



Organised crime movement across local communities: A network approach

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Abstract

This paper explores the structure of organised crime movement across local communities and the drivers underpinning such movement. Firstly, it builds on network analysis to offer a novel methodological approach to empirically and quantitatively study the movement of organised crime offenders across geographical areas. The paper then applies this approach to evidence from Cambridgeshire in the United Kingdom. It reconstructs the movement of organised crime members across local areas based on a large-scale police dataset that includes 41 months of recorded crime events. It identifies organised crime “turf” and “target” areas and then explores the drivers of movement from the former to the latter using Exponential Random Graph Models. Findings confirm that geographical distance matters; however, socio-demographic, urban, economic and crime-related characteristics of communities play a key role. Organised crime group members target urban communities with higher than average illegal market opportunities (proxied by drug-related activity). The work also finds the effect of socio-demographic homophily between turf and target communities, suggesting that organised crime group members might target territories that are similar to their own. While a high level of deprivation makes a community more likely to send organised crime members, its impact on a community’s probability of being a receiver is less clear. Finally, the paper offers a way to identify communities (local areas) at risk of being targeted by criminal organisations, thus providing practitioners with a tool for early interventions.

Keywords Organised crime · Mobility · Social network analysis · Community-based networks

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Introduction

How do organised crime groups move within their local space? While research so far has offered important insights on long-distance and global movement of criminal organisations (see, among others, Varese 2006; 2011a; 2011b; Campana 2011a; 2011b; 2013; Morselli et al. 2011; Kleemans and de Boer 2013; Sciarone and Storti 2014; Calderoni et al. 2016; Spapens 2019), the study of local movement of organised crime groups has lagged. The lack of works attempting to empirically and systematically model such a movement is even more striking. In this paper, we depart from the macro-level approach employed in the study of long-distance movement by adopting a micro-level relational approach capturing the day-to-day operations of organised crime groups across local communities. Such an approach is based on the principles of social network analysis, which is “a way of thinking about social systems that focuses our attention on the relationships among the entities that make up the system” (Borgatti et al. 2013:1), rather than considering each entity – be it offenders or places – as a separate independent unit (see Wasserman and Faust 1994; also Faust and Tita 2019, Bouchard 2020, Smith and Papachristos 2021, and Campana 2023 for applications of network analysis in criminology). A movement (of any kind) is relational by definition as it implies a connection between two different places (e.g., moving from A to B implies a relation between A and B; see also Sect. 4 below); therefore, it is best analysed through the lenses of networks.

In this paper, we follow a network analysis approach in modelling the behaviour of organised crime group members across local communities. We do so by linking organised crime group members to local areas based on recorded crime locations. We identify source and target areas in the context of organised crime movement and then explore the community-level features that drive such movement. We apply our approach to evidence from Cambridgeshire in the United Kingdom by leveraging a granular, large-scale, police dataset that includes crime events recorded between May 2018 and October 2021.

This work seeks to offer both a substantive contribution to the understanding of (a) the structure of organised crime operations across local communities and (b) the factors underpinning such structure, *as well as* a novel methodological approach that can be applied to empirically and quantitatively study the movement of criminal organisations in different locales. Such methodology can be scaled up to study transnational, long-distance movement as well as scaled down by looking at smaller areas such as street segments or hotspots. It can also be expanded by relying on higher frequency data sources (such as time-stamped movement of individuals based on data from mobile phone masts and/or number plates as captured by road cameras), or by looking beyond organised crime and including data on all offenders. The methodology presented in this work can be integrated into broader studies on criminal routine activities and crime pattern analysis. Additionally, the paper will offer a way to identify communities at risk of being targeted by criminal organisations, thus providing a tool for early interventions.

The paper proceeds as follows: the next Section discusses the theoretical background of this work, then Sect. 3 presents the aims of the current study and Sect. 4 its evidence base and methods. Our findings are presented in Sect. 5, while Sect. 6 concludes.

Background

The movement of organised crime

The study of organised crime movement speaks to the broader issue of the geography of organised crime. A key element of the latter is the role of territory. Several authors have stressed the importance of the territory in the operations of organised crime groups (see, among others, Schelling 1971; Reuter 1983; Foster 1990; Gambetta 1993; Paoli 2003; Hobbs 2013; Campana and Varese 2018; Clark et al. 2021). Territories may provide key resources to organised crime groups, including the presence of exploitable markets, a pool of potential recruits, social ties, as well as information and, potentially, protection from authorities (Schelling 1971; Reuter 1983; Gambetta 1993; Varese 2011b; Campana and Varese 2013 and 2022a). Place-based studies of organised crime – and gangs – have started to gain traction, particularly in the US (see, among others, Papachristos and Kirk 2006; Tita and Radil 2011; Papachristos et al. 2013; see also Baldwin et al. 1976 for an earlier example of a place-based study of crime in Sheffield, UK). Previous studies have focused on the characteristics of territories/local communities that might lead to the emergence of criminal organisations, particularly gangs. Research on gangs in the US has highlighted a positive association between a community's socioeconomic disadvantage and gang presence (e.g., Curry and Spergel 1988; Katz and Schnebly 2011; Papachristos and Kirk 2006). Residential instability, high migrant concentration, weak rule of law and closeness to profitable trafficking routes have also been found to increase the likelihood of criminal organisations operating in a given territory (Hall 2010; Katz and Schnebly 2011; Papachristos and Kirk 2006; Wells and Weisheit 2001).

A parallel stream of research has looked at how and why criminal organisations might move across different geographical areas. These studies have primarily focused on the long-distance movement of organised crime groups – both transnationally and within the same country (Varese 2006, 2011b, 2011a; Sciarrone & Storti 2014; Arsovska 2014; Campana 2011a; 2013; Calderoni et al. 2016; Spapens 2019). Such studies have mostly explored long-term expansion or resettlement of organised crime activities into new territories. They have highlighted the importance of jointly looking at supply-side factors, such as the availability (and motivations) of organised crime members as well as demand-side factors, or local conditions, such as the level of trust, presence of newly formed, or booming, markets, strength of illegal markets, and size of the locale (Varese 2011a; 2011b). Not all movements are equal: in some instances, organised crime groups might transplant their core business into new territory, as in the cases studied by Varese (2011b); in other instances, organised crime groups might expand into new territories but change their *modus operandi* across

different geographical areas, for instance by carrying out different types of activities in different areas while keeping the core business in the territory of origin, as in the case of the ‘functional diversification’ described by Campana (2011a). While scholars have provided important insights on the long-distance, long-term movement of organised crime groups, very little attention has been devoted to empirically studying the short-distance, short-term movement of such groups.

The same analytical framework developed in the context of long-distance movement (Varese 2011a; Morselli et al. 2011) can be applied to study the day-to-day operations of organised crime groups across local communities (local movement). On the supply side, one can explore the motivations behind such movement, e.g., the desire to expand certain illegal activities or the need to escape violence from rivals and/or pressure from law enforcement. At the same time, local areas might present specific conditions that make a certain territory attractive and vulnerable to targeting by an organised crime group. These local conditions might include criminogenic characteristics, such as the presence of criminal opportunities (e.g., illegal markets) or the absence of strong competitors, as well as socio-demographic vulnerabilities. In this work, we focus on the role of local conditions in making an area a *target* of organised crime movement. To gain a fuller picture, we will study the characteristics of *target* areas jointly with the characteristics of *turf* areas, meaning the territory in which an organised crime group has its centre of operations. Through a network analysis approach, we will place the connections between turf areas and target areas at the centre of our analysis. This expands – and operationalises – the suggestion put forward by Hall (2010) that to fully understand the geography of organised crime, one has to identify the concentration of organised crime in a specific geographical area and then map “the specific connections that stretch inwards and outwards from these regions” (Hall 2010: 11). We now move to discuss how such connections can be conceptualised, operationalised and analysed.

Community-based offending networks

Criminological research is increasingly recognising the role that networks play in shaping offending behaviour. While most studies have looked at relational dynamics at the individual level, some recent works investigated how connections between communities may influence crime incidence at the community level (e.g., Bastomski et al. 2017; Papachristos et al. 2013; Schaefer 2012; Tita and Greenbaum 2009; Tita and Radil 2011). Inter-community ties can be conceptualised in different ways. Studies so far have mostly focused on connections capturing the offenders’ movement from their community (area) of residence to a different community (area) within their “awareness space” to engage in crime, i.e. their journeys to crime (see, among others, Brantingham and Brantingham 1993; Wiles and Costello 2000). Offenders’ journeys to crime can be conceptualised as a directional relation between a point of origin (normally the offender’s place of residence) and the crime location; the distance between the two can be captured as an attribute of the relation (see, among others, Rengert 2004 and Reid et al. 2014). While journeys-to-crime are relational by definition, studies so far have largely stopped short of employing a formal

network approach to model such journeys. Perhaps due to greater data availability, a growing sub-set of works has relied on networks of street segments to explore how physical infrastructures (e.g. roads) can affect journeys to crime (Reid et al. 2014) as well as the relationship between street networks configurations and crime levels (Beavon et al. 1994; Johnson and Bowers 2010; Davies and Johnson 2015; Summers and Johnson 2017; Kim and Hipp 2020, more generally Hillier 1996. A related strand of work has looked at the impact of crime attractors on crime levels and type, e.g., Groff and Lockwood 2014). Broadly speaking, such works have unpacked some of the mechanisms underpinning routine activity theory and crime pattern theory, as “places easier to access along the street network will be more familiar to offenders [as] they are more likely to be travelled by persons including offenders” (Kim and Hipp 2020: 728); in addition, the “street network configuration can largely determine the number and type of people coming into a place including potential offenders and targets because criminogenic activity nodes are located along the street networks” (Kim and Hipp 2020: 728; busy segments, however, can also have the opposite effect of decreasing crime due to higher levels of guardianship: Kim and Hipp 2020: 729). A related body of work has looked at distances-to-crime, for instance by examining the impact of resident proximity to crime events on their perception of neighbourhood violence (see, e.g., Sydes et al. 2022). Street network distances are employed to operationalise people’s proximity to crime events. While most studies have treated street segments without consideration for the actual movement of people, one way of modelling such networks, which resonates with our approach, is to weigh each segment based on the origin and destination of trips made by, for instance, offenders or the broader population (see Reid et al. 2014; Frith et al. 2017; Kim and Hipp 2020).

A different approach to building place-based offending networks moves beyond street (physical) networks and looks at co-offending relationships established among offenders residing in different areas (communities). While offenders do make use of the physical infrastructure to converge in areas where they co-offend, the focus is shifted from the physical elements of a network to the social elements. Co-offending links allow criminal skills, norms, as well as material resources such as illicit products to diffuse across geographical areas (Schaefer 2012). Communities that have multiple co-offending connections with other areas may be subject to cumulative exposure to risky behaviours (Bastomski et al. 2017). While works so far have mostly focused on inter-community connections stemming from the movement or co-offending relationships of general offenders, Schaefer (2012) discusses how gangs may contribute to connecting spatially distinct communities. Gangs are “perhaps the most spatially bound collective entity” (Schaefer 2012: 142); at the same time, gang members may reside outside the group’s turf, hence connecting places of residence to places of crime, they might try to expand the reach of a gang’s area of operation to spatially proximate neighbourhoods, they may travel to connect with drug consumers residing in other neighbourhoods, or they may have conflictual interactions with other gangs in nearby neighbourhoods (Schaefer 2012). By moving across different neighbourhoods, or communities, gang members create a network of inter-community ties.

So far, works within this strand of research have operationalised inter-community relationships as neighbourhood co-offending networks, meaning they have connected neighbourhoods through the residential addresses of individuals who offended together in relation to a given crime event (Bastomski et al. 2017; Schaefer 2012). In other words, if we have two co-offenders X and Y and two neighbourhoods A and B, the two neighbourhoods are connected if X resides in neighbourhood A and Y resides in neighbourhood B. Following this approach, Schaefer (2012) first built the neighbourhood co-offending network for a large US county and then fitted an Exponential Random Graph Model (ERGM) to investigate the impact of neighbourhood characteristics on co-offending. He found that both spatial and social proximity facilitates the formation of co-offending links between neighbourhoods, with the effect of social distance going above and beyond the effect of spatial distance. Bastomski et al. (2017) investigated how neighbourhood-level criminal networks contribute to the distribution of crime across Chicago. They first calculated the structural embeddedness of each neighbourhood within such neighbourhood co-offending network and then estimated its impact on the neighbourhood-level homicide rate (they employed an OLS regression accounting for both spatial dependency and network effects). These works provided important insights into the impact of the spatial interdependence of neighbourhoods on violent and non-violent neighbourhood crime; however, the actual mechanisms through which social networks influence neighbourhood crime – and the type of inter-neighbourhood connections at play – remain ambiguous (Soller and Browning 2014). Linking communities through neighbourhood co-offending networks emphasizes relational dynamics stemming from people's collaboration in crime. While our work is situated within the field of community-based offending networks, we shift the focus from co-offending to the spatial activity of individual offenders. As we will discuss in more detail below, we consider two communities A and B linked if offender X has committed an offence in both communities. This implies that there has been a movement of offender X between communities A and B. Below we will present a way to enrich this approach by assigning directionality to the movement. Our approach moves beyond street (physical) networks and focuses on the recorded behaviour of offenders; it also departs from – and complements – the approach taken by Schaefer (2012) and Bastomski et al. (2017) in capturing – and modelling – movement across communities (neighbourhoods).

While our approach can potentially be applied to all offenders, in this paper we focus on the movement of people who have been identified by the local police force as organised crime members (see Sect. 4 for a definition of such term in the context of Cambridgeshire). To the best of our knowledge, no previous study has modelled inter-community relationships by considering the spatial activity of offenders who engage in crime in different locations.

Current study

The aim of this study is twofold. Firstly, the work offers a novel methodology to study the movement of criminal organisations across different geographical areas. Such a methodology – based on the principles of network analysis – is relational, quantitative, and empirical. The first step in our approach is to identify a ‘turf’ area for each organised crime offender. We offer a way to do so by leveraging large-scale police crime records (alternative ways might leverage police intelligence records). We then identify all the areas (communities) that have been the recipient of the movement of organised crime group members who have their turf elsewhere. We label those areas as ‘target’. Next, we map the network of organised crime offenders committing crimes in multiple locations by linking the ‘turf’ location with all the other ‘target’ areas in which the same organised crime member has been active. We name this network ‘Organised Crime Mobility Network’. This relational methodology is akin to the one exploited by prior works examining inter-neighbourhood networks (Bastomski et al. 2017; Schaefer 2012); however, it departs from previous studies as it captures community-level connections stemming from the actual operations of organised crime groups (proxied by the geo-localised offences committed by their members). Such a methodology is independent of the size of the local area. While we are interested in movement across local communities, the same approach can be scaled up to study long-distance or transnational movement as well as scaled down to hot spots or street segments. In addition, our methodology can help practitioners identify areas at risk of being targeted by organised crime groups – or organised crime expansion – and develop targeted interventions to prevent the spread of organised crime operations and increase their geographical reach. We offer further details on the methodology in Sect. 4.

Reconstructing the structure of the network capturing organised crime movement only gives us half of the picture. The second objective of this work is to assess the probability of tie formation in the network connecting communities based on socio-demographic, geographical, economic and crime-related community characteristics. Why are certain communities targeted by the movement of organised crime groups? We take a relational approach and look at the characteristics of turf and target areas both separately and jointly. More specifically, we will look at the impact of (a) geographical distance; (b) urban vs rural setting; (c) the presence of illegal market opportunities as proxied by drug market-related offences; (d) deprivation and (e) the percentage of people born outside the UK on the likelihood of organised crime movement from a turf to a target area. In other words, we examine how community-level structural features drive the formation of organised crime mobility networks.

Data and methods

Data

Our analysis leverages crime incident data recorded by Cambridgeshire Constabulary for the period between May 2018 and October 2021. This dataset has been shared with us in a fully anonymised form and includes information on all crime events in which organised crime members appear as either suspects or victims. There is a total of 374 organised crime members identified by the Cambridgeshire Constabulary.¹ The data cover the entire jurisdiction of Cambridgeshire Constabulary, namely the County of Cambridgeshire (including Peterborough unitary authority) in the East of England (UK), with a resident population of 859,830 in 2020 (Office for National Statistics 2021). Peterborough and Cambridge are the two largest cities. Besides crime incident information (e.g., place, date and type of crime), the dataset includes information on the demographic characteristics of offenders (gender, date of birth, and ethnicity). In this work, we follow the definition of organised crime adopted by the police and 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.” (OCGM Manual 2010: 15). This definition is in line with the UN Convention against Transnational Organized Crime (UNTOC 2000).² The UK definition of organised crime is rather broad and encompasses groups engaging in a wide variety of criminal activities, and includes groups that in other jurisdictions, e.g. the US, might come under the label of “gangs” (for a further discussion of the concepts of organised crime and gangs, and their potential overlap, we refer to Decker and Pyrooz 2014; Campana and Varese 2018; Decker et al. 2022: Ch. 1).

To build the community-level criminal network, we focus on the movement of organised crime offenders committing crimes in multiple locations (communities). We operationalise the concept of “community” by relying on LSOAs (Lower layer Super Output Areas) as a unit of analysis. LSOAs are statistical geospatial units specifically constructed to be as consistent in population size as possible (between 1000 and 3000 residents).

¹ When recording crime incident information, the Constabulary assigns a flag to individuals who are known to be members of an organised criminal group.

² The UN Convention against Transnational Organized Crime, first signed in Palermo in 2000 and ratified by 147 signatory countries as of October 2023, defines an organised crime group in rather broad terms as “a structured group of three or more persons, existing for a period of time and acting in concert with the aim of committing one or more serious crimes or offences established in accordance with this Convention, in order to obtain, directly or indirectly, a financial or other material benefit” (Article 2, §a). A “structured group” does not require formally defined roles, “continuity of its membership or a developed structure” (Article 2, §c). A “serious offence” is also broadly defined as any offence “punishable by a maximum deprivation of liberty of at least four years” (Article 2, §b).

LSOA boundaries are drawn following criteria of spatial proximity, natural boundaries and social homogeneity (Office for National Statistics 2022), thus showing significant overlap with residents' perception of their community (Brunton-Smith et al. 2014).

Of the initial number of 374 organised crime offenders, we retain information on 1623 crime events committed by 222 organised crime members who offended more than once over the period and in different LSOAs. Since we operationalise community-level networks exploiting information on the mobility of offenders who commit crime in multiple locations, information on offenders committing only one offence or engaging in multiple offences in the same LSOA does not contribute to the construction of the network. We also exclude from our analysis any domestic abuse offence committed by organised crime members, as these offences are not related to the operations of the criminal group.

Building organised crime mobility networks

To address the first objective of our work, we build a community-level criminal network that we define “Organised Crime Mobility Network” since the ties (i.e., network edges) linking communities (i.e., network nodes) represent the movement of an organised crime offender committing offences in different locations. The resulting network is directed and weighted, and it is built following the steps detailed below (Fig. 1 provides a graphical representation of the process of network-building). First, we consider the set of 222 organised crime members who offended in multiple LSOAs and we operationalise their “focal community” by identifying for each individual the LSOA in which they commit the majority of their crimes (i.e. their modal LSOA). We can also think of a “focal community” as the gang/organised crime group’s turf. We assume that the focal community of a gang/organised crime member is the geographical space in which they commit the majority of their offending. We then connect each focal community to all the other communities in which the same individual offended. We define these latter communities as ‘target’ communities. By repeating the same exercise for all organised crime offenders, we build the overall organised crime mobility network. This network is directed as it captures the movement of organised crime members from their focal communities (turfs) to target communities. Besides being directed, the network is also weighted as for each link between communities we capture the strength of the relation based on the number of travels there have been between the two communities (to commit a crime), which can be multiple travels of a single organised crime member or single travels of multiple individuals. In sum, our network captures directed movements between LSOAs; nodes in the networks are LSOAs and links (edges) represent the intensity of movement of organised crime members. We note that there is also a geographical component to the network, as communities (LSOAs) are spatially distributed over the Cambridgeshire county, hence network nodes (LSOAs) can be spatially placed over a map.

The final network built for this work includes information on 1073 crime events committed by 121 organised crime offenders.³ The distribution of crime types is as

³ While we believe our strategy to operationalise the idea of a turf/focal community whilst also being able to assign directionality to the movement is solid and fruitful, it nonetheless leads to discarding information on 101 offenders for whom we were unable to identify a modal LSOA due to multiple modal values. A longer time span, however, would alleviate such limitation.

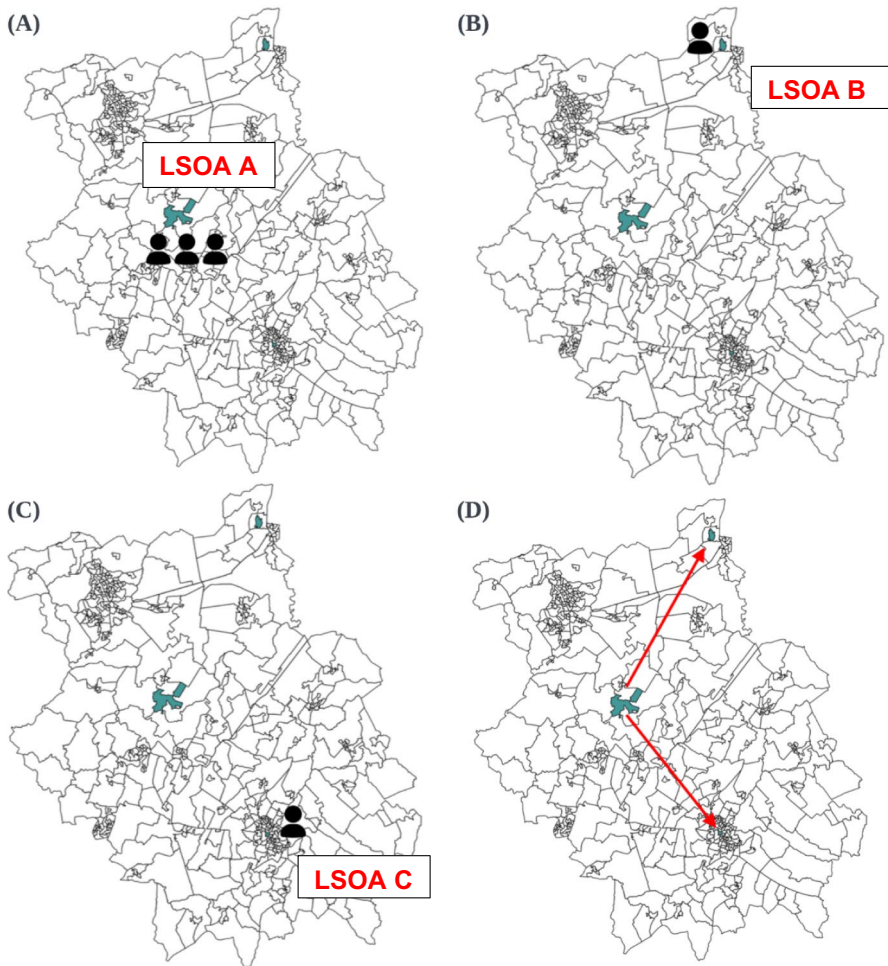


Fig. 1 Constructing links in Organised Crime Mobility Networks. Notes: This figure shows how links are built in the Organised Crime Mobility Network in Cambridgeshire. We observe Offender X committing three offences in LSOA A (Panel (A)), one in LSOA B (Panel (B)) and one in LSOA C (Panel (C)). We can identify LSOA A as the “focal community” as it is the community in which Offender X commits the majority of their offences. We then establish two directed links going from LSOA A to LSOA B and from LSOA A to LSOA C

follows: 22.4% are drug-related crime events (both possession and trafficking of any type of drugs), 16.3% concern thefts and burglaries, 6.2% robberies, 7.9% criminal damage, 13.2% relate to violent crime with injury, 7.4% to violent crime without injury and 14% to threats and harassment (the remaining crime events are mostly public order offences, frauds, arsons and weapon-related offences).

It should be noted that links in the Organised Crime Mobility Network do not capture the actual day-to-day movement of offenders as we were not able to track their physical travels across geographical areas. We proxy such movement based on

recorded crime incidents as they tell us that an individual was present in LSOA A to commit recorded crime a , and they were present in LSOA B to commit recorded crime b . This implies that they must have travelled at a certain point between A and B. We believe this is a reasonable approximation of offenders' criminal mobility. We are well aware that recorded crime is only a fraction of the actual volume of crime committed and that police data come with limitations such as the level of enforcement, policing priorities, recording practices and resource constraints (Morselli 2009; Malm and Bichler 2011; Faust and Tita 2019; Campana and Varese 2022b). In the case of Cambridgeshire, while the level of enforcement is unlikely to have drastically changed during the period under consideration, police recording practices changed in May 2018 with the implementation of a new recording system. To take this change into account, we have decided not to include any crime event registered before May 2018 in our data. More generally, police data have been widely used to reconstruct networks of co-offenders in several countries, including the United States, Canada, Sweden, Denmark, Italy and the United Kingdom (see Faust and Tita 2019 and Campana 2023 for a discussion), providing key insights on an otherwise very-hard-to-reach population.

Statistical analysis

After constructing the Organised Crime Mobility Network in Cambridgeshire, we estimate the probability of tie formation – and its strength – between any two nodes (i, j) in the network. In other words, we want to understand if certain community characteristics can explain why organised crime offenders have their turf in community i and move into community j to carry out some criminal activity. We consider the features of both the source and target nodes (community/LSOA), as well as their geographical and social distance. To estimate such effects we rely on a generalisation of exponential-family random graph models (ERGMs) to valued networks (see Krivitsky 2012). ERGMs allow to model the presence (and value) of ties based on predictors measured at the node, edge, and network level (Lusher et al. 2012; Robins et al. 2007). The dependent variable of the model is the entire network, i.e., the probability of observing the specific set of ties that form the Organised Crime Mobility Network we have built. The model can be formulated as follows:

$$P(Y = y) = \frac{h(y)\exp(\eta(\theta)g(y, X))}{k(\theta)}$$

where $y_{i,j} = y(i, j)$ is the value of the (i, j) edge, which can take the value of any natural number (or be equal to 0); θ is the vector of model coefficients and η is the function mapping such vector to canonical parameters ($\eta(\theta) = \theta$ in the linear case); $g(y, X)$ is a vector of network statistics and X represents a matrix of dyad-independent covariates; $k(\theta)$ is a normalizing constant ensuring that the above-presented probability sums to 1; and h defines the reference distribution, i.e. the distribution relative to which the exponential form is specified (Krivitsky 2012). Specifically, h sets the baseline shape of the dyad distribution, thus constraining

the parameter space; in our case, this is set to behave as a Poisson distribution with $h(y) = \prod_{(i,j)} (y_{i,j}!)^{-1}$. The models presented in this work are estimated using the *stanet* suite of packages (Krivitsky et al. 2023) of R Statistical Software (R Core Team 2021).

We estimate a set of models with the ERGM specifications discussed below (see Table 1 for the source and descriptive statistics of the variables included in the models). We first estimate a baseline model where we include a term for the sum of all dyad values (which represents the model intercept for valued ERGMs) and the geographical distance between any two nodes in the network, which is included as an edge covariate term. The geographical distance is computed as the “as the crow flies” distance on an ellipsoid between two LSOA centroids. Since each LSOA covers on average a relatively small geographical area (696 hectares), we believe it is important to control for the distance between any two of them to account for the impact of geographical proximity on the probability that an offender engages in crime in two locations. We control for the possibility of non-linearity of this relationship by including a distance squared term. Second, we estimate a model where we include a control for urban areas (both for the source and target community) to capture additional geographical dynamics.

Third, we estimate two models where we include two features of target communities – the level of deprivation and the extent of available illegal market opportunities – as node covariates. We do so to assess whether these characteristics make a community vulnerable to organised crime expansion, as suggested by previous literature (Curry & Spergel 1988; Hall 2010; Katz & Schnebly 2011; Papachristos & Kirk 2006). The two models differ only in the way geography is considered: by including the distance squared term or the urban community dummy. We operationalise the level of deprivation by relying on the score of the Income Deprivation Index from the 2019 Index of Multiple Deprivation (Office for National Statistics 2019), which measures the proportion of the population in the LSOA experiencing deprivation related to low income. In tables A1 and A2 in the Appendix, we present results from specifications considering alternative measures of deprivation. Available illegal market opportunities are proxied by the number of drug-related crimes committed in the LSOA by offenders who are not part of any organised crime group, thus measuring the extent of drug-related activities that are *not* linked to organised crime.⁴ We include the level of deprivation and the extent of available illegal market opportunities measured also for the source community to explore how these features affect the probability of tie formation when considered vis-à-vis the same characteristics of the community targeted. Additionally, we also include a variable accounting for the similarity in the demographic profile of any two pairs of communities – measured by the absolute difference in the share of the resident population born outside the UK – as we expect a tendency towards homophily when choosing a community to target. This set of source and target covariates emerged as the optimal following a model optimization procedure that considered our

⁴ We take drug-related offences, both trafficking and possession offences, as a proxy of economic opportunities stemming from drug markets. While operating at different levels in the supply chain, both trafficking and possession offences capture drug-related economic transactions.

Table 1 Source and descriptive statistics of variables included in the ERGMs

Variable	Source	Mean	St. Dev	Min	Max	N
<i>Node-level</i>						
Dummy for urban community	ONS Geography data	0.61	0.49	0	1	487
N drug-related non-OC crimes	Authors' elaboration on Cambridgeshire Constabulary data	11.37	19.16	0	206	487
Income deprivation	Office for National Statistics (2019)	0.10	0.07	0.01	0.37	487
Share population born outside the UK	UK 2011 Census	14.76	10.45	2.50	61.20	487
<i>Edge-level</i>						
Edge value	Authors' elaboration on Cambridgeshire Constabulary data	1.50	0.94	1	7	432
Geographical distance	Authors' elaboration on ONS Geography data	29.79	16.29	0.23	82.85	236,682

research objectives together with different model selection criteria (e.g., AIC, BIC), regression diagnostics, and model convergence.

Our set of ERGMs are dyad-independent models since the observed network is modelled considering node and edge features only and $g(y) = \sum_{(i,j)} y_{i,j}$, i.e., the only network-level term that we include is the sum of the edge values. ERGMs have only recently been extended to the estimation of valued networks (Krivitsky 2012; Krivitsky & Butts 2017); their current implementation in R (see Krivitsky et al. 2023) does not allow for the inclusion of the vast majority of dyad-dependent parameters that are available for binary networks to explore higher-level network structures. We decided not to dichotomise the network as discarding the value (strength) of edges would have meant losing a key piece of information to understand the movement of organised crime.

Results

We start by plotting the distribution of organised crime-related offences in Cambridgeshire (Fig. 2). Organised crime groups are more prevalent in urban rather than rural communities, with the former also displaying a higher level of criminality overall. Communities recording the highest number of organised crime-related offences between May 2018 and October 2021 are located in the central and southern areas of Peterborough (in the north-west of the county), in the central and some peripheral areas of Cambridge (south of the county), and in the urban areas of Huntington and St Ives (centre-west of the county). Some rural communities also display a non-negligible organised crime presence, especially in the area of St Neots and at the north-east of Ely (Littleport and surrounding areas).

We exploit the mobility network methodology that we have developed to map the mobility network of organised crime offenders in Cambridgeshire (Fig. 3; Figure A1 in the Appendix shows the same mobility network with the node size proportional to weighted out-degree instead of in-degree). The network includes 487 nodes (all the Cambridgeshire communities proxied by LSOAs) connected by 432 edges; 252 nodes are network isolates, meaning they are not connected to any other node in the network (Table 2). Hence, slightly less than half of the communities in Cambridgeshire are impacted by organised crime movement – either as ‘target’ areas or as ‘turf’ areas. The network density is rather low (0.002), meaning that existing links are only a minor fraction of the total possible links in the network. A visual exploration of the network suggests that, broadly speaking, organised crime offenders tend to move into communities that are within close geographical distance or, alternatively, between the major urban areas of the county. Some of the most active nodes in the network appear to act both as source and target communities of organised crime activities, receiving an inflow of organised crime offenders whose main area of operation is elsewhere and acting as turf communities for organised crime members who also offend elsewhere. Other communities have a clearer role as either a stronghold of organised crime activities or as a target of organised crime expansion. Geographically, nodes appear to be part of five clusters: Peterborough, Cambridge, Huntington and St Ives, St Neots, and Littleport. Nodes within the first three clusters appear to be well-connected with other nodes within the same cluster, but also show relevant connections with nodes in the other two clusters.

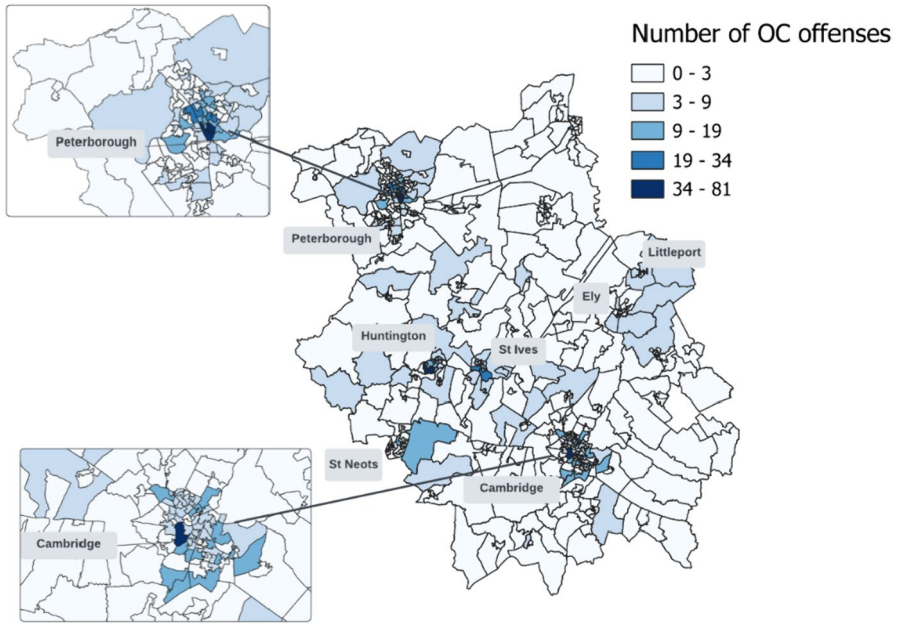


Fig. 2 Distribution of organised crime-related offences across communities in Cambridgeshire

Nodes in the St Neots and Littleport clusters have mostly local connections, with just a few links reaching out to the major hubs in the county.

Table 3 shows the results of the four valued ERGM models we ran to estimate the probability of tie formation in the Organised Crime Mobility Network. All variables included in the four models are statistically significant at the 0.1 per cent level, with the exception of the income deprivation for the target community that is significant at the 1 percent level in Model 3 and not significant in Model 4. Figure A2 in the Appendix shows the diagnostics plots.⁵ Such plots suggest that the Markov chain process (the computational process upon which the models rely to estimate the parameters) is working properly, with the sample statistics varying randomly around the observed values at each step and exhibiting a bell-shaped distribution when plotted in a non-ordered fashion.

As expected given the low density of the overall network, the coefficient for the “sum” term – which serves as the model intercept and represents the probability of the strength of a connection between any two given communities – is negative. This means that, without prior knowledge of community characteristics, if one were to randomly pick any two communities in the network, they would be more likely to show no connection between them than to have a connection of any strength. Moreover, and in line with our expectations, the negative coefficient for geographical

⁵ The statistics generated by the Markov Chain Monte Carlo (MCMC) process are plotted as a function of the iteration number (plots on the left-hand side) and in a histogram-like fashion without regard to their order in the MCMC process (plots on the right-hand side).



Fig. 3 Mobility network of organised crime offenders in Cambridgeshire. Notes: Communities (nodes) are placed on the figure based on their geographical coordinates. Edge thickness is proportional to edge weight. Node size is proportional to a node's weighted in-degree

distance (across all specifications) indicates that organised crime offenders are more likely to move into spatially close communities.⁶ In other words, geographical distance matters. Yet, it is only part of the story.

Urban communities are more likely to be both source and target of movement. Illegal market opportunities (proxied by drug-related offences) play a key role in shaping the movement of organised crime members – even when controlling for

⁶ The distance-tie probability relation appears to be non-linear as suggested by the distance squared term: lower distance predicts a tie formation but as distance decreases, the effect of distance on tie formation gets smaller (Model 1 and 3).

Table 2 Descriptive statistics of Cambridgeshire Organised Crime Mobility Network

Measure	Value
N nodes	487
N isolates	252
N edges	432
Mean edge value	1.50
Network density	0.002
Mean indegree	0.89
Mean weighted indegree	1.33

Mean (weighted) indegree equals mean (weighted) outdegree as the network is directed

geographic distance and urban characteristics. Models 3 and 4 show that communities that have more illegal market opportunities are more likely to be the target of organised crime movement (we remind the reader that illegal market opportunities are measured as the number of drug offences committed in the area that are not related to organised crime). Similarly, high illegal market opportunities increase the likelihood of an area being a source of movement. As for income deprivation, the more deprived a community is, the more it is likely to be a source of movement; at the same time, income deprivation appears to have a more marginal role (Model 3), if any (Model 4), in making a community a target of organised crime movement.⁷ We refer the reader to Tables A1 and Table A2 in the Appendix presenting models including alternative measures of deprivation and displaying results aligned with those in Table 3.

Finally, we find some homophily with respect to the socio-demographic profile of communities that are connected by organised crime movement: an increase in the absolute difference in the share of community residents born outside the UK is related to a smaller probability of tie formation between two communities.

Overall, our results suggest that organised crime offenders have their turf in the most deprived and criminally active communities of the county, and they tend to move into areas where illegal market opportunities are present and with a similar socio-demographic profile. Such movement is also more likely to happen between urban communities.

Discussion and conclusions

This work has explored how organised crime group members move across local communities. Following the principles of network analysis, this paper has offered a novel approach to empirically and quantitatively analyse movement across geographical spaces. Such an approach is based on the idea that two geographical

⁷ When introducing the urban area dummy (Model 4), the effect of income deprivation of the target community is no longer statistically significant. Further works with larger datasets will be able to tell whether this is the consequence of a lack of statistical power due to the small size of our sample or a 'true' effect.

Table 3 Estimating network ties in the Organised Crime Mobility Network

	Model 1			Model 2			Model 3			Model 4		
	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig	Coeff	SE	Sig
Sum of edge values	-3.490	0.062	***	-6.260	0.150	***	-4.562	0.120	***	-6.270	0.149	***
<i>Edge covariates</i>												
Distance	-0.221	0.007	***	-0.061	0.003	***	-0.183	0.007	***	-0.053	0.003	***
Distance squared	0.003	0.000	***				0.002	0.000	***			
<i>Node covariates</i>												
Dummy for urban community (target)				1.151	0.113	***				0.743	0.121	***
N drug-related non-OC crimes (target)							0.015	0.001	***	0.015	0.001	***
Income deprivation (target)							1.400	0.526	**	0.463	0.580	
Dummy for urban community (source)				1.200	0.121	***				0.589	0.132	***
N drug-related non-OC crimes (source)							0.021	0.001	***	0.021	0.001	***
Income deprivation (source)							2.739	0.512	***	2.267	0.563	***
<i>Homophily terms</i>												
Abs. diff. in share born outside the UK							-0.043	0.004	***	-0.043	0.004	***
AIC	-485,165			-481,450			-464,310			-462,774		
BIC	-485,134			-481,408			-464,227			-462,681		

SE=Standard Error; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

spaces (or communities) are linked if an individual has committed a crime in both areas. This relational approach is particularly suitable for large-scale police records, but it can be applied to any source of data. While in this work we have empirically shown how this approach can capture the movement of organised crime group members across the local communities in which they offend, the same approach can be scaled up to study transnational, long-distance, movement as well as scaled down focussing on smaller geographical areas (e.g., hotspots). Higher frequency (or indeed lower frequency) data sources can be also utilised. In addition, the same approach can be extended to study the movement of any offender – or it can be restricted to the movement related to specific types of crime. This approach builds on – and departs from – previous studies on community-based offending networks (see, for example, Schaefer 2012; Bastomski et al. 2017; Papachristos and Bastomski 2018).

By relying on 41 months of crime records from Cambridgeshire Constabulary, this work has first reconstructed the structure of organised crime operations across local communities in Cambridgeshire as captured by the underlying offenders' mobility network and then explored the factors underpinning such structure. The paper has shown that slightly less than half of the communities in Cambridgeshire are impacted by the movement of organised crime – as source and/or target areas. It has confirmed that geographical distance matters when organised crime members move across areas. However, and crucially, it has also shown that socio-demographic, economic and crime-related characteristics of communities play a key role – even after accounting for geographical distance and level of urbanisation. Organised crime group members appear to target communities that have higher than average illegal market opportunities. In other words, the presence of economic (market) opportunities makes a community attractive to organised crime – controlling for distance, level of urbanisation and deprivation. There is strong evidence that income deprivation increases the probability of a territory sending organised crime members while its impact on being a receiver of such movement is less clear. Finally, we find an effect of socio-demographic homophily between turf and target communities, suggesting that, when moving, organised crime group members select territories that are similar to their own. Jumping into the 'unknown' may be seen as too difficult or too risky.

In line with findings from works on the long-term expansion of organised crime activities into new (and often far away) territories (Varese 2006, 2011b, 2011a; Sciarrone & Storti 2014; Campana 2011a; 2013; Calderoni et al. 2016; Spapens 2019), we find that local conditions (demand-side factors) of a receiving territory play a role also in the context of short-distance movement, e.g., the presence of illegal markets that can be exploited (and potentially expanded) by organised crime. Clearly, the short-term, short-distance type of movement can respond more quickly to the emergence of new opportunities. The approach presented in this paper can be expanded by adding a time dimension to both organised crime movement and the emergence of local conditions to further explore the dynamic features of such movement. Adding a time dimension would be particularly important in shedding further light on the causal mechanisms underpinning movement, including whether such movement remains a short-term endeavour

or morphs into a fully-fledged expansion of organised crime activities into new territories.

Our work has also contributed to prior research exploring the local determinants and impact of neighbourhood co-offending networks (e.g., Bastomski et al. 2017; Schaefer 2012). In line with results from Schaefer (2012), we find that offender mobility networks are also driven by spatial and social proximity. Our work adds to the literature on neighbourhood offending networks by showing that neighbourhood characteristics impact the spatial criminal activity of individual offenders (and organised crime groups) besides the formation of co-offending links across neighbourhoods.

Our analysis comes with some limitations. Firstly, police records do not capture the full extent of criminal activities (the ‘grey figure’ of crime) and might be subject to errors, omissions and biases. These biases are common to all works using police data. Our analysis presents a handful of additional, study-specific, limitations. Firstly, to build the mobility networks one has to first identify a focal community for each offender. We operationalised the focal community (‘turf’) as the area where the individual has committed the highest number of recorded crimes. In our case, this strategy has led to a drop in the number of organised crime offenders that entered the analysis (losing around 27% of registered organised crime offenders). Future works might wish to address this limitation by increasing the granularity of their data and/or identifying turf areas based on intelligence. A longer time span could also alleviate this limitation. Secondly, our work assumes that each crime committed by an organised crime member is carried out on behalf of the group. We took great care in excluding offences related to domestic abuse to mitigate this limitation, yet some offences committed by organised crime members might not have been sanctioned by their group. On balance, however, we believe it is reasonable to assume that offences committed by organised crime members are more likely than not to be sanctioned by their group. Finally, future studies might wish to replicate our approach using data from larger jurisdictions with a larger, more active, set of organised crime members to see if our mechanisms hold in areas with hardened, longer-standing, organised crime groups. By relying on larger datasets and taking advantage of future developments in the applications of ERGMs to valued networks, future research can expand the set of network effects and explore higher-order (dyad-dependent) effects. Moreover, replicating this study in other jurisdictions will be particularly important to ascertain the external validity of the results presented in this work.

Yet, we believe the approach presented in this work remains of great value to systematically capture organised crime – and more generally offenders’ – movement across communities, and then quantitatively examine the drivers of such movement. Crucially, it adopts a relational approach to study an intrinsically relational phenomenon, hence offering a better match between the phenomenon we are interested in and the way we study it. The approach presented in this paper has also the great advantage of being scalable and portable across contexts. Furthermore, this work has pointed to the importance of analysing relational (structural) characteristics of movement together with spatial, socio-demographic, economic and crime-related characteristics of the communities affected by such movement. The goal of this paper was to offer a first exploration of the mechanisms underpinning the local movement of organised crime members as much as to offer a methodological approach that can be applied to other contexts and to datasets that are larger, more granular and covering longer periods.

Finally, we believe our relational approach – and thinking in terms of source and target areas – can be relevant for law enforcement agencies and policy makers. It can allow them to map the movement of organised crime members (and, by extension, their groups), across territories and – if repeated over time – to be able to pick up emerging trends, including changes in the strength of movement and patterns. Law enforcement might also restrict the focus of our approach to specific types of crime, e.g., the flows of drug offenders or violent offenders. Knowing how organised crime, drug dealing, violence or any other crime spreads across communities can help devise short-term and medium-term interventions. In addition, the inclusion of socio-demographic and economic characteristics of communities, besides crime-related ones, can help devise longer-term (structural) interventions. If the exercise is repeated over time, our approach can help law enforcement and policy makers alike to track the effectiveness of their interventions, be them short, medium or long term.

Appendix



Fig. 4 Mobility network of organised crime offenders in Cambridgeshire. Notes: Communities (nodes) are placed on the figure on the basis of their geographical coordinates. Edge thickness is proportional to edge weight. Node size is proportional to a node's weighted out-degree

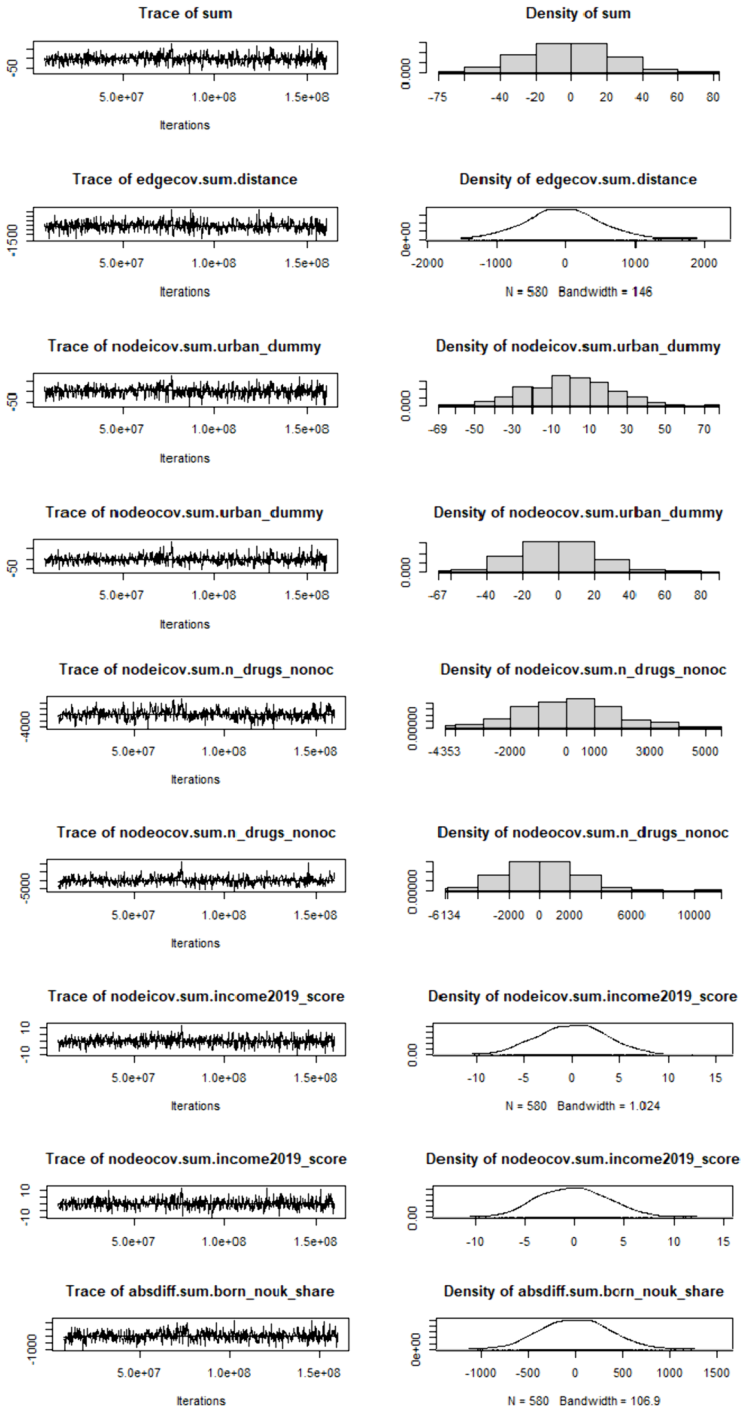


Fig. 5 MCMC diagnostics for the full ERGM model (Model 4)

Table 4 Estimating network ties in the Organised Crime Mobility Network: alternative measures of deprivation (I)

	Model 1			Model 2			Model 3		
	Estimate	SE	Sig	Estimate	SE	Sig	Estimate	SE	Sig
Sum of edge values	-4.592	0.117	***	-4.443	0.130	***	-4.425	0.103	***
<i>Edge covariates</i>									
Distance	-0.183	0.007	***	-0.185	0.007	***	-0.183	0.007	***
Distance squared	0.002	0.000	***	0.002	0.000	***	0.002	0.000	***
<i>Node covariates</i>									
N drug-related non-OC crimes (target)	0.015	0.001	***	0.016	0.001	***	0.015	0.001	***
Index of Multiple Deprivation (target)	0.009	0.003	**						
Employment deprivation (target)				1.827	0.755	*			
Education deprivation (target)							0.003	0.002	
N drug-related non-OC crimes (source)	0.021	0.001	***	0.021	0.001	***	0.021	0.001	***
Index of Multiple Deprivation (source)	0.018	0.003	***						
Employment deprivation (source)				2.236	0.802	**			
Education deprivation (source)							0.012	0.002	***
<i>Homophily terms</i>									
Abs. diff. in share born outside the UK	-0.044	0.004	***	-0.041	0.004	***	-0.044	0.004	***
AIC	-463,520			-462,846			-464,353		
BIC	-463,437			-462,763			-464,270		

SE = Standard Error; * $p < .05$, ** $p < .01$, *** $p < .001$

Table 5 Estimating network ties in the Organised Crime Mobility Network: alternative measures of deprivation (II)

	Model 1			Model 2			Model 3		
	Estimate	SE	Sig	Estimate	SE	Sig	Estimate	SE	Sig
Sum of edge values	-6.282	0.154	***	-6.172	0.157	***	-6.214	0.145	***
<i>Edge covariates</i>									
Distance	-0.053	0.003	***	-0.054	0.003	***	-0.053	0.003	***
<i>Node covariates</i>									
Dummy for urban community (target)	0.728	0.114	***	0.766	0.111	***	0.762	0.114	***
N drug-related non-OC crimes (target)	0.015	0.001	***	0.015	0.001	***	0.015	0.001	***
Index of Multiple Deprivation (target)	0.004	0.003							
Employment deprivation (target)				0.337	0.802				
Education deprivation (target)							0.000	0.002	
Dummy for urban community (source)	0.562	0.120	***	0.676	0.117	***	0.582	0.122	***
N drug-related non-OC crimes (source)	0.021	0.001	***	0.021	0.001	***	0.021	0.001	***
Index of Multiple Deprivation (source)	0.015	0.003	***						
Employment deprivation (source)				1.213	0.780				
Education deprivation (source)							0.010	0.002	***
<i>Homophily terms</i>									
Abs. diff. in share born outside the UK	-0.044	0.004	***	-0.041	0.004	***	-0.044	0.004	***
AIC	-465,517			-464,811			-467,710		
BIC	-465,423			-464,717			-467,616		

SE = Standard Error; * $p < .05$, ** $p < .01$, *** $p < .001$

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