edge office bearer	0.42	0.87	0.49	0.63	

Signif.: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

Short Term Instrumental Acts

The TERGM for 'short term instrumental acts' indicated that the network was sparse and had a high closure effect. The effects of closure, homophily gang and different office bearer persistence had to be excluded from the model because the inclusion of the effect would cause the model not to converge.

Table 10 Public Order

	Estimate	Std.Error	z value	Pr(>|z|)	
Formation					
Edges	− 10.99	0.26	− 42.18	< 0.001	***
Closure	3.58	0.06	61.48	< 0.001	***
Homophily gang	− 0.29	0.18	− 1.60	0.11	
Edge rank	0.10	0.04	2.14	0.03	*
Different rank	− 0.03	0.06	− 0.54	0.59	
Edge office bearer	0.21	0.24	0.88	0.38	
Different office bearer	− 0.35	0.28	− 1.27	0.20	
Persistence					
Edges	− 1.29	0.94	− 1.36	0.17	
Homophily gang	− 1.31	1.03	− 1.27	0.20	
Edge rank	− 0.26	0.19	− 1.41	0.16	
Different rank	0.10	0.24	0.41	0.68	
Edge office bearer	− 0.15	0.61	− 0.25	0.80	
Different office bearer	− 0.50	0.76	− 0.66	0.51	

Signif.: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

Table 11 Violence

	Estimate	Std.Error	z value	Pr(>|z|)	
Formation					
Edges	− 9.68	0.30	− 32.25	< 0.001	***
Closure	4.88	0.11	44.03	< 0.001	***
Homophily gang	0.30	0.16	1.85	0.06	
Edge rank	0.08	0.05	1.72	0.09	
Different rank	0.02	0.07	0.32	0.75	
Edge office bearer	0.49	0.23	2.11	0.03	*
Different office bearer	− 0.53	0.27	− 1.92	0.06	
Persistence					
Edges	− 1.40	0.97	− 1.44	0.15	
Homophily gang	− 0.37	0.62	− 0.59	0.55	
Edge rank	− 0.29	0.19	− 1.50	0.13	
Different rank	0.20	0.24	0.86	0.39	
Edge office bearer	− 1.08	0.66	− 1.63	0.10	

Signif.: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

Public Order

The TERGM for Public Order indicated that the network was sparse and had a high closure effect. OMCG affiliates of higher rank tended to form more ties with co-offenders over time compared with affiliates of lower rank. The effect of closure for persistence

Table 12 Other offences against the person

	Estimate	SE	z value	Pr(>lzl)
Formation				
Edges	– 8.57	0.59	– 14.55	< 0.001***
Closure	6.35	0.33	19.31	< 0.001***
Homophily gang	– 0.27	0.38	– 0.71	0.48
Edge rank	0.02	0.10	0.18	0.86
Different rank	0.07	0.14	0.51	0.61
Edge office bearer	0.85	0.31	2.79	0.01**
Different office bearer	– 1.04	0.41	– 2.56	0.01*
Persistence				
Edges	– 0.36	2.98	– 0.12	0.90
Edge rank	– 1.11	0.93	– 1.20	0.23

Signif.: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

Table 13 Results of simulation 1 ($p = 0.01$)

Effects	Coef	Exp (coef)	SE (coef)	z	Pr(>lzl)	Sig
individual.activity	0.10	1.10	0.00	65.90	< 2e–16	***
dyadic.shared.activity	2.20	9.03	0.04	57.60	< 2e–16	***
average.rank	– 0.10	0.91	0.01	– 11.03	< 2e–16	***
rank.difference	– 0.16	0.85	0.02	– 8.32	< 2e–16	***
gang.difference	– 0.82	0.44	0.03	– 26.00	< 2e–16	***

had to be excluded from the model because the inclusion of the effect would cause the model not to converge.

Violence

The TERGM for Violence again indicated that the network was sparse and had a high closure effect. Office bearers tended to have more co-offenders compared with non-office bearers. The effect of closure and difference office bearer for persistence had to be excluded from the model because the inclusion of the effect would cause the model not to converge.

Other Offences Against the Person

The TERGM for 'other offences against the person' once again indicated that the network was sparse and had a high closure effect. Office bearers tended to have more co-offenders and they tended to co-offend with other office bearers. The effects of closure, homophily gang, different rank, edge office bearer, and different office bearer for persistence had to be excluded from the model because the inclusion of the effect would cause the model not to converge (Tables 7, 8, 9, 10, 11, 12).

Table 14 Results of simulation 1 ($p = 0.05$)

Effects	Coef	Exp (coef)	SE (coef)	z	Pr(>|z|)	Sig
individual.activity	0.10	1.10	0.00	66.09	<2e−16	***
dyadic.shared.activity	2.39	10.93	0.04	63.20	<2e−16	***
average.rank	−0.10	0.91	0.01	−11.08	<2e−16	***
rank.difference	−0.20	0.82	0.02	−8.87	<2e−16	***
gang.difference	−0.83	0.44	0.04	−23.15	<2e−16	***

Table 15 Results of simulation 2 ($p = 0.01$)

	Coef	Exp (coef)	SE (coef)	z	Pr(>|z|)	Sig
individual.activity	0.10	1.11	0.00	60.13	<2.00E−16	***
dyadic.shared.activity	2.50	12.13	0.05	50.92	<2.00E−16	***
average.rank	−0.09	0.91	0.01	−10.44	<2.00E−16	***
rank.difference	−0.19	0.83	0.03	−7.06	<1.62E−12	***
gang.difference	−0.89	0.41	0.04	−20.67	<2.00E−16	***

Table 16 Results of simulation 2 ($p = 0.05$)

Effect	Coef	Exp (coef)	SE (coef)	z	Pr(>|z|)	Sig
individual.activity	0.10	1.10	0.00	64.19	<2.00E−16	***
dyadic.shared.activity	2.47	11.80	0.04	56.50	<2.00E−16	***
average.rank	−0.10	0.91	0.01	−11.33	<2.00E−16	***
rank.difference	−0.21	0.81	0.03	−7.60	<2.99E−14	***
gang.difference	−0.89	0.41	0.04	−20.43	<2.00E−16	***

Appendix 4: Simulation Results

We performed a limited number of analyses with simulated data in which we randomly distort our empirical data to mimic some assumed pattern of missing data. The goal of both simulation experiments is to assess how much our results might change if we analyzed slightly different data. Specifically, we consider two data-distortion mechanisms. In "simulation 1" we assume that in our empirical data we missed some event participants and consequently we add randomly selected additional actors to the arrest events in our data. In "simulation 2" we assume that in our empirical data there is a certain percentage of "wrong" event participants and we replace some participants with randomly selected other actors. We then analyze the distorted data with the RHEM for all crime types and compare obtained coefficients with the ones obtained from analyzing the empirical (undistorted) data.

Simulation 1

Missing nodes: we iterate over the events and with probability p (in our simulation we used $p = 0.05$ and $p = 0.1$) we add an additional randomly selected event participant. This data distortion mechanism assumes that we have missed some of the “true” event participants in our empirical data and we test with the simulated data whether such missing participants are likely to result in very different findings.

Simulation 2

Distorted nodes and edges: we iterate over all participants of all events and with probability p (again we used $p = 0.05$ and $p = 0.1$ in our simulation) we exchange the current event participant with a randomly selected actor. This data distortion mechanism assumes that in our empirical data we occasionally have the “wrong” event participants.

In all simulation experiments, the coefficients obtained from analyzing the distorted data would yield qualitatively the same results as those obtained from analyzing the empirical, undistorted data (Tables 13, 14, 15, and 16).

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