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The structure of cooperation among organized crime groups: A network study of Merseyside, UK

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ABSTRACT

This study reconstructs the cooperation network among 134 organized crime groups (OCGs) operating in an urban setting by leveraging a dataset of 5239 police crime reports (January 2015 to March 2018). While 63 % of groups cooperated with at least another group (median 2.8, maximum 9), cooperation remains subject to constraints, with a maximum of 3.3 % of all possible ties being established, and there is a strong tendency towards clusterization.

Moving to the determinants of such structure, the study finds that only one type of revenue-generating criminal activity has a *structuring* effect on the OCG landscape: drug trafficking. This sets drug trafficking apart from acquisitive crime. Results also suggest that OCGs decrease risk by collaborating with groups that also collaborate with a partner OCG. This holds when controlling for spatial proximity. This work also shows that more central groups in the cooperation network tend to use violence more often.

This study points to two main implications. Firstly, it highlights the importance of considering self-organized groups of offenders as entities in their own right when developing interventions; secondly, it stresses the importance of group-level relational mapping and associated mechanisms. Methodologically, it emphasizes the importance of criminal groups as a unit of analysis.

1. Introduction

No person is an island, and neither are organized crime groups (OCGs). Yet, very limited attention has been paid by criminologists to the relational patterns established among criminal groups operating within the same locale. Debates around organized crime have focused on the nature of groups and their activities (e.g., Campana, 2011; Campana & Varese, 2018; Gambetta, 1993; Paoli, 2008; Reuter, 1983; Schelling, 1971; Smith, 1975; Varese, 2001, 2010; Campana, Varese, & Meneghini, 2025), on their internal structure (e.g., Catino, 2019; Densley, 2013; Paoli, 2008) as well as the impact of organized crime (and gangs) on neighborhoods, cities or countries, including on economic development (Acemoglu, De Feo, & De Luca, 2020; Lavezzi, 2008; Pinotti, 2015), neighborhood trust and state legitimacy (Blattman, Duncan, Lessing, & Tobón, 2021), level of violence (Cohen & Tita, 1999; Huebner, Martin, Moule Jr, Pyrooz, & Decker, 2016; Molzahn, Ríos, & Shirk, 2012; Robinson et al., 2009) and level of "ordinary" crime (Aziani, Favarin, & Campedelli, 2020). While these streams of research have provided key insights, they have either focused on the micro-level (internal) mechanisms or the macro-level (aggregated) impact of OCGs (and gangs) on specific settings. This work brings meso-level mechanisms into the picture by focusing on inter-OCG relational patterns. Understanding such patterns is crucial to furthering our knowledge of organized crime, gangs, and criminal markets. This work moves from the idea that a meso-level (inter-group) analysis is very well suited to explore the complex setting in which OCGs (and gangs) operate.

While the relational study of violence has been gaining some traction among scholars (see, e.g., Papachristos, 2009; Tita & Radil, 2011; Papachristos, Hureau, & Braga, 2013; Bichler, Norris, Dmello, & Randle, 2019; Gravel et al., 2023; Niezink & Campana, 2023), works on the structure of cooperation are lagging. Yet, we believe that understanding mechanisms underpinning cooperation is as vital as the study of violence as successful – and sustained – cooperation can generate stronger, more resilient and more entrenched OCGs, with harmful consequences for the well-being of individuals, communities and – in most serious cases – countries. Cooperation between OCGs potentially unlocks fresh resources, for example, through division of labor, collusion in price setting, or improved market access (Fijnaut, Bovenkerk, Bruinsma, &

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Van de Bunt, 1998; Levitt & Venkatesh, 2000). Successful OCGs can then invest resources in expanding operations or minimizing the odds of being displaced by competing groups.

While collaboration among individuals has attracted criminological attention since the early works on co-offending (Reiss Jr, 1988; Reiss Jr & Farrington, 1991), the relational study of cooperation between groups has received much more limited interest. This is surprising – and problematic – as OCGs (and gangs) are more than just the sum of their parts (as empirically shown, e.g., by Papachristos, 2009; Bouchard & Morselli, 2014; Ouellet, Bouchard, & Charette, 2019; Lewis & Papachristos, 2020, Gravel et al., 2023). The aim of this work is twofold: first, to advance the stream of research on collaboration and co-offending by investigating the structure and determinants of cooperation among OCGs. Secondly, to explore the relationship between centrality in the cooperation network and the use of violence by OCGs. To this end, we leverage a novel dataset including all OCGs-related crime events recorded by Merseyside Police (Liverpool, UK) between January 2015 and March 2018.

In this work, we follow the definition of organized crime adopted by the police and based on the guidelines included in the "Organised Crime Group Mapping Manual": "Individuals, normally working with others, with the capacity and capability to commit serious crime on a continuing basis, which includes elements of: planning/ control/coordination/ structure/ group decision making [form an OCG]. Serious crime is defined [...] as crime that involves the use of violence, results in substantial financial gain or is conducted by a large number of persons in pursuit of a common purpose, or crime for which a person aged 21 or over on first conviction could reasonably expect to be imprisoned for three or more years." (UK Government, 2010: 15). This definition is in line with the one set out in the 2000 UN Convention against Transnational Organized Crime (UNTOC, 2000), which has become a template for definitions adopted by more than a hundred countries across the world (incidentally, it is also similar to the definition followed in Malm, Bichler, & Nash, 2011). It is important to note that the UK definition of organized crime is rather broad and encompasses groups engaging in a wide variety of criminal activities; this includes groups that in other jurisdictions, e.g. the United States, might come under the label of "gangs" (for a further discussion on the concepts of organized crime and gangs, and their potential overlap, we refer to Decker & Pyrooz, 2014; Campana & Varese, 2018; Decker, Pyrooz, & Densley, 2022: Ch. 1).

The paper is organized as follows: In the next section, we place our contribution within the existing literature; in Section 3, we introduce our data and methods and discuss the limitations of this work; in Section 4, we present a descriptive picture of organized crime in Merseyside and the structure underpinning cooperation among groups; in Section 5, we explore the determinants of such a structure (cooperation network); in Section 6, we assess the relationship between the centrality in the cooperation network and a group's use of violence. Section 7 concludes.

2. Background

Already in their 1931 *Report on the Causes of Crime*, Shaw and McKay highlighted that around 82 % of juvenile offenders who appeared in Cook County juvenile court (Chicago) committed the offence for which they were judged with at least another offender, and therefore were classified as "group offender" (Shaw & McKay, 1931: 194). Today, we would consider them as involved in co-offending. Sixty years later, in their longitudinal study of 411 male youth offenders in London, Reiss Jr and Farrington, (1991: 374) found that slightly more than half of them had co-offended up to the age of 32. Estimates based on police records from England, the United States, and Canada put the quota of co-offenders at about 30 % of the overall offenders' population (Carrington & van Mastrigt, 2013). Co-offending can be defined in multiple ways – and can be more or less stable over time (McGloin & Piquero, 2010; McGloin, Sullivan, Piquero, & Bacon, 2008; Reiss Jr, 1988; Tremblay, 2017). However defined, co-offending remains an important phenomenon. Crucially, it is also a relational phenomenon as it involves establishing a cooperative tie between at least two individuals in the pursuit of (illegal) goals. Despite its relational nature, co-offending has not been subject to a formal relational treatment until the work of Sarnecki (2001), who applied a social network analysis approach to the study of youth offenders in Stockholm. Subsequently, McGloin and Piquero (2010) reconstructed the ego-networks of a sample of juvenile offenders in Philadelphia (US) and showed that juveniles with less redundant (overlapping) co-offending networks tended to engage in a greater variety of crimes; those with more redundant co-offending networks, on the contrary, were more likely to engage in the same type of offenses "when committing group crimes". This held when controlling for network size (number of co-offenders), suggesting that "it is not the size of the criminal network that matters for offending versatility but rather the *pattern of linkages* within this network" (McGloin & Piquero, 2010: 78, italics added). They interpret this finding as the result of greater access to information, skills, and opportunities that non-redundant networks provide. Charette and Papachristos (2017) have further shown that relational factors, such as age and gender homophily, gang membership as well as geographical proximity, increase the likelihood of sustained co-offending partnerships. Additional structural factors, such as higher centrality in the co-offending network and transitivity, also play a role in sustaining such partnerships (see also McGloin et al., 2008).

Several authors have highlighted the importance of understanding cooperation within the context of illegal markets (Campana & Varese, 2013; Neske, 2006; Reuter, 1983, 1985, among others). However, empirical studies of how cooperation is achieved in such markets remain scarce. Looking at local drug markets in Newport, Wales (UK), Baika and Campana (2020) found that offenders dealing in heroin and cocaine possessed a higher average degree and lower network fragmentation than offenders dealing in cannabis. Furthermore, organized crime members recorded a significantly higher degree centrality in the all-drugs network than non-members. Bright, Koskinen, and Malm (2019) found that Australian drug offenders showed a tendency to minimize connections outside their local cluster and relied on brokers instead as a strategy to reduce risk. Campana (2018) also found a tendency towards clusterization among individuals involved in human smuggling between the Horn of Africa and Scandinavian countries (via Libya and Mediterranean crossings into Italy); cooperation has been shown to be more likely to happen within the same stage of the long-distance process and within rudimentary hierarchies. Taken together, these studies have highlighted tendencies towards clusterization in the cooperative interactions among market-oriented offenders.

The quantitative (relational) study of cooperation at the group level – be they OCGs or gangs – has received significantly more limited interest. Some authors have focused on cooperation *within* OCGs and gangs. For example, Campana and Varese (2013) have shown that shared kinship and violence homophily increase cooperation within Mafia-like organizations. Grund and Densley (2015) found a positive effect of ethnic homophily within a London street gang. Bright, Sadewo, Cubitt, Dowling, and Morgan (2022) showed that, within Australian outlaw motorcycle gangs, there exist informal small cliques similar to clubs within clubs, bringing together members dealing in illegal activities (although some structural differences can be traced depending on the type of criminal activity). These studies show that the level – and intensity – of cooperation within criminal organizations can vary, and it is influenced by several relational factors. However, only a handful of studies have explicitly examined cooperation among groups and highlighted several significant findings. Malm et al. (2011) studied co-offending with and between groups operating in Canada and made of different ethnic (e.g., Asian, Eastern European, Hispanic, Italian) and functional (e.g., Outlaw motorcycle gangs) compositions. They found that, while functionally-derived groups tend to be more homogeneous, ethnically-derived groups vary in their co-offending behavior and structure of their network, with the Asian groups showing the highest level of brokerage (Outlaw motorcycle gangs, conversely, possess low brokerage and higher density).

Ouellet et al. (2019) studied the survival of Haitian street gangs in Montreal and provided crucial evidence on the impact of successful cooperation on a gang's survival prospects. More specifically, they show that a gang's ability to build cooperative relations with other gangs (as proxied by alliances) increases its chances of survival over nine years. Finally, Coutinho, Diviák, Bright, and Koskinen (2020) explored inter-group cooperation between organized crime groups and outlaw motorcycle gangs in Alberta, Canada. By employing a multilevel network approach, they exploit information on individuals known or suspected to be involved in organized criminal activities, the criminal collaborative ties between them, their OCG memberships, the locations in which they were active, and the illegal activities in which they were involved to determine under what conditions members of larger organized criminal groups collaborate with one another. In this study, illegal market overlap between groups is defined in terms of OCG members engaging in drug trafficking activities in the same geographic location. They found that the tendency for OCG offenders to form ties across larger OCGs depends not only on spatial co-location, but also on the type of groups to which offenders are affiliated, as well as the embeddedness of those groups in spatially-situated illegal markets: overall, large OCGs tend not to collaborate when their respective (drug) markets overlap.

In this work, we build on these insights to explore cooperation (co-offending) between OCGs in Merseyside, UK, using a formal network approach. What drives the structure of cooperation among fully-fledged OCGs operating in an urban setting? We expand on previous works by considering the impact of a broader range of revenue-generating activities on the *intensity* of cooperation among OCGs. Such a range of activities includes both predatory crimes (theft and fraud, burglaries, robberies) as well as trafficking of both Class A drugs (e.g., heroin and cocaine) and Class B & C (e.g., cannabis). We also consider the impact of geographical proximity and the age composition of groups.

After reconstructing the network of cooperation, we then also examine the relationships between the structural position of an OCG within such a network and its use of violence. The importance of jointly studying cooperation and violence was previously suggested by Kennedy, Braga, and Piehl (1997) in their pioneering work on focused deterrence among Boston gangs. However, while their findings on violence have profoundly influenced the field and shaped various intervention programs globally, their investigation into cooperative relationships (alliances) has received little attention – and their joint analysis of violence and alliances remains only qualitatively outlined. Are more central groups also more inclined to resort to violence, or does centrality within cooperation networks enable groups to economize on their use of violence? Earlier studies indicate that groups may need to employ violence to achieve a central position and defend it against rivals (Papachristos, 2009; also Gravel et al., 2023). Niezink and Campana (2023) have shown that prior co-offending among OCG members is a strong predictor of future violence among those same members, suggesting that more active groups in terms of cooperative ties might be more likely to be entangled in conflicts. We further investigate this issue by looking beyond intra-OCG episodes of violence and considering the use of violence by OCGs against any type of victim. This has implications for violence-reduction programs.

In this work, we follow Kennedy et al. (1997), Papachristos (2009), Malm et al. (2011), and Ouellet et al. (2019), among others, in stressing the importance of considering (criminal) groups as the main focus of the analysis.

3. Data and methods

Merseyside is the fourth largest metropolitan area in the UK, with a population of 1.38 million and a surface of 645 square km. It records the highest number of OCGs per million population in England and Wales (127 groups/million), more than double the national average (47 groups/million) and 25 % more groups than Greater London (100 groups/million; HMICFRS, 2018:94). Crucially for this work, the force has been ranked as "outstanding" in tackling serious and organized crime, including its ability to collect intelligence on those groups (HMICFRS, 2018: 127–129, it should be noted that only three forces out of 43 received an outstanding rating, which is the highest possible in England and Wales). The high intensity of organized crime activities and the high effectiveness of police procedures make Merseyside an exceptionally suitable setting to study organized crime-related dynamics.

The evidence for this work comes from 5239 crime reports handled by Merseyside Police between January 2015 and March 2018 involving 1211 OC members belonging to 134 OCGs. Each police record includes information on the type of crime, place and time of the occurrence, individual(s) identified as offenders and, if relevant, as victims. For each individual, we have information on their age and ethnicity. Each OC member is associated with a unique OCG numbered from 1 to 134: this association was carried out by the police prior to data sharing based on police intelligence. Individuals and groups are fully anonymized, and we had no access to personal information or additional qualitative evidence on both individuals and groups. As our focus is on activities likely to be coordinated – and sanctioned – at the group level, we have excluded from the analysis events classified by the police as domestic incidents.[1] Police records include not only individuals who were arrested but also those suspected in relation to a crime event. Crime types follow the official classification adopted in England and Wales and include 384 distinct offenses. Table 1 presents the distribution of such offenses re-categorized into 15 macro-classes (please see Section 4 for a discussion of the different types of drug classes).

When looking at the ethnicity of the perpetrator, 93.4 % of crime events were committed by White offenders, 2.5 % by Black offenders and for 2.2 %, no ethnicity was recorded (the remaining events are linked to Asian and mixed-ethnicity offenders).

As our crime records are spatially situated, we include in our models a variable capturing the geographical area where a crime took place. To this end, we employ the Middle Super Output Areas (MSOA) created by the UK Office for National Statistics (ONS). These are small-area census units that provide a good approximation of neighborhoods as they are designed taking into account geographical barriers, e.g., rivers, main

Table 1
Criminal events by crime macro-classes (all OCGs).

Crime type	N event	%
Arson	31	0.59
Burglary	671	12.81
Criminal Damage	313	5.97
Drug Possession (A)	115	2.20
Drug Possession (B/C)	711	13.57
Drug Trafficking (A)	310	5.92
Drug Trafficking (B/C)	228	4.35
Threats	276	5.27
Other	432	8.25
Robbery	130	2.48
Sexual offence	8	0.15
Theft or Fraud	803	15.33
Violence without Injury	171	3.26
Violence with Injury	799	15.25
Weapons	241	4.60
Sum	5239	100

[1] Domestic incidents are incidents where the individuals involved are personally connected due to marriage or civil partnerships (present, past or due to be), an intimate personal relationship (past or present) or have a parental relationship to the same child.

roads, and rail tracks. In Merseyside, each MSOA includes, on average, around 8000 individuals. To each OCG, we have then associated a main MSOA (approximating their turf) operationalized as the geographical area where the highest number of their members has been recorded committing a crime across the entire timespan.

3.1. Modeling strategy

In this work, we conceptualize (and operationalize) cooperation as co-offending between two OCGs (in line with Malm et al., 2011 and Coutinho et al., 2020). To build the co-offending network, we started from a bipartite network of crime events by organized crime members (OCGMs) and then built the 1-mode projection OCGMs-by-OCGMs to capture co-offending. Next, we moved from individuals to groups by leveraging the unique OCG membership attached to each OCGM. This group-level network is our network of cooperation among OCGs. In this network, a link (tie) between two OCGs exists if at least one member from each group have co-offended together in a crime event of any type. By construction, our network is undirected (like all co-offending networks) and weighted, capturing the strength of cooperation (i.e., the number of cooperative interactions between two groups). The organized crime cooperation network includes 134 OCGs (1211 OCGMs) and 192 ties.

We employ a set of Exponential Random Graph models (ERGMs) to study tie formation in the cooperation network. As tie formation between any two actors in a network is hardly an independent process but rather a function of the behavior and characteristics of all the actors in a given network, models of network formation are usually estimated through ERGMs. Such models expand traditional logit models by allowing for correlation in tie formation. In its binary version (i.e., when links populating a network matrix $\boldsymbol{G}$ either exist or not, and with no weight attached, so that $\boldsymbol{G} = \boldsymbol{G}^B$), the basic idea behind ERGMs is to specify a vector of sufficient network statistics $S(\boldsymbol{G}^B)$ and OCG-specific covariates $\boldsymbol{X}$ and formulate the probability of observing the actual network as a function of these statistics with all networks possessing the same sufficient statistics being drawn with equal probability conditional on OCG-specific covariates. Coefficients are then estimated to maximize the likelihood of obtaining the observed network. Formally, the ERGM specifies the probability P(·) of observing a network G^B possessing network attributes S conditional on covariates X such as

$$P_\gamma(\boldsymbol{G}^B|\boldsymbol{X}) = \frac{exp(\gamma \cdot S_X(\boldsymbol{G}^B))}{\sum_{G^B} exp(\gamma \cdot S_X(\boldsymbol{G}^B))}$$

where the denominator is a normalizing constant computed on all possible networks and γ is the vector of parameters to be estimated. Since the computation of the normalizing constant is computationally impossible due to the size of the set of interactions, Markov chain Monte-Carlo (MCMC) methods are routinely implemented.[2]

To capture the *strength* of cooperation between OCGs, we adopt the *valued* ERGM approach pioneered by Krivitsky (2012).[3] Valued ERGMs extend standard ERGMs by taking as a dependent variable the count of cooperation events as opposed to a binary variable indicating whether cooperation exists or not. This way, valued ERGMs allow for network structures made of ties of potentially varying intensity (Krivitsky, 2012), thus addressing the question of whether a covariate increases or decreases the *intensity* of a relation (value of a tie) between network actors.

As the space of potential interactions in valued ERGMs is potentially infinite,[4] a reference distribution has to be specified (Krivitsky, 2012). We opt for a Poisson distribution to model the reference linkage distribution for two main reasons. First, from standard network theory (see, e.g., Jackson, 2010), it can be shown that the Poisson degree distribution is the stationary outcome for a plethora of random graph formation protocols when the probability of linkage is small relative to the size of the reference population, a common occurrence in co-offending networks. This result holds even in the presence of homophilic processes (Giovannetti, 2021). Second, Poisson protocols are a standard modeling choice for describing counts of events (in this case, co-offending events) within a predetermined temporal horizon. Such a distribution has been applied in other works modeling relational offending data (see, e.g., Ouellet et al., 2019) and non-crime data (e.g., Krivitsky, 2012; Krivitsky, Handcock, Raftery, & Hoff, 2009).[5]

To study the relationship between centrality in the cooperation network and the use of violence, we employ a battery of Poisson regression models with robust standard errors estimated with a standard Sandwich linearized estimator. Given the structure of the cooperation network observed in Fig. 1, we expect decision-making to be potentially correlated across OCGs, thus creating interdependencies across groups. To consistently account for cross-OCG correlations, we cluster observations at the network component level, whereby any component corresponds to the set of all OCGs directly or indirectly linked to each other through the cooperation network. This is similar to the strategy Kramer,

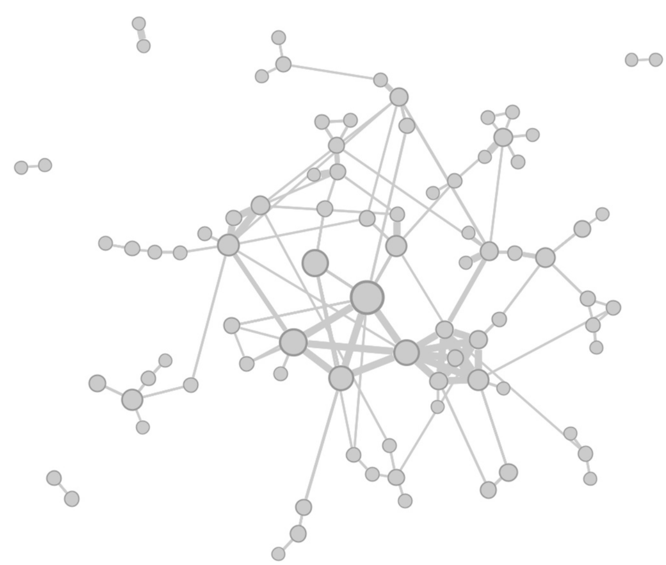

Fig. 1. Organized crime cooperation network in Merseyside.
Note: each node represents an organized crime group; the size of a node is proportional to the number of cooperative partners (degree centrality); the size (thickness) of a link is proportional to the intensity of cooperation. Isolates are removed from the picture.

[2] The idea behind MCMC methods is to create a Markov chain on the set of nodes in $\boldsymbol{G}^B$, where the equilibrium distribution equals $P_\beta(\boldsymbol{G}^B|\boldsymbol{X})$. Once the equilibrium distribution is reached through the iterative procedure, random draws can be computed for the J observations of $\boldsymbol{G}^B$ necessary to maximize an approximate log-likelihood function. See Lusher et al. (2013) for a description and various implementation examples of the methodology.

[3] Alternative examples of usage of valued ERGMs are contained in Wood et al. (2019) and Ouellet et al. (2022).

[4] Whereby such space is constrained to 2^K potential edges for binary ERGMs.

[5] The Poisson distribution is a conservative modeling choice for social network processes as it presumes a simple random network formation protocol as opposed to, for instance, a preferential attachment protocol (which would require us to engage in several ad-hoc assumptions), and it is equivalent to a binomial distribution for networks large enough (see, for an analytic taxonomy of random networks and candidate formation protocols, Jackson, 2011). We calibrate the Poisson distribution parameter λ to achieve a best fit with the observed edge distribution, such that $\lambda = 1.55$.

Blokland, Kleemans, and Soudijn (2024) adopted to explore money laundering networks. Unlike the ERGMs discussed above, where the dependent variable is a (valued) network, hence a dyadic relationship, in these models our dependent variable is a count of (violent) crime events, thus a monadic variable. The Poisson estimation framework employed in Table 4 is analytically coherent with the distributional structure we imposed on the valued ERGM and naturally fits the estimation of count models (e.g., Kirchmaier, Langella, & Manning, 2024). We favor a Poisson model over alternative negative binomial models (Hausman, Hall, & Griliches, 1984) as the former does not impose conditional independence, it is fully robust to any distributional misspecification, and it allows any serial correlation under clustering of errors (Wooldridge, 1999). In Appendix C, we run standard misspecification tests to show that the Poisson modeling choice is appropriate for the current context and that the full specification models perform well in capturing the underlying data-generating process.

Network variables enter the models as independent variables. More specifically, we model two distinct conceptualizations of centrality: degree centrality and betweenness centrality. Degree centrality captures the number of connections (links) established by each node; betweenness centrality captures the number of times each node sits on the shortest path between any two other nodes in the network (Wasserman & Faust, 1994: 178–80). The latter is often interpreted as a measure of brokerage – the ability of nodes (groups in our case) to bridge otherwise disconnected or poorly connected parts of a network.

3.2. Limitations

It is important to acknowledge that, by relying on police records, our study is subject to the well-known biases and limitations intrinsically linked to such a data source. Firstly, recorded crime is only a fraction of the actual volume of crime committed in any given area, and police enforcement can be selective, with some individuals/groups being targeted more depending on ethnicity or place of residence (Black, 1970). Additionally, changes in the level of enforcement, policing priorities, recording practices and resource constraints can all impact what gets recorded in the police dataset (Campana & Varese, 2022; Faust & Tita, 2019; Malm & Bichler, 2011; Morselli, 2009).

In our case, there has been no significant change in recording practices or policing priorities in the relatively short period covered by the data. An extensive literature correlates over-policing with ethnicity and status (see Papachristos & Bastomski, 2018 for a review). Crucially, Merseyside has a rather ethnically homogenous population that is predominantly White British: 83 % of the overall population and 93 % of organized crime group members. This moderates concerns of ethnicity-induced over-policing.

Moreover, OCG membership is based on intelligence and judgment of police officers and analysts: while these officers are very experienced and possess a deep knowledge of the organized crime landscape, there remains a risk of errors in membership attribution. However, we believe that shifting the focus from individuals to groups significantly reduces the impact of such errors. While a single individual might get mislabelled as an organized crime member (or misassigned to a group), it is less likely that an entire set of individuals gets mislabelled as part of a non-existing OCG or misassigned *en bloc*.

Despite their limitations, police data remain crucial in providing quantitative insights into an otherwise very hard-to-reach population. They have been widely used to reconstruct networks of co-offenders in several countries, including the United States, Canada, Italy, Denmark, Sweden, and the United Kingdom (see Faust & Tita, 2019 and Campana & Varese, 2022 for a discussion).

Finally, it is important to note that, by construction, our data only capture interactions within Merseyside and not with groups operating outside the jurisdiction of Merseyside police. While such interactions exist – and they can be subject to future studies using different sources of data – our inclusion criteria generate a clear-cut network boundary, thus offering a (neat) solution to the boundary specification problem affecting network studies (see Laumann, Marsden, & Prensky, 1989 for a general discussion on defining boundaries in social network analysis and Campana & Varese, 2022 for an organized crime-specific discussion).

4. Organized crime landscape in Merseyside

As already mentioned, police records show a total of 134 OCGs operating in the area between January 2015 and March 2018, with a total of 1211 police-identified OC members. OCGs have an average size of 12 members (minimum 2, maximum 51): 67 % of OCGs consist of 2 to 10 members and only 6.7 % of OCGs are made of more than 20 members (corresponding to 9 OCGs). Strikingly similar distributions have been found in previous studies on organized crime in different settings across the Western world (Bouchard & Morselli, 2014; Niezink & Campana, 2023). For example, studying a sample of incarcerated dealers in Quebec, Bouchard (2006) found that a majority of dealers were active in organizations of two to ten members (60 %) and only 13.7 % had more than 20 members. In an analysis of 557 drug dealing cases collected from police files in Baltimore, Eck, Gersh, and Taylor (2000) found that 35 % of OCGs consisted of 2 to 10 offenders, and only 7.1 % had more than 20 members.

It is important to note that OCGs operating in Merseyside are not youth gangs but are comprised of primarily adult offenders: the average age is 27.5 years (median 26), with the youngest offender aged 11 and the oldest aged 61; 16.2 % of offenders are under 18 (277 individuals) and 1.4 % are under 14 (17 individuals). This is broadly in line with the median age of 32 years found by Campana and Varese (2022: 8) among OCGs identified by Thames Valley Police, also in the UK. In terms of ethnicity, OCGs are overwhelmingly composed of White offenders (95 % of OCGMs are of any White background, and 93.1 % are White British).

OCGs operating in Merseyside are involved in a variety of criminal activities (Table 2). The three main classes of revenue-generating activities are Thefts/Frauds (69.4 %), Burglaries (62.7 %), and Trafficking Class A drugs (61.2 %); these are followed by Trafficking Class B&C drugs (46.2 %) and Robberies (37.3 %). In England and Wales, Class A drugs include cocaine and crack cocaine, ecstasy (MDMA), heroin, LSD, and methamphetamine. Cannabis is the main illegal drug listed in Class B&C; other drugs include ketamine, codeine, amphetamines, khat, and GHB/GBL. In this work, we focus on drug trafficking, which includes importation, production, drug supply or intent to supply and possession with intent to supply, and we leave aside crime events recorded as personal possession.

Most OCGs use violence to carry out their activities: some 80 % have been involved in violent events causing injuries, 52 % in weapon-carrying, and some 10 % carried out arson attacks. Only a marginal fraction of OCGs were involved in sexual offenses (3.7 %).

Moving to cooperation, we observe that 85 OCGs in our data have established a partnership with at least another OCG during the period under consideration (that is, 63.4 % of all OCGs active in Merseyside).

Table 2
OCGs criminal activities.

Crime type	N OCGs	% OCG
Arson	14	10.4
Burglary	84	62.7
Criminal Damage	81	60.4
Drug Trafficking: Class A	82	61.2
Drug Trafficking: Class B and C	62	46.2
Threats	79	58.9
Robbery	50	37.3
Sexual offence	5	3.7
Theft or Fraud	93	69.4
Violence without Injury	82	61.1
Violence with Injury	107	79.8
Weapons	70	52.2

Note: OCGs can be involved in multiple activities.

The median number of partners is 2.8 and the maximum is 9 (i.e., the maximum degree).

Fig. 1 shows the structure of the cooperation network among OCGs with the size of each node (OCG) capturing the degree centrality of a group, meaning the number of different partners a group has cooperated with (Fig. A1 in the Appendix shows the same network highlighting the betweenness centrality for each group; Fig. A2 also in the Appendix shows the degree distribution across all OCGs).

The cooperation network has a density of 0.013, meaning that only 1.3 % of all possible ties have been established (when isolates are removed, density increases to 0.033). This is consistent with the idea that cooperation is the result of intentional decision-making – and that there are (strong) limits to cooperation. The cooperation network also records a modularity score of 0.663, pointing to an underlying tendency to clusterization among the OCGs operating in Merseyside.[6] This is in line with findings from other studies looking at cooperative interactions in local drug markets (Baika & Campana, 2020), transnational human smuggling (Campana, 2018) and among drug offenders within Outlaw Motorcycle Gangs (Bright et al., 2019). In other words, connections are not created at random.

5. Explaining the structure of cooperation

We now turn to explore the determinants of the structure of cooperation among OCGs. To model the strength of cooperative interactions (as opposed to a binary tie/no-tie approach), we employ a series of valued Exponential Random Graph Models (ERGMs, Table 3). The dependent variable is the entire network, i.e., the probability of observing the specific set of ties forming the organized crime cooperation network we have built and described above.

We first consider the level of involvement of each OCG in five revenue-generating criminal activities: trafficking in Class A drugs, trafficking in Class B&C drugs, burglary, robbery, theft & fraud. As we investigate cooperation among OCGs in the context of illegal market activities, we focus our analysis on revenue-generating activities, thus excluding from the models the use of force, threats, and criminal damages. In other words, we see OCGs as profit-oriented groups for which violence is not an end in itself. We explore violence in a separate set of models.[7]

To take into account the variation in size across OCGs, we have divided each count of crime activity by the number of members in a group. In Model 1, we also consider the age difference between two OCGs. Next, we assess the impact of local network effects by including triadic closure in tie formation (Model 2). Finally, we enrich our model by adding a spatial dimension to our analysis, captured by spatial proximity in criminal activity (Model 3). Two OCGs are considered spatially proximate if most of their crimes are located within the same MSOA (any recorded crime, including non-revenue generating activities).

The 'sum' term is similar to the intercept in linear regression models and represents the probability of the strength of a cooperative relationship between any two OCGs. The effect is negative, meaning that if one randomly picks any pair of OCGs, it is more likely to observe no cooperation of any strength rather than cooperation (this is expected as the overall network density is lower than 0.50). What drives cooperation, then? It is clearly the involvement in drug trafficking activities – both Class A and Class B&C – that increases the intensity of cooperation between groups. Drug trafficking includes importation, production, drug supply, intent to supply and possession with intent to supply. It excludes simple personal possession with no intention to supply (Model 1).

This effect holds across all model specifications. We can conjecture that this could be the result of a greater complexity of drug trafficking activities relative to theft & fraud (no effect), robbery (no effect) and burglary (a much more tenuous effect that disappears when introducing local network effects and spatial effects). Drug dealing involves managing supply chains, distributions, and potentially some degree of territorial control to keep competitors at bay. It requires contacts, skills, and resources, potentially calling for greater cooperation across groups than the other revenue-generating criminal activities considered. In other words, drug trafficking has an apparent, strong, *structuring* effect on cooperation among OCGs.

We also find a small effect of age in establishing cooperation: the smaller the difference in the average age of their members, the more likely it is that two groups will cooperate.

In Model 2, we find a positive effect of triadic closure in tie formation: OCGs are more likely to cooperate with an OCG if any of their partners are cooperating with that OCG. In other words, two OCGs that intensively cooperate with the same common partner are more likely to establish direct cooperation between them. Plausibly, this is a strategy to decrease risk when selecting partners, particularly in a context characterized by low trust and the absence of enforceable contracts (Campana & Varese, 2013; Reuter, 1983).[8] These results hold when controlling for spatial proximity (Model 3). (The non-zero parameter addresses the potential skew towards zero of the observed link distribution. In the case of sparse networks, i.e., networks with a zero-inflated distribution as the Organized Crime Cooperation analyzed in this work, the parameter is

Table 3
Estimating tie formation in the organized crime cooperation network.

	Model 1	Model 2	Model 3
Sum of edge values	−0.594*	−0.579*	−0.620*
	(0.255)	(0.236)	(0.235)
Drug Trafficking Class A (sum)	0.412**	0.342**	0.346**
	(0.131)	(0.115)	(0.118)
Drug Trafficking Class B&C (sum)	0.315***	0.231*	0.255**
	(0.115)	(0.101)	(0.099)
Theft and Fraud (sum)	0.018	0.017	0.023
	(0.050)	(0.045)	(0.044)
Burglary (sum)	0.088*	0.064	0.067
	(0.042)	(0.036)	(0.038)
Robbery (sum)	0.289	0.250	0.217
	(0.182)	(0.161)	(0.169)
Age (abs diff)	−0.059**	−0.053**	−0.056**
	(0.019)	(0.018)	(0.019)
Non zero parameter	−4.071***	−4.146***	−4.117***
	(0.290)	(0.275)	(0.271)
Triadic closure (transitive weights)		0.583***	0.577***
		(0.141)	(0.140)
Territory (same MSOA)			0.383
			(0.210)
N	3570	3570	3570
AIC	−6447.6	−6459.9	−6455.4
BIC	−6398.1	−6404.3	−6393.6

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parenthesis.

[6] Calculated based on the modularity score optimization algorithm developed by Blondel, Guillaume, Lambiotte, and Lefebvre (2008) and implemented in Gephi 10.

[7] We have also excluded from the analysis sexual offenses both for statistical (very low N) and substantive reasons (it is not clear that these are revenue-generated activities).

[8] It is worth further exploring this point by employing an event-based, longitudinal approach to tease out selection mechanisms and minimize the potential impact of the data structure (1-mode projection of a bipartite network) on the clustering coefficient (see Diviák, 2022 and Nieto, Davies, & Borrion, 2022 for a discussion of the clustering coefficient in bipartite projections; Bright et al., 2024 and Niezink & Campana, 2023 for a relational event-based approach to modeling criminal networks longitudinally).

significant and negative; in Appendix B, we present Goodness-of-fit and MCMC diagnostics).

6. Network centrality and violence

Next, we explore the impact of centrality in the cooperation network on the use of violence by an OCG. Is a more central position in the cooperation network associated with a higher level of violence? Table 4 presents the result of a series of Poisson regression models looking at degree centrality and betweenness centrality on the likelihood of resorting to violence. In all models, our dependent variable is a count of violent events carried out by an OCG. Our violence variable is based on the 'violence with injury' category defined by Merseyside Police. Such a category includes murder and attempted murder, assaults occasioning actual bodily harm, wounding with intent to do grievous bodily harm, inflicting grievous bodily harm, malicious wounding, and racially or religiously aggravated actual bodily harm. This variable captures violent events against any type of victim, including other OC members, non-OC offenders, as well as individuals with no criminal records. In other words, we look at violence both within the OC space and beyond. In Models 3 and 4, we include as controls the same criminal activities as in Table 3.

Firstly, we simply look at the effect of degree centrality, which is the number of cooperative links established by a group, on the likelihood of resorting to violence with injury. We find that, as the degree centrality increases, groups are more likely to use violence (Model 1). In Model 2, we look at centrality from a different angle, namely betweenness centrality, which captures a group's brokerage/bridging power in connecting any other two groups within the cooperation network. We find that, as brokerage power increases, the likelihood of resorting to violence also increases. No matter how we conceptualize centrality, we find that more central groups – because they are more active or occupy high brokerage positions – tend to use violence more. This holds when controlling for the type of activities carried out by groups (Models 3–4). In all models, we also control for the size of a group (showing that there is strength in numbers).

The reasons for these findings can be multiple. Our results are consistent with the finding by Niezink and Campana (2023) that prior co-offending among OCG members is a strong predictor of future violence among the same members: more active groups in terms of cooperative ties are therefore also more likely to be entangled in conflicts. They can also be driven by the necessity to resort to violence to gain a central position and defend it from competitors – in line with Papachristos (2009) and Gravel et al., 2023). Additionally, as in our analysis we look at violence not only within the organized crime space but against any victim, it is possible that groups feel bolstered by their central position in the organized crime space and therefore resort to violence more frequently also outside such a space. Unfortunately, our data do not include any information on victims of violence, thus making it impossible to explore further the mechanisms suggested above. Future works might wish to take a longitudinal approach and shed further light on the mechanisms linking centrality in the cooperation network to violence (expanding, e.g., on Gravel et al., 2023 and Niezink & Campana, 2023). Yet, such a finding points to an important policy implication: high centrality OCGs tend to be associated with high levels of interpersonal violence that stretch beyond the organized crime milieu. This is an important element for violence-reduction programs as knowing a group's position in the cooperation network can also inform strategies to curb violence.

7. Conclusions

This work has explored the structure and mechanisms of cooperation among organized crime groups (OCGs) operating in Merseyside, UK. It has also offered an exploration of the relationship between central positions in an organized crime cooperation network and the use of violence by OCGs. While most studies so far have focused on either the macro-level impact of OCGs – and gangs – on characteristics of neighborhoods, cities or counties, or micro-level mechanisms underpinning OCGs' internal organization, our work has shifted the focus to group-level mechanisms by offering a meso-level analysis of cooperative interactions among OCGs. We contended that understanding the mechanisms underpinning cooperation among criminal groups is crucial –yet largely neglected by criminologists. As cooperation is, by definition, a relational endeavor, we further contended that it is very well suited to be explored through a formal network approach.

OCGs operating in Merseyside are involved in a variety of revenue-generating activities, ranging from drug trafficking to burglaries, robberies, thefts and frauds. Some 80 % of groups have been engaged in violence causing injuries. They are not youth gangs but more established groups made up of older members (median age 27.5 years); however, they also include a portion of under-age individuals (around 16 % of

Table 4
Network centrality and violence.

	Model 1	Model 2	Model 3	Model 4
Degree Centrality	0.803***		0.810***	
	(0.19)		(0.21)	
Betweenness Centrality		0.816***		0.893***
		(0.14)		(0.16)
Drug Trafficking Class A			0.135	0.163
			(0.14)	(0.15)
Drug Trafficking Class B&C			0.007	0.114**
			(0.05)	(0.05)
Theft and Fraud			0.029	0.029
			(0.03)	(0.03)
Burglary			0.038	0.042
			(0.04)	(0.03)
Robbery			0.272	0.273
			(0.20)	(0.21)
Number of OCG Members	0.052***	0.060***	0.051***	0.057***
		(0.01)	(0.2)	(0.21)
Constant	0.949***	1.631***	0.783***	0.772**
	(0.26)	(0.32)	(0.29)	(0.32)
AIC	860.983	1214.109	845.565	846.323
BIC	869.295	1216.88	859.418	860.176
R square	0.39	0.13	0.4	0.4

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis.

members are under 18). Interestingly, the OCG landscape is not made of individuals from ethnic minorities but reflects the broader population of Merseyside: 95 % of OCG members are White, and so is 83 % of the overall population in the area. This is a significant departure from studies on, e.g., gangs in the US, which tend to observe an over-representation of individuals from minority groups. Therefore, this study furthers our understanding of criminal dynamics among majority ethnic groups.

In this work, we conceptualize cooperation as co-offending between two OCGs (in line with Malm et al., 2011 and Coutinho et al., 2020). In the co-offending network, a cooperative link between two OCGs exists if at least one member from each group has co-offended together in a crime event of any type. While this is in line with previous works and remains an effective, pragmatic, choice given the nature of data, we fully acknowledge that this operationalization of cooperation is open to the risk of both over- and under-estimate cooperation: over-estimate it as two individuals belonging to two different OCGs might co-offend without such behavior being sanctioned by their respective groups, and under-estimate it as cooperation might take various forms that go beyond what police co-offending records capture. Future works might wish to expand the type of evidence by, e.g., eliciting information at the group level directly from key informants (as in Kennedy et al., 1997) or by looking at direct communications among OCG members, e.g., via wiretapped calls or messages (as in Campana & Varese, 2013).

Leveraging crime reports handled by Merseyside Police, we found that some two-thirds of OCGs operating in Merseyside have established a cooperative link with at least another group; the median number of partners is 2.8 and the maximum is 9. Cooperation remains subject to constraints: only between 1.3 % and 3.3 % of possible cooperative ties have been established (depending on whether isolates are considered). Furthermore, groups show a tendency towards clusterization, thus suggesting a non-random behavior. What drives cooperation, then?

Based on a series of valued Exponential Random Graph Models that take into consideration also the strength of cooperation – and not just the presence – we showed that only one type of revenue-generating criminal activity has a *structuring* effect on the organized crime cooperation landscape: drug trafficking. We suggest that this might reflect the higher complexity of drug trafficking vis-à-vis other revenue-generating criminal activities, e.g. in managing supply chains and local distribution as well as potentially exerting some degree of territorial control to keep competitors at bay. This translates into more contacts, more skills, and more resources needed.

Secondly, we also found support for the idea that in a context characterized by low trust and the absence of enforceable contracts (Campana & Varese, 2013; Reuter, 1983), OCGs decrease risk by collaborating with groups that collaborate with a partner OCG. In network terms, we found an effect of triadic closure in the cooperation network. More work adopting a longitudinal, event-based approach is needed to shed further light on the selection mechanisms while minimizing the potential effect of the bipartite nature of the data employed in this work.

Finally, we explored the impact of centrality in the cooperation network on the use of violence by OCGs. We found that a more central position in the cooperation network – both in terms of degree and betweenness centrality - comes with a higher propensity to use violence. This holds when controlling for crime activity and group size. The reasons for this could be multiple, including prior co-offending turning sour (as found by Niezink & Campana, 2023), the use of violence strategically to gain power and prestige, and defend it from competitors (Gravel et al., 2023; Papachristos, 2009) as well as the fact that groups might be emboldened by their central position in a web of alliances and thus be more prone to use violence beyond the OC space. More work is needed to disentangle the mechanisms underpinning the interaction between cooperation and violence – ideally with a longitudinal approach.

Our work points to two main implications. Firstly, it highlights the importance of considering self-organized groups of offenders as entities in their own right when developing interventions aiming at curbing their activities as well as the workings of illicit markets more broadly. It is particularly important to understand how groups select their partners in their local areas to improve the efficacy of interventions. Secondly, our findings stress the importance of group-level relational mapping if we are to understand the workings of illicit markets as well as OCG-instigated violence. The positive relationship between centrality and violence points to the presence of friction in OCGs' revenue-generating activities.

This work has also made a methodological contribution in emphasizing the importance of criminal groups as a unit of analysis, as OCGs and gangs are arguably more than just the sum of their parts (as empirically shown by, among others, Papachristos, 2009; Bouchard & Morselli, 2014; Ouellet et al., 2019; Gravel et al., 2023). Such a unit of analysis has the additional benefit of being less subject to biases (e.g., biases in individual membership identification) and arguably more stable over time. While in our study we look at (mostly) adult OCGs, our approach can be extended to the study of cooperative interactions among youth gangs. Further, a note on terminology: groups labeled as OCGs (organized crime groups) in the UK, as in our study, can be referred to as (adult) 'gangs' in other jurisdictions, including the United States.

Finally, it is important to acknowledge that by relying on police records, our study is subject to the well-known biases and limitations of such data, e.g., the level of enforcement, policing priorities, recording practices, and resource constraints. Despite such limitations, we believe that our study complements prior works on networked violence by looking at, so to speak, the other side of the coin: cooperation. And successful, sustained cooperation can lead to stronger, more resilient, and more entrenched OCGs, with adverse consequences for the well-being of individuals and communities.

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CRediT authorship contribution statement

Paolo Campana: Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Andrea Giovannetti:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None.

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Appendix A. Additional network measures

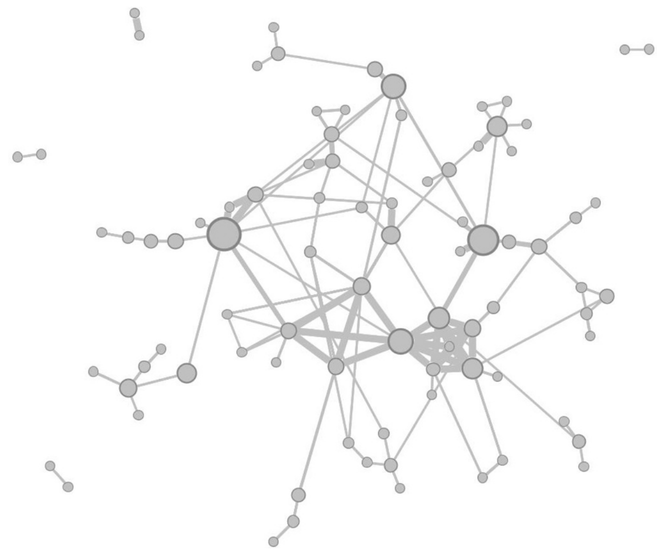


Fig. A1. Organized crime cooperation network in Merseyside (betweenness centrality).

Note: each node represents an organized crime group; the size of a node is proportional to the betweenness centrality of that node; the size (thickness) of a link is proportional to the intensity of cooperation. Isolates are removed from the picture.

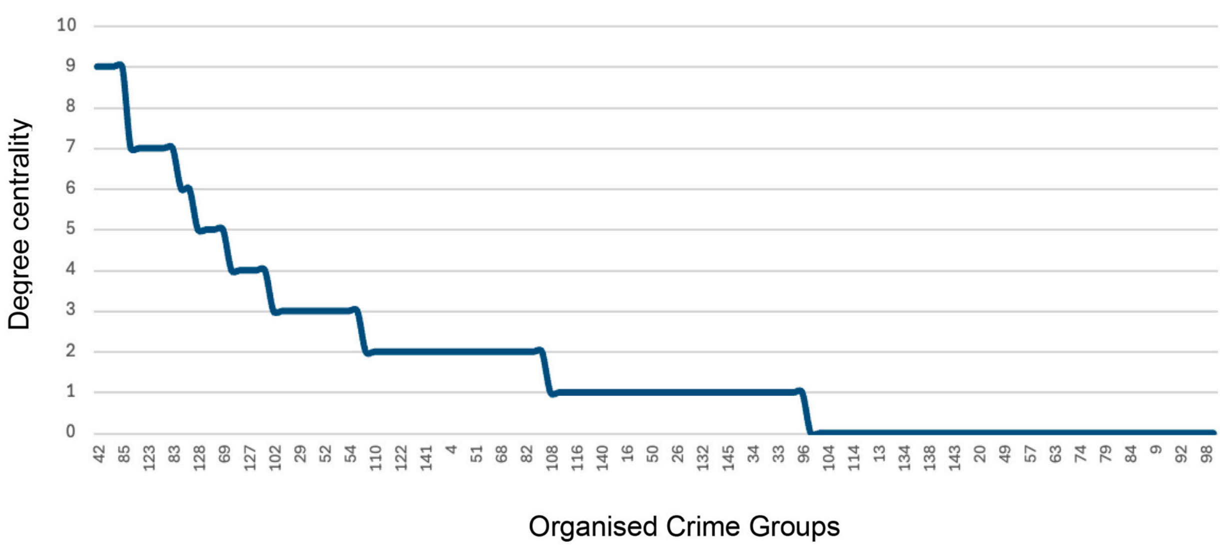
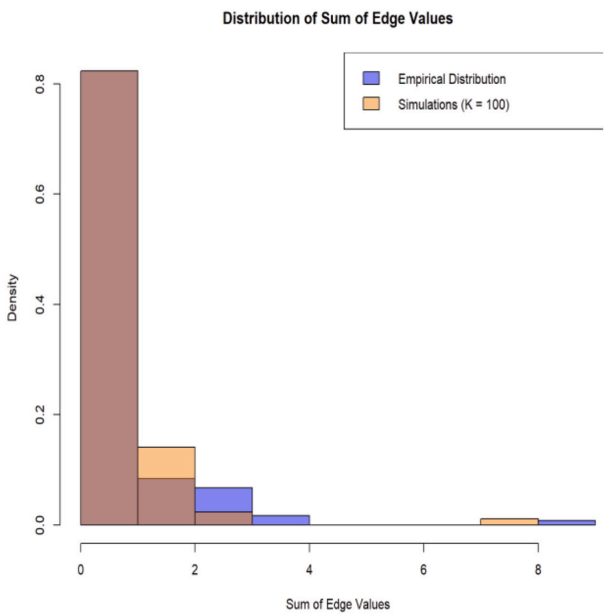


Fig. A2. Degree distribution (all OGCs).

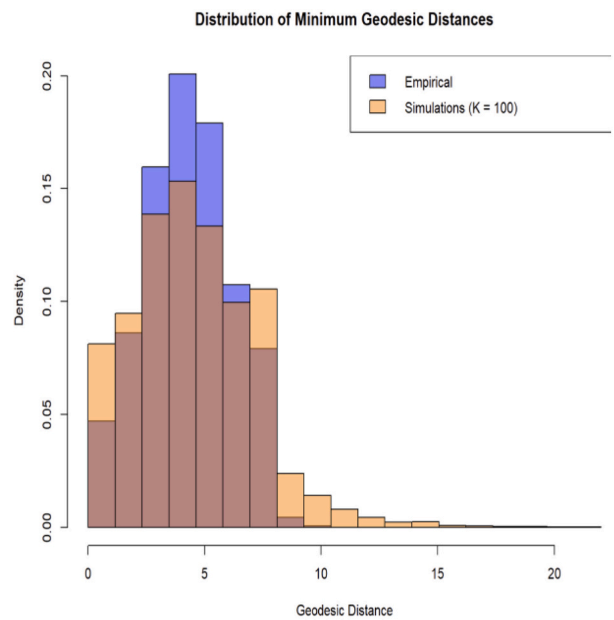
Note: the tail of the distribution is truncated.

Appendix B. Goodness-of-fit and convergence tests for ERGMs estimations

B.1. Goodness-of-fit



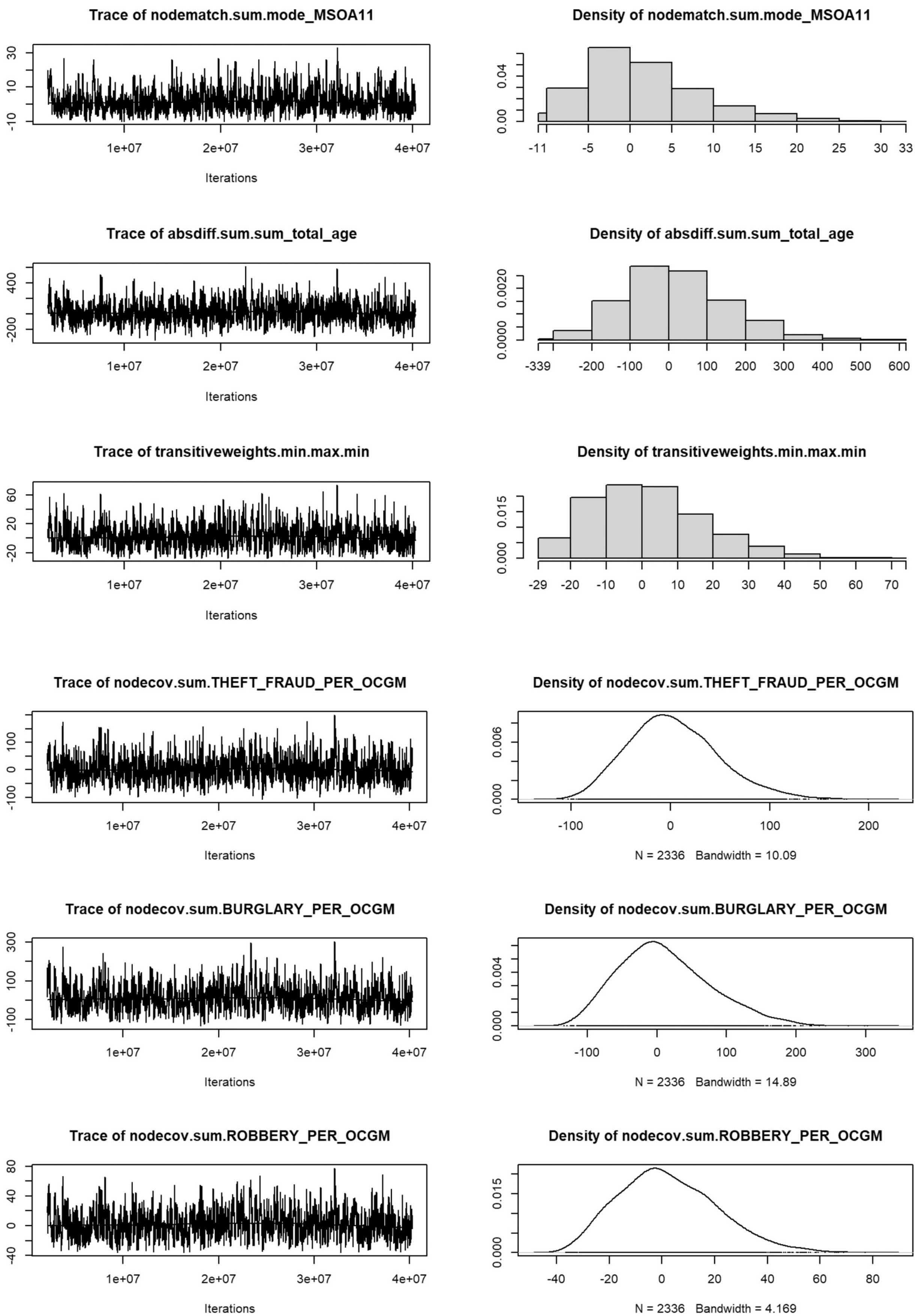
(a) Distribution of the minimum geodesic distances as computed for the empirical OCG network (blue histogram) and for the configuration of Model 3 of Section 5 (light brown histogram). The latter distribution is obtained by pooling across K = 100 simulations. Shadowed area indicate intersections across histograms.

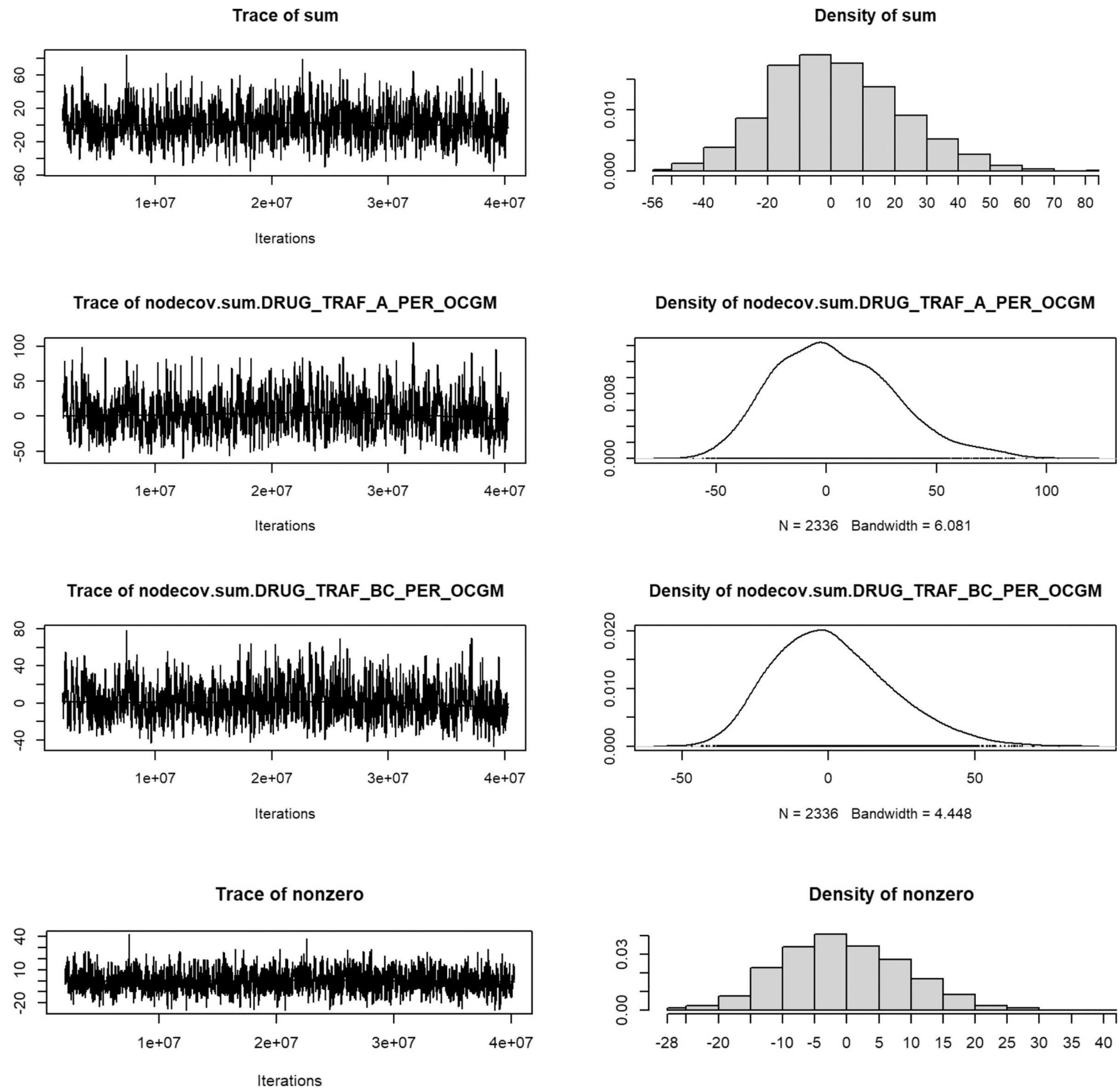


(b) Distribution of the minimum geodesic distances as computed for the empirical OCG network (blue histogram) and for the configuration of Model 3 of Section 5 (light brown histogram). The latter distribution is obtained by pooling across K = 100 simulations. Shadowed area indicate intersections across histograms

Note: GOF measures are computed by the Authors as no such measures are currently implemented in the R package for Valued ERGMs (“ERGM count”).

B.2. MCMC convergence diagnostics


Trace of nodematch.sum.mode_MSOA11
Iterations
Density of nodematch.sum.mode_MSOA11
Trace of absdiff.sum.sum_total_age
Iterations
Density of absdiff.sum.sum_total_age
Trace of transitiveweights.min.max.min
Iterations
Density of transitiveweights.min.max.min
Trace of nodecov.sum.THEFT_FRAUD_PER_OCGM
Iterations
Density of nodecov.sum.THEFT_FRAUD_PER_OCGM
N = 2336 Bandwidth = 10.09
Trace of nodecov.sum.BURGLARY_PER_OCGM
Iterations
Density of nodecov.sum.BURGLARY_PER_OCGM
N = 2336 Bandwidth = 14.89
Trace of nodecov.sum.ROBBERY_PER_OCGM
Iterations
Density of nodecov.sum.ROBBERY_PER_OCGM
N = 2336 Bandwidth = 4.169



Note: Diagnostics presented are those calculated for Model 3 (full model).

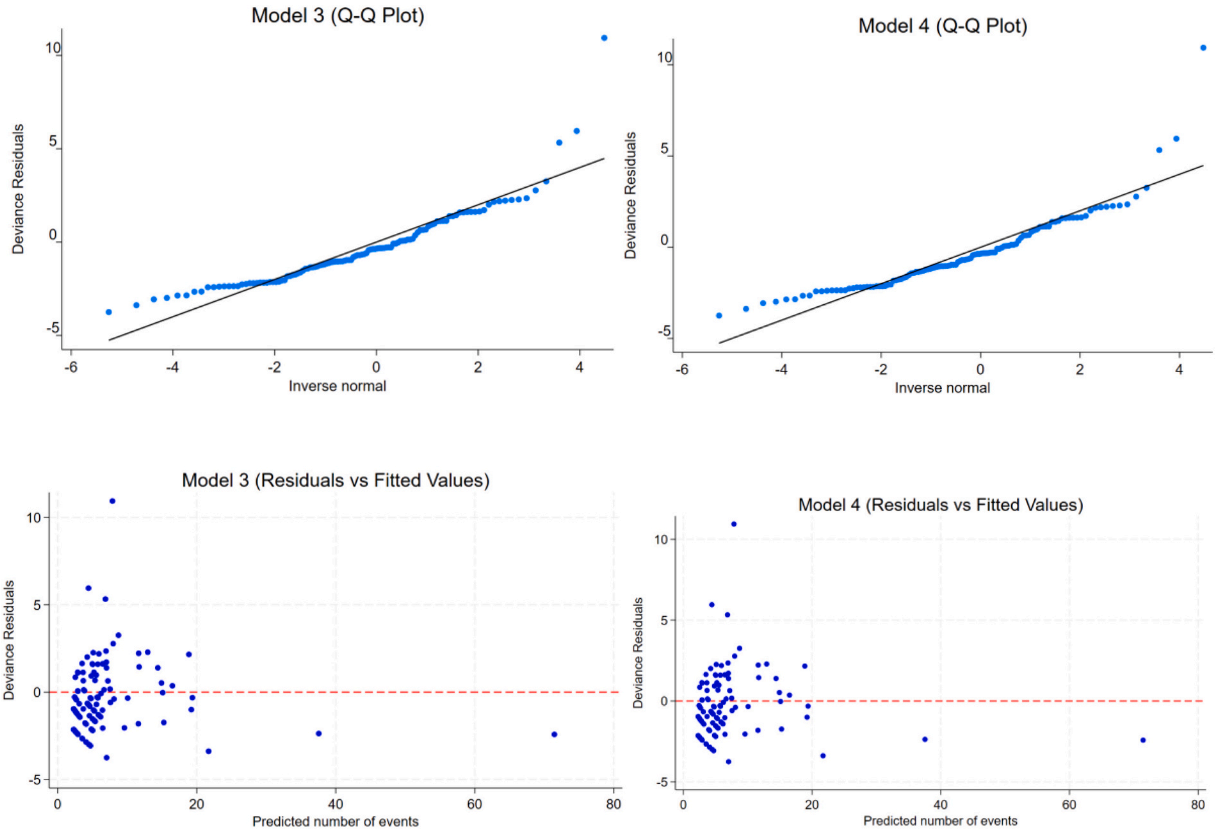
Appendix C. Diagnostic tests on Poisson estimation framework

To evaluate the adequacy of the model specification for the Poisson models presented in Table 4, we inspect the properties of the distributions related to the model residuals. As Poisson residuals are by construction non-stationary (as the variance increases with the mean), hence scale-dependent, we analyze the distribution properties of the deviance residuals. Deviance is a standard metric for assessing model fit in count data models, and it indicates the gap between the fit to the data of the actual model and the fit of an ideal model for which the maximum log-likelihood corresponds to the log-likelihood observed in the data (see, e.g., Cameron & Trivedi, 2009). For any Poisson distribution and observation *i*, deviance is given by:

$$d_i = sign[y_i - \widehat{\lambda}_i]\sqrt{2\left\{y_i log\left(\frac{y_i}{\widehat{\lambda}_i}\right) - (y_i - \widehat{\lambda}_i)\right\}}$$

We perform two standard diagnostic inspections for Model 3 and 4, respectively. First, we inspect a Q-Q plot to assess whether the deviance residuals align with a normal distribution. Second, we examine a scatter plot of residuals versus fitted values to test for systematic patterns that might suggest heteroskedasticity, omitted variables, or other violations of model assumptions.

Both plots demonstrate a reasonable fit for the Poisson model. The Q-Q plot shows that residuals closely follow the reference line at the 25–75 percentile interval, with minor deviations in the tails. The second plot does not reveal discernible patterns in the residuals. Taken together, these diagnostics suggest that the Poisson model performs well in capturing effects on the mean.



References

Acemoglu, D., De Feo, G., & De Luca, G. D. (2020). Weak states: Causes and consequences of the sicilian mafia. *The Review of Economic Studies, 87*(2), 537–581.

Aziani, A., Favarin, S., & Campedelli, G. M. (2020). Security governance: Mafia control over ordinary crimes. *Journal of Research in Crime and Delinquency, 57*(4), 444–492.

Baika, L., & Campana, P. (2020). Centrality, mobility, and specialization: A study of drug markets in a non-metropolitan area in the United Kingdom. *Journal of Drug Issues, 50* (2), 107–126.

Bichler, G., Norris, A., Dmello, J. R., & Randle, J. (2019). The impact of civil gang injunctions on networked violence between the bloods and the crips. *Crime & Delinquency, 65*(7), 875–915.

Black, D. J. (1970). Production of crime rates. *American Sociological Review*, 733–748.

Blattman, C., Duncan, G., Lessing, B., & Tobón, S. (2021). *Gang rule: Understanding and countering criminal governance (No. w28458)*. National Bureau of Economic Research.

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment, 2008*(10), Article P10008.

Bouchard, Martin (2006). *"Segmentation et structure des risques d'arrestation dans les marchées de drogues illéegales"*. School of Criminology, University of Montreal. PhD Dissertation.

Bouchard, M., & Morselli, C. (2014). Opportunistic structures of organized crime. In *, 1. The Oxford handbook of organized crime* (pp. 288–302).

Bright, D., Koskinen, J., & Malm, A. (2019). Illicit network dynamics: The formation and evolution of a drug trafficking network. *Journal of Quantitative Criminology, 35*, 237–258.

Bright, D., Sadewo, G., Cubitt, T. I., Dowling, C., & Morgan, A. (2022). Co-offending networks among members of outlaw motorcycle gangs across types of crime. *Trends in Organized Crime*, 1–23.

Bright, D., Sadewo, G. R. P., Lerner, J., Cubitt, T., Dowling, C., & Morgan, A. (2024). Investigating the dynamics of outlaw motorcycle gang co-offending networks: The utility of relational hyper event models. *Journal of Quantitative Criminology, 40*(3), 445–487.

Cameron, A., & Trivedi. (2009). Pravin. In *Microeconometrics Using Stata*. College Station, Texas: Stata: Press.

Campana, P. (2011). Eavesdropping on the mob: The functional diversification of mafia activities across territories. *European Journal of Criminology, 8*(3), 213–228.

Campana, P. (2018). Out of Africa: The organization of migrant smuggling across the Mediterranean. *European Journal of Criminology, 15*(4), 481–502.

Campana, P., & Varese, F. (2013). Cooperation in criminal organizations: Kinship and violence as credible commitments. *Rationality and Society, 25*(3), 263–289.

Campana, P., & Varese, F. (2018). Organized crime in the United Kingdom: Illegal governance of markets and communities. *The British Journal of Criminology, 58*(6), 1381–1400.

Campana, P., & Varese, F. (2022). Studying organized crime networks: Data sources, boundaries and the limits of structural measures. *Social Networks, 69*, 149–159.

Campana, P., Varese, F., & Meneghini, C. (2025). Criminal governance in a large European city: the case of gangs in London. *European Journal of Criminology*. Forthcoming.

Carrington, P. J., & van Mastrigt, S. B. (2013). Co-offending in Canada, England and the United States: A Cross-National Comparison. *Global Crime, 14*(2–3), 123–140.

Catino, M. (2019). *Mafia organizations*. Cambridge University Press.

Charette, Y., & Papachristos, A. V. (2017). The network dynamics of co-offending careers. *Social Networks, 51*, 3–13.

Cohen, J., & Tita, G. (1999). Diffusion in homicide: Exploring a general method for detecting spatial diffusion processes. *Journal of Quantitative Criminology, 15*, 451–493.

Coutinho, J. A., Diviák, T., Bright, D., & Koskinen, J. (2020). Multilevel determinants of collaboration between organised criminal groups. *Social Networks, 63*, 56–69.

Decker, S., & Pyrooz, D. (2014). Gangs another form of organized crime? In L. Paoli (Ed.), *The Oxford handbook of organized crime*. New York: Oxford University Press.

Decker, S., Pyrooz, D., & Densley, J. (2022). *On gangs*. Philadelphia, PA: Temple University Press.

Densley, J. (2013). *How gangs work*. New York: Palgrave Macmillan.

Diviák, T. (2022). Key aspects of covert networks data collection: Problems, challenges, and opportunities. *Social Networks, 69*, 160–169.

Eck, J. E., Gersh, J. S., & Taylor, C. (2000). Finding crime hot spots through repeat address mapping. In *Analyzing crime patterns: Frontiers of practice* (pp. 49–64).

Faust, K., & Tita, G. E. (2019). Social networks and crime: Pitfalls and promises for advancing the field. *Annual Review of Criminology, 2*(1), 99–122.

Fijnaut, C., Bovenkerk, F., Bruinsma, G., & Van de Bunt, H. (1998). *Organized crime in the Netherlands*. The Hague: Kluwer Law International.

Gambetta, D. (1993). *The sicilian mafia*. Cambridge (MA): Harward University Press.

Giovannetti, A. (2021). How does bank credit affect the shape of business groups' internal capital markets? *Quantitative Finance, 21*(10), 1621–1645.

Gravel, J., Valasik, M., Mulder, J., Leenders, R., Butts, C., Brantingham, P. J., & Tita, G. E. (2023). Rivalries, reputation, retaliation, and repetition: Testing plausible mechanisms for the contagion of violence between street gangs using relational event models. *Network Science, 11*(2), 324–350.

Grund, T. U., & Densley, J. A. (2015). Ethnic homophily and triad closure: Mapping internal gang structure using exponential random graph models. *Journal of Contemporary Criminal Justice, 31*(3), 354–370.

Hausman, J., Hall, B. H., & Griliches, Z. (1984). Econometric models for count data with an application to the patents-R & D relationship. *Econometrica: Journal of the Econometric Society*, 909–938.

HMICFRS. (2018). *PEEL: Police effectiveness 2017. A National Overview*. London: Her Majesty's Inspectorate of Constabulary and Fire Rescue Services.

Huebner, B. M., Martin, K., Moule, R. K., Jr., Pyrooz, D., & Decker, S. H. (2016). Dangerous places: Gang members and neighborhood levels of gun assault. *Justice Quarterly, 33*(5), 836–862.

Jackson, M. O. (2010). *Social and Economic Networks*. Princeton University Press.

Jackson, M. O. (2011). An overview of social networks and economic applications. *Handbook of Social Economics, 1*, 511–585.

Kennedy, D., Braga, A., & Piehl, A. (1997). The(un)known universe: Mapping gangs and gang violence in Boston. In D. Weisburd, & J. T. McEwen (Eds.), *Crime mapping and crime prevention* (pp. 219–262). New York: Criminal Justice Press.

Kirchmaier, T., Langella, M., & Manning, A. (2024). Commuting for crime. *The Economic Journal, 134*(659), 1173–1198.

Kramer, J. A., Blokland, A. A., Kleemans, E. R., & Soudijn, M. R. (2024). Money laundering as a service: Investigating business-like behavior in money laundering networks in the Netherlands. *Trends in Organized Crime, 27*(3), 314–341.

Krivitsky, P. N. (2012). Exponential-family random graph models for valued networks. *Electronic Journal of Statistics, 6*, 1100–1128.

Krivitsky, P. N., Handcock, M. S., Raftery, A. E., & Hoff, P. D. (2009). Representing degree distributions, clustering, and homophily in social networks with latent cluster random effects models. *Social Networks, 31*(3), 204–213.

Laumann, E. O., Marsden, P. V., & Prensky, D. (1989). The boundary specification problem in network analysis. *Research Methods in Social Network Analysis, 61*(8).

Lavezzi, A. M. (2008). Economic structure and vulnerability to organised crime: Evidence from Sicily. *Global Crime, 9*(3), 198–220.

Levitt, S. D., & Venkatesh, S. A. (2000). An economic analysis of a drug-selling gang's finances. *The Quarterly Journal of Economics, 115*(3), 755–789.

Lewis, K., & Papachristos, A. V. (2020). Rules of the game: Exponential random graph models of a gang homicide network. *Social Forces, 98*(4), 1829–1858.

Lusher, D., Koskinen, J., & Robins, G. (Eds.). (2013). *Exponential random graph models for social networks: Theory, methods, and applications*. Cambridge: Cambridge University Press.

Malm, A., & Bichler, G. (2011). Networks of collaborating criminals: Assessing the structural vulnerability of drug markets. *Journal of Research in Crime and Delinquency, 48*(2), 271–297.

Malm, A., Bichler, G., & Nash, R. (2011). Co-offending between criminal enterprise groups. *Global Crime, 12*(2), 112–128.

McGloin, J. M., & Piquero, A. R. (2010). On the relationship between co-offending network redundancy and offending versatility. *Journal of Research in Crime and Delinquency, 47*(1), 63–90.

McGloin, J. M., Sullivan, C. J., Piquero, A. R., & Bacon, S. (2008). Investigating the stability of co-offending and co-offenders among a sample of youthful offenders. *Criminology, 46*(1), 155–188.

Molzahn, C., Ríos, V., & Shirk, D. A. (2012). *Drug violence in Mexico: Data and analysis through 2011*. San Diego: Trans-Border Institute, University of San Diego.

Morselli, C. (2009). *Inside criminal networks* (Vol. 8). New York: Springer.

Neske, M. (2006). Human smuggling to and through Germany. *International Migration, 44*(4), 121–163.

Nieto, A., Davies, T., & Borrion, H. (2022). "Offending with the accomplices of my accomplices": Evidence and implications regarding triadic closure in co-offending networks. *Social Networks, 70*, 325–333.

Niezink, N. M., & Campana, P. (2023). When things turn sour: A network event study of organized crime violence. *Journal of Quantitative Criminology, 39*(3), 655–678.

Ouellet, M., Bouchard, M., & Charette, Y. (2019). One gang dies, another gains? The network dynamics of criminal group persistence. *Criminology, 57*(1), 5–33.

Ouellet, M., Maimon, D., Howell, J. C., & Wu, Y. (2022). The network of online stolen data markets: How vendor flows connect digital marketplaces. *The British Journal of Criminology, 62*(6), 1518–1536.

Paoli, L. (2008). *Mafia brotherhoods: Organized crime, Italian style*. Oxford University Press.

Papachristos, A. V. (2009). Murder by structure: Dominance relations and the social structure of gang homicide. *American Journal of Sociology, 115*(1), 74–128.

Papachristos, A. V., & Bastomski, S. (2018). Connected in crime: The enduring effect of neighborhood networks on the spatial patterning of violence. *American Journal of Sociology, 124*(2), 517–568.

Papachristos, A. V., Hureau, D. M., & Braga, A. A. (2013). The corner and the crew: The influence of geography and social networks on gang violence. *American Sociological Review, 78*(3), 417–447.

Pinotti, P. (2015). The economic costs of organised crime: Evidence from southern Italy. *The Economic Journal, 125*(586), F203–F232.

Reiss, A. J., Jr. (1988). Co-offending and criminal careers. *Crime and Justice, 10*, 117–170.

Reiss, A. J., Jr., & Farrington, D. P. (1991). Advancing knowledge about co-offending: Results from a prospective longitudinal survey of London males. *The Journal of Criminal Law and Criminology, 82*, 360.

Reuter, P. (1983). *Disorganized crime: The economics of the visible hand*. Cambridge, MA: MIT press.

Reuter, P. (1985). *The organization of illegal markets: An economic analysis. 84*. US Department of Justice, National Institute of Justice. No. 9.

Robinson, P. L., Boscardin, W. J., George, S. M., Teklehaimanot, S., Heslin, K. C., & Bluthenthal, R. N. (2009). The effect of urban street gang densities on small area homicide incidence in a large metropolitan county, 1994–2002. *Journal of Urban Health, 86*, 511–523.

Sarnecki, J. (2001). *Delinquent Networks: Youth Co-Offending in Stockholm*. Cambridge: Cambridge University Press.

Schelling, T. C. (1971). What is the business of organized crime. *Journal of Public Law, 20*, 71.

Shaw, C. R., & McKay, H. D. (1931). *Social factors in juvenile delinquency. Volume II of report on the causes of crime, national commission on law observance and enforcement. Report no. 13*. Washington, D.C.: U.S. Government Printing Office.

Smith, D. C. (1975). *The mafia mystique*. New York: Basic Books.

Tita, G. E., & Radil, S. M. (2011). Spatializing the social networks of gangs to explore patterns of violence. *Journal of Quantitative Criminology, 27*, 521–545.

Tremblay, P. (2017). Searching for suitable co-offenders. In R. V. Clarke and M. Felson (eds), Routine activity and rational choice (pp. 17–36). Routledge, pp. 17–36.

UK Government. (2010). *Organised crime groups mapping manual*. London: Her Majesty's Government.

UNTOC. (2000). *United nations convention against transnational organized crime and the protocols thereto*. New York: United Nations.

Varese, F. (2001). *The Russian mafia: Private protection in a new market economy*. Oxford: Oxford University Press.

Varese, F. (2010). What is organised crime? In F. Varese (Ed.), *I. Organised crime: Critical concepts in criminology* (pp. 11–33). London: Routledge.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. Cambridge: Cambridge University Press.

Wood, G., Roithmayr, D., & Papachristos, A. V. (2019). The network structure of police misconduct. *Socius, 5*. https://doi.org/10.1177/2378023119879798

Wooldridge, J. M. (1999). Distribution-free estimation of some nonlinear panel data models. *Journal of Econometrics, 90*(1), 77–97.