Journal of Quantitative Criminology
https://doi.org/10.1007/s10940-022-09540-1

ORIGINAL PAPER

When Things Turn Sour: A Network Event Study of Organized Crime Violence

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Accepted: 29 November 2021

Abstract

Objective This study examines the mechanisms underpinning the emergence of violence among individuals in the organized crime milieu.

Methods Relying on criminal event data recorded by a UK Police Force, we apply a longitudinal network approach to study violent interactions among offenders. The data span the period from 2000 to 2016 and include 6,234 offenders and 23,513 organized crime-related events. Instead of aggregating these data over time, we use a relational event-based approach to take into consideration the order of events. We employ an actor-oriented framework to model offenders' victim choices in 156 violent events in the OC milieu.

Results We find that the choice of offenders to target a particular victim is strongly affected by their mutual history. A violent act is often preceded by a previous act of violence, both in the form of repeated violence and reciprocated violence. We show that violence is strongly associated with prior co-offending turning sour. We uncover a strong effect for previous harassment as a retaliation *cum* escalation mechanism. Finally, we find evidence of conflicts within organized crime groups and of violence being directed to offenders with the same ethnic background.

Conclusions Relational effects on victimization are consistently stronger than the effects of individual characteristics. Therefore, from a policy perspective, we believe that relational red flags (or risk factors) should play a more central role. A focus on harassment could be valuable in the development of an early intervention strategy.

Keywords Organized crime · Gangs · Violence · Harassment · Co-offending · Social network analysis · Longitudinal modeling · Event-based analysis

NN was supported by the CMU Berkman Faculty Development Fund. PC has received support from the Leverhulme Trust (Research Grant RPG-2018-119). We gratefully acknowledge both sources.

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Published online: 12 April 2022

Introduction

The use of violence – or its credible threat – is a constitutive element of organized crime (Reuter and Rubinstein 1978, p. 46; Gambetta 1993, pp. 40-43; see also HMG 2018, p. 11, for a practitioners' view). Organized crime violence is often a cause of concern among citizens, law enforcement agencies and policy-makers. An obvious example is Mexico, where between half and two-thirds of homicides are thought to be linked to organized crime (Heinle et al. 2013, pp. 18-21): this translates into around 10,000 homicides per year between 2009 and 2016 (Heinle et al. 2017, p. 13). Organized crime violence, however, does not just occur in Mexico. While countries characterized by a high level of violence have attracted media and scholarly attention, the presence of organized crime violence is by no means limited to those areas. According to the United Nations Office on Drugs and Crime (UNODC 2019, p. 12), roughly 65,000 homicides every year have been estimated to be related to organized crime and gangs over the period 2000 to 2017, and 19% of all global homicides in 2017 have been linked to organized crime and gangs. The impact of organized crime groups – and the violence associated with their operations – on the lives of individuals and local communities cannot be underestimated also in countries that are not commonly associated with severe organized crime problems (Campana and Varese 2018).

In the United Kingdom, for instance, the Director-General of the National Crime Agency, Lynne Owens, recently stated that violence related to serious and organized crime "affects more UK citizens, more often, than any other security threat" and "leads to more deaths in the UK each year than all other national security threats combined" (Dearden, 2018). The city of Malmö, in Sweden, has recently experienced waves of organized crime violence, including shootings and bombings – a situation similar to what Gothenburg, the second-largest city in the country, has also witnessed (Isenson 2019; Gothenburg struggling to stop gang crime). While violence is a constitutive element of organized crime, the conditions under which such violence might erupt remain a still under-explored issue, particularly from an empirical and quantitative angle. In this paper, we seek to further explore this issue by focusing on micro-level mechanisms that might lead to the emergence of organized crime violence in a given setting. In other words, what are the drivers of violence within what we can call the organized crime 'milieu'?

To answer this question, we will take a social network analysis approach. Such an approach will allow us to jointly consider individuals and their relations when looking for clues about what might increase the likelihood for an individual who is part of the organized crime milieu to become a victim of violence. We believe that modeling relations directly is particularly important if we are to further our understanding of organized crime violence as both organized crime and violence are inherently relational phenomena. To explore victimization relations, we leverage on a novel data set we obtained from a UK Police Force which includes 23,513 organized crime-related events logged by the police during the period 2000–2016 (see Sect. "Organized Crime in Thames Valley" below for further details).

The paper continues as follows: the next section further explores the issue of violence from a relational perspective, discussing the (so far) limited body of research exploring organized crime violence. Next, we discuss our strategy to model victimization, proposing a model that extends a class of existing network event models for potentially group-based action. Section "Organized Crime in Thames Valley" presents the context of the study, i.e., the jurisdiction of Thames Valley Police in the United Kingdom, including a description of the organized crime milieu in the area, the co-offending networks at play, and the use of violence. The results of our analyses are outlined in Sect. "Results". Finally, Section "Discussion and Conclusions" concludes with a discussion of the results and policy implications.

Networked Violence

Violence is an inherently relational act as, by definition, it is committed by an actor against another actor. As such, the emergence of violence is best studied from a relational perspective. In this paper, we define a network by a finite set of actors and the relations among them (Wasserman and Faust 1994, p. 20). This is different from a competing view, also present in organized crime studies, which sees networks as a specific form of organization: see Campana (2016) for a discussion of this debate in criminology. Following Papachristos (2009) and Bichler et al. (2019), we can term a network-based approach to the study of violence as 'networked violence'.

More generally, the relational approach taken in this work is in line with Donald Black's idea that social structures are important to understand how violence is generated (Black, 2004b). We echo here his 'social geometry of conflict' (Black 2004b, see also Campbell and Manning 2018), and his emphasis on relational distance as an important element in explaining conflict (Black 1976, also Black 1983). While Black's insights have inspired an important qualitative body of works exploring the mechanisms leading to violent conflicts, including violent predation and violent retaliation (Topalli et al. 2002; Jacques and Wright 2008; Jacobs and Wright 2006; Jacques et al. 2014), and a smaller set of quantitative works (Jacques and Rennison 2013a, b; Phillips 2003; Bouchard et al. 2021), the formal application of network analysis to fully capture the structural (relational) dimension of violence has lagged behind.

Among the handful of studies to have applied formal network modeling to the study of violence, Papachristos et al. (2012) looked at the risk of gunshot injury based on one's 'high-risk' social network; Schreck et al. (2004) explored violent victimization in delinquent peer groups; Petering et al. (2014) studied violence in the social networks of homeless youth; Bond and Bushman (2017) investigated the contagion of violence among US adolescents; and Sijtsema et al. (2010) focused on aggression in adolescents. The application of social network analysis to study organized crime violence has been rather limited.

Kennedy et al. (1997) pioneered the use of social network analysis to map gang-level conflicts in Boston. Using descriptive network measures, they identified which gangs were more central (in terms of degree and eigenvector centrality) in the undirected network of conflicts among gangs, with the idea that the most central gangs would be a primary target for focussed intervention. Using data from Los Angeles, Radil et al. (2010) and Tita and Radil (2011) expanded on the gang-level analysis of conflict by integrating geo-spatial measures and social network measures (see also Randle and Bichler 2017). Through a series of spatial dependence models, Tita and Radil (2011) showed that considering the socio-spatial dimensions of gangs, including their matrix of rivalries, is a superior strategy than just looking at adjacency-based measures of gang territories.

The idea that relations matter when explaining violence has been further explored in a series of empirical studies carried out in the US by Papachristos and his colleagues. Papachristos (2009) modeled gang-related homicides using incident-level data from the Chicago Police Department between 1994 and 2002. In this work, an instance was defined as gang-related if either the victim or the offender had been identified as gang member. The longitudinal nature of the evidence was broken into three cross-sectional data sets for the years 1994, 1998 and 2002. This study found that “gang murders create an enduring social structure that is produced through dominance disputes and the social contagion of prior interactions” (Papachristos 2009, p. 115). Papachristos et al. (2013) expanded the analysis of gang-level violence to two cities: Chicago and Boston. They relied on cross-sectional exponential-family random graph models (ERGMs) to predict, respectively, the 2008–2009 murders network in Chicago and the 2009 fatal and non-fatal shootings network in Boston. They found that prior conflicts tend to drive violence: “a history of conflict between groups exerts an effect above and beyond spatial proximity” (Papachristos et al. 2013, p. 439). This holds true also when controlling for gangs’ racial and ethnic composition as well as neighborhood structural characteristics. Papachristos et al. (2015) built a co-offending network based on Chicago Police arrest data from 2006 to 2012 and predicted gunshot victimization using a series of logistic regression models. They found that gang members, who constituted about 39% of the sample, were three times more likely to be a victim of gunshot and that such victimization increased with exposure to violence in one’s social network (Papachristos et al. 2015, p. 146). Papachristos et al. (2015) studied one year of gunshot injuries in Newark, New Jersey, and found that the risk of being a victim of a fatal or non-fatal gunshot increases the closer one is to a gang member in a co-offending network: for a non-gang member who is connected to a gang member such probability is 94% higher (Papachristos et al. 2015, p. 643). In their analysis, they treated their longitudinal evidence as a single cross-sectional data set and used logistic regression models.

A few studies have taken a different approach and, instead of explaining the emergence of violence, have looked at violence as a mechanism to foster cooperation both within and across OCGs. Campana and Varese (2013) have looked at the role of violence within, respectively, a Russian Mafia group and a Camorra group using a network analysis of phone conversations wiretapped by the police while Coutinho et al. (2020) considered collaboration across members of different Outlaw Motorcycle Gangs in Alberta, Canada. Both studies have found that violence homophily (i.e., having been jointly involved in an act of violence) positively impacts criminal non-violent relations. In this work, we focus on explaining the emergence of violence and we leave aside the separate issue of explaining collaboration.

In our study, we focus on violence within the organized crime milieu. We define this ‘milieu’ as all the individuals who have at any point co-offended with one or more organized crime group (OCG) members. Our approach models any act of violence instigated by an OCG member against either another OCG member or another participant in the organized crime milieu. Note that this is different from – and complementary to – studying the search for suitable violent co-offenders, investigated for instance by McCuish et al. (2015). Our definition of ‘milieu’ combines the idea of co-offending (as in McGloin and Nguyen 2013; Morselli et al. 2015; Hashimi et al. 2016 and Charette and Papachristos 2017 among others) with a seed-based extraction targeted to OCG members similar to Ouellet et al. (2019) (see also below).

We do not model violence against by-standers or, more generally, against victims with no recorded involvement in criminal activities. In this, we follow the idea of ‘systemic violence’ elaborated by Goldstein (1985) (see also MacCoun and Reuter 2001, 2001; Andreas and Wallman 2009; Bouchard et al. 2021). However, we move beyond the original scope of Goldstein’s work by considering not just violence associated to the pattern of interactions within the system of drug distribution, but all criminal interactions.

In our work we will seek to answer the following question: why does an OCG member decide to victimize person X instead of all the other individuals also present in the OC milieu at the time he/she makes his/her choice? We will be looking at the effect of individual characteristics of the victims, such as their personal criminal history (e.g., past violent events both as victim and as perpetrator) as well as their gender, OCG membership and ethnicity. Crucially, we will also be looking at joint (relational) characteristics shared by both offenders and victims, such as their prior co-offending, shared ethnicity and shared OCG group membership. Finally, we will look at the effect of mechanisms such as repeated violence, escalation (increasing the severity of the attack from harassment to violence), retaliation (responding to a previous violent act) and retaliation *cum* escalation (responding to harassment with violence).

In this paper, we build on the existing literature on 'networked violence' and advance the current scholarships on organized crime violence in four different ways. Firstly, we take time into consideration and model time-stamped event data *directly* using an event-based model. Secondly, we model victimization choices using an actor-oriented approach specifically designed for organized crime, i.e., modeling the possibility of group co-offending. Thirdly, we move beyond homicides and shootings to include a more comprehensive conceptualization of violence (see Sect. "Analytic Plan" below for details). Finally, we offer the first study of organized crime violence in a setting not characterized by high intensity of generalized violence, thus advancing a complementary view to that captured in places such as Chicago (and arguably more similar to the situation faced by many locales, at least in Europe).

Next, we turn to present in greater detail our modeling approach.

Modeling Victimization

As discussed in the previous section, relational data among offenders derived from sources such as police records or wiretapped phone calls are often aggregated over time when analyzed in the form of co-offending networks. By treating longitudinal data in a cross-sectional way, one creates a single network summarizing all known connections between the individuals under study. Much can be learned from such a representation, for instance how cohesive the criminal network is and whether some individuals are more central than others - characteristics that can shed light on how the criminal underworld operates. However, there are also important limitations to this approach. Firstly, it disregards a considerable amount of valuable information related to time. Secondly, if the time periods under consideration are relatively long, collapsing the data into a single cross-sectional data set might create an artificial network that hardly matches reality (Diviák 2019; Campana and Varese 2020). Therefore, treating such data longitudinally places us in a much better position. In many secondary data sources, exact times are associated with individual data entries, whether these are phone calls or police-recorded criminal events. These timestamps allow us to study criminal networks at a much granular level, i.e. at the relational event level.

In this paper, we use data extracted from police records to study victimization among offenders. For this, we employ a relational event framework in which the units of analysis are instances of social (offending) behavior between individuals (Butts 2008; Stadtfeld 2012). By considering the sequentiality of events we can assess the role of offenders' and victims' individual *as well as* relational criminal history in explaining a victimization event. The model proposed here is based on the intuition that an offender or a group of offenders *chooses* to victimize a certain individual, and not others. Models of choice among a finite set of possibilities have a rich history in econometrics (e.g., McFadden 1974; Pudney

1989). The idea that networks are the result of actions of individual network actors was first proposed in the stochastic actor-oriented models for network evolution (Snijders 2001; Steglich et al. 2010; Niezink and Snijders 2017). Later, as more and more network event stream data started to become available, this idea was extended for relational event data (Stadtfeld and Geyer-Schulz 2011; Stadtfeld et al. 2017).

Broadly speaking, there are two components to actor-oriented relational event models: (a) opportunity (i.e., who initiates the next event and when) and (b) choice (i.e., who will be targeted as 'receiver' in the event). Here we focus on the second. Suppose we want to study victimization events $1, \ldots, K$ among a group of individuals $\mathcal{N} = \{1, \ldots, n\}$. Let t_k denote the time at which event k takes place, and denote the set of individuals involved as offender by $\mathcal{O}_k$ and as victim by v_k. Due to the covert nature of criminal activities, it is unknown who can be considered part of the criminal system at a certain point in time. Moreover, the composition of the system may change over time, which is especially relevant if a study spans multiple years. In other words, the exact delineation of $\mathcal{N}$ is unknown and individuals in $\mathcal{N}$ may be active in the criminal system only during a specific period. However, police records have the advantage of providing evidence on the fact that at the time of an event k, offenders $\mathcal{O}_k$ are known to be part of the system. We therefore approximate the period in which individual v was active by

$$\text{active}(v) = \left[t_{\text{first}(v)} - \Delta t, t_{\text{last}(v)} + \Delta t\right], \tag{1}$$

where first(v) and last(v) are the indices of the first and last event individual v was involved in and Δt is a time interval to be specified. For the definition of active(v), we do not restrict ourselves to merely the victimization events, but use all available information, i.e., every time an offender has entered the police recording system for a law-breaching behavior (including as a suspect). We estimate the set of individuals who are active in the criminal system at time t by

$$\mathcal{A}_t = \{v \mid t \in \text{ active}(v)\}\,. \tag{2}$$

We will exclude individuals from this set whose death by homicide was reported in police records before time t. No further information is available about people leaving the system because of other causes, such as relocation or natural death.

Further, suppose we consider p individual covariates and q dyadic covariates (that is, covariates pertaining to pairs of individuals). Let vector $\boldsymbol{x}_i^k = (x_{i1}^k, \ldots, x_{ip}^k)$ contain the individual covariates of person i at the time of event k. The $n \times p$ matrix $\boldsymbol{x}^k$ summarizes the covariates of all individuals at the time of event k. These variables can be constant (e.g., dummy variables coding ethnicity) or time-varying (e.g., the number of times individual i has committed a violent act prior to event k). The dyadic covariates at the time of event k are summarized in $n \times n \times q$ array $\boldsymbol{w}^k$ with its entries w_{ijl}^k denoting the value of attribute l of the relation of individual i with individual j at time t_k. These variables too can be constant (e.g., i and j having the same ethnicity) or time-varying (e.g., the number of times individuals i and j have co-offended prior to event k). In this paper, we focus on individual and dyadic covariates only, but the model elaborated below can be extended straightforwardly to include higher-order relational mechanisms (e.g., the tendency to not co-offend with prior co-offenders' victims). Let $\boldsymbol{w}_{\mathcal{G}}^k$ denote the $|\mathcal{G}| \times |\mathcal{G}| \times q$ array consisting of the dyadic variables among the individuals in group $\mathcal{G}$ at the time of event k, with $|\mathcal{G}|$ the size of group $\mathcal{G}$.

We use a conditional logit model to model the probability that offenders $\mathcal{O}_k$ at event k select victim i_k:

$$p(i_k \mid \boldsymbol{\beta}, \mathcal{O}_k, \boldsymbol{x}^k, \boldsymbol{w}^k) = \frac{\exp\left(\boldsymbol{\beta}^\top \boldsymbol{s}(\boldsymbol{x}^k_{i_k}, \boldsymbol{w}^k_{\{i,\mathcal{O}_k\}})\right)}{\sum_{j \in \mathcal{A}_{t_k} \setminus \mathcal{O}_k} \exp\left(\boldsymbol{\beta}^\top \boldsymbol{s}(\boldsymbol{x}^k_j, \boldsymbol{w}^k_{\{j,\mathcal{O}_k\}})\right)}, \quad i_k \in \mathcal{A}_{t_k} \setminus \mathcal{O}_k, \tag{3}$$

where $\mathcal{A}_{t_k} \setminus \mathcal{O}_k$ denotes the individuals at risk of being victimized – the offenders choose to victimize someone not in the offender group who is currently active in the criminal system. Expression (3) can be interpreted from a utility maximization perspective (McFadden 1974), where we assume that offenders $\mathcal{O}_k$ choose their victim by maximizing the utility function given by $\beta^\top s(\cdot)$ plus a random term with standard Gumbel distribution.

In existing actor-oriented network models, there usually is a single sender and a single receiver involved in a social tie or in an event (Snijders 2001; Stadtfeld 2012). In the context of criminal offending, however, more than one individual can be involved as offender. To take this into consideration, the model proposed here takes the statistics $s(\cdot)$ to be functions of characteristics of the offender group (or solo offender) and the victim.

Estimation

We estimate parameters $\boldsymbol{\beta}$ using maximum likelihood estimation. Since we are only focusing on modeling the victim choices and not the timing of the victimization events, the likelihood is

$$L(\boldsymbol{\beta}) = \prod_{k=1}^{K} p(i_k \mid \boldsymbol{\beta}, \mathcal{O}_k, \boldsymbol{x}^k, \boldsymbol{w}^k). \tag{4}$$

This likelihood is equal to the partial likelihood of a full relational event model (e.g., Stadtfeld and Block 2017) and to that of a special case of a Cox proportional hazards model (Aalen et al. 2008). It follows from Perry and Wolfe (2013) that, under some technical assumptions, the maximum likelihood estimator (MLE) based on (4) is consistent, and that the corresponding covariance matrix can be estimated by the inverse of the observed Fisher information matrix, the negative Hessian of $\log L(\boldsymbol{\beta})$ evaluated at the MLE.

Organized Crime in Thames Valley

In this work, we study organized crime violence in the jurisdiction of the largest non-metropolitan police force in England and Wales: Thames Valley Police (TVP). TVP covers a population of about 2.1 million people in the South East of England and includes cities such as Oxford (pop. 170,350 in 2016), Reading (pop. 255,615), Milton Keynes (pop. 182,265), Slough (pop. 155,749) and High Wycombe (pop. 106,996) (Office for National Statistics 2018). In terms of OCGs per million population, TVP ranked around average across all forces in England and Wales (HMIC 2017). For our study, we rely on a novel data set that includes all police-recorded events in which at least one OCG member was involved as well as their co-offenders between 2000 and 2016. We use the (very sparse) data we have on events before 2000 only to inform the start time of offenders' activity in the criminal milieu.

Groups are classified as organized crime by TVP following the guidelines included in the 'Organised Crime Group Mapping Manual'. Such definition of organized crime is rather broad and thus able to include a wide variety of groups in terms of both size and activities: "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." (NCO 2010, pp. 15).

The TVP definition of organized crime is in line with the national UK definition adopted by the National Crime Agency Agency as well as the definition set out in the 2000 UN Protocol on Transnational Organized Crime (UN 2000), which has over the years become a template for many definitions across the world. The average size of the organized crime groups operating in the TVP jurisdiction is 5.4 members, and the largest group includes 21 members (the average size is in line with results from the US and Canada: see Bouchard and Morselli (2014) for a survey of such studies). It is important to note that what is classified as 'organized crime' by UK police forces may be classified as 'gangs' by their American counterparts – for a further discussion on the concepts of organized crime and gangs, we refer to Decker and Pyrooz (2013), Campana and Varese (2018).

Offenders are then classified by the police as member of an OCG on the basis of a value judgment by analysts and police officers, which in turn is based on confidential evidence, official police records and members' self-identification. As we only obtained access to fully anonymized police records – and not to confidential intelligence about groups and individuals – in this paper we can only rely on police-based membership attribution as well as police-based groups' boundary specification; this is a rather common strategy adopted by scholars when using police-generated data to study organized crime networks (see, for example, Papachristos et al. 2013, 2015; Ouellet et al. 2019; Calderoni 2012; Varese 2013; Campana and Varese 2013). Police data come with well-known limitations: they might be influenced by the level of enforcement, policing priorities, recording practices and resource constraints (Morselli 2009; Malm and Bichler 2011; Campana and Varese 2012; Faust and Tita 2019; Campana and Varese 2020). Yet, Faust and Tita (2019), Campana and Varese (2020) show that this source of data can still provide insightful information that is otherwise not accessible to researchers. The studies discussed in "Networked Violence" testify to the wide use of police data in studying networked violence.

The data provided to us were extracted from the police data system using OCG members as seed individuals. This means that we have information on all the events in which at least one OCG member was involved, either as offender or victim, together with information on other offenders and victims connected to these events. This gives us complete network information – as far as the police coverage goes – on links (a) among OCG members and (b) between OCG members and non-OCG members. Records of offenses perpetrated by non-OCG members in which no OCG member was involved do not appear in the data. All personal information has been fully anonymized by the police prior to data sharing.

Our data set includes 23,513 organized crime-related events and 15,895 individuals. In this paper, we focus on the 6,234 individuals who appeared as offender in the data at least once. We will refer to these individuals as the organized crime 'milieu' (OC 'milieu') – all of them were either an OCG member or had co-offended with one. The 'events' included in our data set are not limited to instances where an individual was arrested. Rather, they include instances where a person was simply 'detected' as well as when he or she was considered a 'suspect', or 'charged'. We have also included instances in which 'no further action' was taken. Additionally, we have events labelled as 'Postal requisition' (a type of summon) and a residual 'other' category. The nature of events is the broadest possible based on police records, and offer the best proxy for a criminal milieu short of access to confidential intelligence information.

Most likely, offenders in our data are not part of the OC milieu for the entire period of 16 years that our data cover. To account for this change in composition of the OC milieu, we define the time during which an individual is active in the milieu as the period between two years before the individual's first occurrence in the data and two year after the final occurrence. This is equivalent to setting $\Delta t = 2$ in expression (1).[1] Since a time-window approach has never been applied to this type of data or analysis, we broadly follow Pyrooz, Sweeten, and Piquero (2013, pp. 259) and Ouellet et al. (2019, pp. 12) in setting the ± 2 year time-window in our models.

Operationalizing Violence

In this paper, we take a broader approach to violence that goes beyond homicides and shootings. Our operationalization of violence encompasses the following crime types: murder and attempted murder; assault wounding others (endangering life), assault with injury and assault occasioning actual bodily harm; grievous bodily harm with and without intent; and manslaughter. It also includes racially aggravated actual bodily harm and racially aggravated grievous bodily harm. We treat harassment and threats separately from violence.

In our data set, there is a total of 2,047 events of violence against a person recorded between 2000 and 2016. Of these 2,047 events, 407 events involve a victim who is also in the OC milieu.[2] Although domestic violence did occur in the OC milieu, we disregard it in this study (112 events) because of its different nature and underlying mechanisms.[3] The OCG nature of the offender(s) and victim involved in the 295 non-domestic violent events is summarized in Table 1. We focus on the 156 OCG-instigated violent events (that is, events instigated by an OCG offender or an offender group with at least one OCG member) in our statistical analysis, since we know their complete victimization behavior within the OC milieu. Violent events can be thought of the result of the victim choice process undertook by an offender or group of offenders and, as such, they constitute our network dependent variable. Information on violence directed outside the OC milieu as well as information on violence from non-OCG members to OCG members is only incorporated in covariates.

[1] Our data do not give information about how long an arrest lasted and whether the individuals were subsequently convicted. If available, this information could be leveraged in the definition of when an individual is active.

[2] For seven violent events, police records indicate that they involved multiple victims in the OC milieu. We scrutinized these events further and found that only one was the actual victim ('aggrieved' in police terminology) while the others were either a vulnerable witness or a person reporting the crime. We decided to consider the 'aggrieved' individual as the primary victim and to disregard the other actors.

[3] We gratefully acknowledge one of the reviewers who advised us to look into domestic violence. Violent events in the data were not originally coded as domestic versus non-domestic. However, the data did contain (non crime) domestic incidents as a separate category of events. We therefore defined a violent event to be domestic if the victim and (one of) the offender(s) had been co-involved in a (non crime) domestic incident. Such events were then removed from the analysis.

Table 1 Number of violent events in the criminal milieu

	Victim	
	OCG member	Non-OCG member
OCG-instigated	27	129
Non OCG-instigated	139	–

Of the 156 OCG-instigated violent events, 27 targeted OCG members and 129 targeted non-OCG members. Violence among non-OCG members is not included in the data.

Analytic Plan

To explore the antecedents of violent victimization in the OC milieu, we apply the relational event framework discussed in Sect. "Modeling Victimization" to the data on organized crime in Thames Valley. That is, we model the choices of offenders and offender groups to target a particular victim in the OC milieu. In our analysis, we consider three models with different individual and network predictors.

In Model 1, the baseline model, we include individual characteristics of the victim, such as gender, ethnicity, an indicator for OCG membership, and whether he or she shares the same ethnicity with the offender(s). We also include a variable capturing whether the victim is a member of the same OCG as the offender(s). We treat a violent event with multiple offenders as follows: if more than half of the individuals in the offender group have the same ethnicity as the victim, we set the 'same ethnicity' variable to 1, otherwise to 0.[4] For OCG membership, if any of the individuals in the offender group is part of the same OCG as a victim, we set the 'same OCG' variable to 1.

In Model 2, we add covariates that take into account the individual criminal history of the victim, that is, whether or not a victim has ever participated in various types of criminal activities (fraud, theft, etc.). We choose to code an individual's criminal history in binary terms instead of how often an individual has participated in these events to minimize biases associated to the nature of police records, and thus obtain a more robust measure for our models. In Model 3, we add joint relational information on the victims' *and* offenders' criminal history. We include a binary covariate indicating whether anyone from the offender group has ever co-offended with the victim on any type of criminal activity. We also include a variable capturing whether the victim has ever been victimized by anyone in the offender group before (repeated violence) or has ever victimized anyone in the offender group (reciprocated violence). We include the same variables for harassment, considering whether the victim has ever been harassed by anyone from the offender group in the past or has harassed any of the offenders.

[4] We set the same ethnicity variable to 0 for any comparison with an individual whose ethnicity was not identified. Since 0 can represent a pair having both the same ethnicity as well as a potentially yet unknown different one, this setup will make it more difficult to detect a same ethnicity effect.

Results

We now turn to present the results of our analysis, beginning with a description of the OC milieu in Thames Valley and the violence associated.

The OC Milieu

Of the 6,234 individuals observed in the OC milieu, 833 (13.4%) are classified as OCG member, operating in 164 police-identified groups, and 5,401 (86.6%) as non-OCG member. These individuals were likely not part of the milieu during the entire period of 16 years, and Figure 1 (left) shows the numbers of the OCG and non-OCG members active in the OC milieu over time, estimated according to definition (1), with $\Delta t = 2$ years. The number of OCG members in the milieu is fairly stable during the whole period. The number of non-OCG members, however, increases over time as more events are recorded from 2005 on. Figure 1 (right) shows the number of OCG-instigated violent events by year, which reflects this trend.

Table 2 presents a summary of gender, ethnicity and activity statistics for both OCG members and non-members. The overwhelming majority of OCG members are male (93.2%); this percentage is slightly lower for non-OCG members (84.5%). To code ethnicity, we created a simplified categorization relying on police-reported ethnicity when the self-identified ethnicity was either mixed (e.g., 'white and Asian') or missing. Half of the OCG members are white, while both black and Asian individuals constitute roughly one-fourth of the OCG population. The number of OCG members classified as Middle Eastern is negligible. For 13.3% of the non-members, both self- and police-reported ethnicity information is missing. This is true for only 1.1% of the OCG members.

In terms of activities, OCG members are much more active in drug dealing – both hard drugs (Class A) and cannabis – than non-OCG members: 60.3% of the OCG members have been involved in hard drugs-related offenses and 41.7% in cannabis-related offenses (this is, respectively, 15.6% and 1.7% for the other offenders in the OC milieu). OCG members are also more likely to resort to criminal damage (43.2%) than non-members (7.7%).

Violence

Table 3 offers a summary picture of the involvement of individuals in the OC milieu in (non-domestic) violence and harassment. Roughly half of the OCG members have been involved in an act of violence as offender (51.0%) and one-fourth have been victim of violence (25.6%). Among the non-members, these percentages decrease to, respectively, 17.2% and 2.1%.

Violence appears to be mostly a group endeavor with 82.2% of offenders having acted in group in our data. We reconstructed the structure of the network of co-offending in violence (aggregated over time), and we found it rather fragmented with only 2.8% of all nodes in the OC milieu being in the largest component. Of the offenders who have been violent, 13.1% was part of this largest component. This could be a reflection of the lack of coordination across OCGs, i.e., they act independently when dealing with violence.

Figure 2 plots the violent victimization relations (451 ties) among members of the OC milieu between 2000 and 2016. Note that, in this figure, a tie can reflect more than one victimization event. At the same time, if an event involves multiple offenders, it gives rise

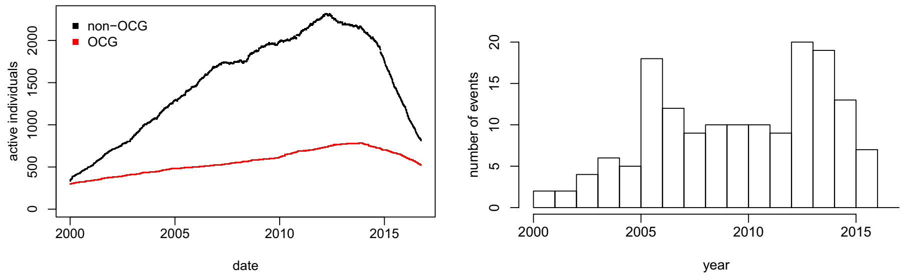

Fig. 1 Left: number of OCG and non-OCG members active in the OC milieu at the time of each of the events in the data, for $\Delta t = 2$ years. Right: number of OCG-instigated violent events by year

to multiple ties in this network. Of the 236 victims of violence in the OC milieu, 192 were victimized once by other individuals also active in the OC milieu (81.4%), 33 were victimized twice, and 11 more than two (up to five) times.

Zooming into OC-instigated violence, there are 156 events of violence in the OC milieu instigated by an OCG offender or an offender group with at least one OCG member. Figure 3 shows the characteristics of violent events. In 89 events, the victim had previously been a violent offender and in 35 events the victim had been a prior violence victim. For harassment, these figures are, respectively, 23 and 12.

Furthermore, of the 156 events, 42 involved a female victim (for a total of 34 individual women). In 27 events, the victim was an OCG member and in 15 the victim was part of the same OCG as the offender (or at least one individual in the offender group). We find that in 34 events the victim had co-offended with the offender(s) prior to the violence event of interest. In 17 events, the victim had been a prior violence victim of the offender(s) and in 6 events the victim had previously been violent towards the offender(s). When looking at harassment, the number of events is, respectively, 4 (prior victim) and 5 (prior harassment).

Relational Event Models

We now turn to present the results of our models (Table 4). The models in this table estimate the determinants of organized crime-instigated violence strictly conceived, i.e., they are estimated on the 156 events in which at least one of the offenders was an OCG member.

Model 1 shows that, in the OC milieu, OCG members are generally less likely to be a victim of organized crime-instigated violence. To put it in another way, OCG members are more likely to victimize non-OCG members. However, this does not apply to cases in which the victim belongs to the same OCG as the offender(s). In our analysis, we find a quite strong effect of internal violence within the same OCG. Further, women who are active in the OC milieu are more susceptible to violent victimization than men: of the 833 women in the OC milieu, 34 (4.1%) became a victim of OCG-instigated violence at some point, while this was true for 104 out of the 5401 men (1.9%). Finally, violence tends to happen within the same ethnicity as offenders tend to select victims with whom they share the same ethnic background.

Model 2 adds the victim's individual criminal history to the analysis. We find that a person who has been subject to prior violent victimization is more likely to become a victim of violence. In Model 3, we further explore the relationship between past violence/harassment and future victimization. While Model 2 looked at the victims' criminal history

Table 2 Demographics for offenders in the OC milieu, and the extent to which they participated in various criminal activities

		OCG members		Non-members	
		N	(%)	N	(%)
Gender	Male	776	(93.2)	4566	(84.5)
	Female	56	(6.7)	777	(14.4)
	Missing	1	(0.1)	58	(1.1)
Ethnicity	White	418	(50.2)	2930	(54.2)
	Black	202	(24.2)	863	(16.0)
	Asian	202	(24.2)	877	(16.2)
	Middle Eastern	2	(0.2)	11	(0.2)
	Missing	9	(1.1)	720	(13.3)
Activity	Theft	559	(67.1)	2453	(45.4)
	Hard drugs	502	(60.3)	840	(15.6)
	Criminal damage	360	(43.2)	417	(7.7)
	Cannabis	347	(41.7)	94	(1.7)

Table 3 Violence and harassment in the OC milieu

		OCG members		Non-members		All
		N	(%)	N	(%)	N
As Offender	Violence	425	(51.0)	931	(17.2)	1356
	Harassment	396	(47.5)	324	(6.0)	720
As Victim	Violence	213	(25.6)	113	(2.1)	326
	Harassment	160	(19.2)	70	(1.3)	230

in isolation, in Model 3 we take a relational criminal history approach. In other words, we shift the focus onto pairs "offender(s)–victim", and look if a pair has been involved in any joint activity in the past. When accounting for pair-specific effects, we see that the effect of the individual victimization history disappears and that repeated interactions among pairs best explain the violent victimization patterns we observe in the data. More specifically, we find a strong effect for repeated violence (once a victim enters a violent interaction, he/she is more likely to be victimized again) and that violence tends to be reciprocated. We also find an effect of previous harassment from the victim against the offender. Thus, when a victim is targeted, not only prior violence but also prior harassment appears to have a strong effect. This is a novel, relevant, finding that calls for further exploration using additional data sets.

Finally, when including an effect for previous co-offending, we see that the effect of co-membership in the same OCG significantly reduces in strength: this indicates that prior co-offending accounts for a large part of within-group victimization.

To summarize our results, in Fig. 4 we present the odds ratios for the variables included in Model 3 which, once again, looks at organized crime-instigated violence.[5] What are the factors, then, that drive OCG-instigated victimization in the OC milieu? In our analysis, we observe a very strong effect of repeated victimization: having been a victim before increases the odds of future violent victimization by a factor of 212. An equally strong effect – and perhaps more surprisingly – is the key role played by past harassment perpetrated by the future victim against his or her future offender: having previously harassed the offender increases the odds of victimization by a factor of 243. Since violent victimization is a more severe response to previous harassment, we can term this mechanism as 'retaliation *cum* escalation'. Violence is also likely to be reciprocated: having attacked the victim in the past increases the odds of being attacked by the former victim by a factor of 479. Note that these very large numbers are partially due to our small event sample size. Although the effects are clearly positive and statistically significant, future research should shed further light on effect sizes.

Previous co-offending has an impact on future victimization, increasing the odds of future victimization at the hands of the co-offender(s) by slightly more than 56 times. Things do turn sour among co-offenders.

[5] The confidence intervals for some of the odds ratios are quite wide, especially for the victim-offender(s) dyadic effects of previous harassment and violence. This indicates that the odds ratio estimates from the sample are imprecise. However, we should note that, in most of these cases, the entire confidence interval range corresponds to a considerable effect on the odds of being victimized. Future research based on more events should shed further light on effect sizes.

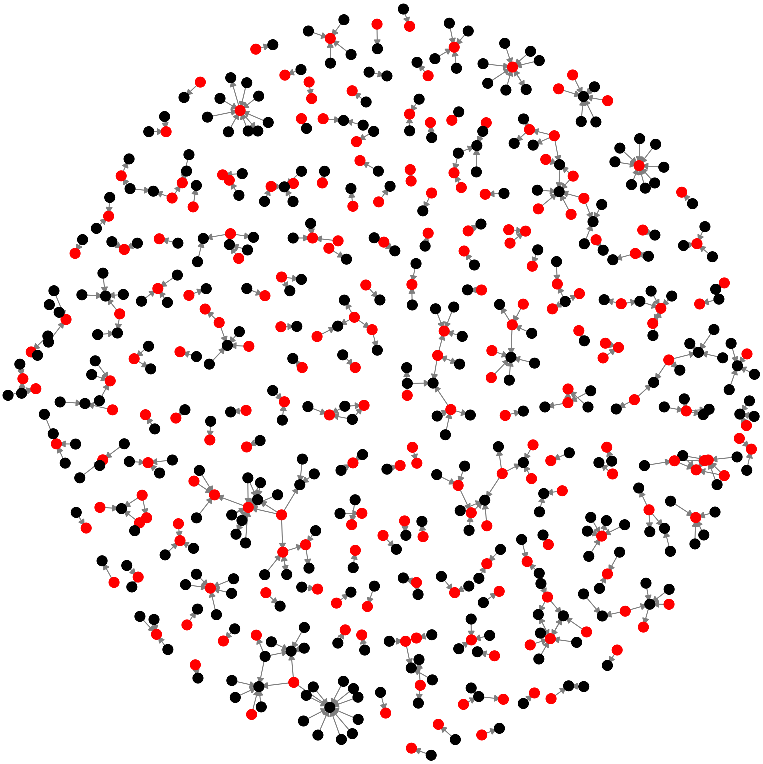

Fig. 2 Victimization network for violence against a person aggregated over the period 2000 to 2016. The red nodes represent OCG members, the black nodes represent non-members

Finally, three more insights emerge from the data. Firstly, internal violence within OCGs is strongly present: being part of the same group as the offender(s) increases the odds of being 'chosen' as a victim by a factor of 7.8. Secondly, violence is more likely to happen within the same ethnicity: sharing the same ethnic background with the offender(s) increases the odds by a factor of 3.2. Finally, being a woman active in the OC milieu increases the odds of victimization by a factor of 2.2.[6]

[6] When repeating the analysis for a different definition of when an offender is active in the OC milieu ($\Delta t = 1$ year in equation (1)), we obtain the same results as in Model 3. When we run the analysis on the 112 events that only involve men, the effect of a history in theft on being victimized reduces and is no longer significant. The other effects remain roughly the same. Further research on a larger sample of violent events is needed to shed light on the differential factors contributing to the victimization of women in the OC milieu.

Fig. 3 OCG-instigated violent event characteristics related to the history of the involved victims (e.g., for 35 events the victim had been a victim of violence prior to the violence event of interest)

Discussion and Conclusions

In this paper, we explored the micro-level mechanisms that underpin the emergence of organized crime-instigated violence. We did so by adopting a network approach, modeling interactions among organized crime members and other individuals operating in what we have defined the 'OC milieu' (i.e., individuals who were an OCG member or, at any stage, co-offended at least once with an OCG member). To model such interactions, we relied on police-recorded events between 2000 and 2016.

Compared to previous works on 'networked violence', we shifted the focus from settings in the mist of a 'gun epidemic' or characterized by chronic high levels of violence to more 'middle-of-the-road' places. The jurisdiction of Thames Valley Police in the UK is one of such places: it records an average number of OCGs compared to England and Wales, and it is situated in a national jurisdiction – England and Wales – with an overall low homicide rate (1.2 per 100,000 population in 2017 compared to a World average of 6 and the US average of 5.3; UNODC 2019). Yet, OCGs *do* operate in such settings and violence *does* happen - although the mechanisms underpinning such violence have yet received very little empirical attention.

Our relational analysis of violence is built around two key elements: (a) time and (b) the offender's choice of victim. We furthered previous works on networked violence by fully taking into account the sequence of events. We did so by relying on a relational event-based approach. Secondly, we tackled the issue of victimization from the perspective of the perpetrator(s) modeling their choice of victim. We did so by using an actor-oriented approach. Broadly speaking, we sought to answer the following question: why did an OCG member choose to victimize person X instead of all the other individuals also present in the OC milieu at the time he/she has made his/her choice? To take into account the specificity of organized crime, we have extended our models to contemplate the possibility of multiple offenders acting in concert at the same time.

In this work, we defined violence in broader terms than homicides and gun shootings, including various types of assaults causing injuries. Roughly half of the OCG members have been involved in an act of violence in the period under consideration and one fourth have been recipient of violence. In the context of organized crime, violence is mostly a group endeavor with more than 80% of offenders acting in group. The network of co-offending in violence is rather fragmented, suggesting a lack of coordination across OCGs when dealing with violence (i.e. they act independently).

Our analysis has clearly pointed to the importance of relational factors to explain the emergence and persistence of violence in the OC milieu. Such factors play a very strong role. When both individual and relational factors are modeled, the effects for victim-offender relationships are constantly stronger than victims' personal and criminal characteristics. In short, relations *do* matter – and to a great extent (in line with Black 2004a's social geometry of conflict).

Our analysis has shown that the emergence - and persistence - of violence can be explained by four main sets of mechanisms. The first relates to violence itself. In the OC milieu, violence is likely to be reciprocated and repeated (this is in line with previous findings, e.g., Papachristos 2009; Papachristos et al. 2013). As an activity, violence can be subject to a 'tit-for-tat' mechanism that generates cycles of violent events. Secondly, we found strong evidence of an escalation mechanism linked to previous harassment, i.e. a former victim of harassment deciding to retaliate and escalate at the same time by resorting to violence.

Table 4 Results for the three models of OCG-instigated violence in the OC milieu

	Model 1		Model 2		Model 3	
	par.	s.e.	par.	s.e.	par.	s.e.
Female	0.84***	0.19	0.78***	0.19	0.78***	0.20
OCG member	− 1.28***	0.30	− 1.76***	0.38	− 0.95**	0.36
Ethnicity - Asian	0.35	0.23	0.32	0.24	0.28	0.25
Ethnicity - black	− 0.10	0.26	− 0.02	0.26	− 0.14	0.28
Same OCG	4.18***	0.40	4.23***	0.40	2.05***	0.46
Same ethnicity	1.33***	0.20	1.33***	0.20	2.05***	0.46
Has been						
Violence victim			0.53***	0.14	0.16	0.22
Violence offender			0.04	0.06	− 0.03	0.07
Harassment victim			0.59	0.36	0.12	0.46
Harassment offender			0.38	0.30	− 0.07	0.36
Hard drugs offender			0.10	0.25	− 0.09	0.27
Cannabis offender			− 0.77	0.45	− 0.63	0.48
Theft offender			− 0.34	0.20	− 0.47*	0.21
Damage offender			0.28	0.28	0.22	0.31
Has co-offended on						
Any activity					4.02***	0.28
Repeated violence					5.35***	0.54
Reciprocated violence					6.17***	0.83
Been harassed by offender(s)					1.60	0.96
Has harassed offender(s)					5.49***	0.95

**$p < 0.05$, ***$p < 0.01$, $p < 0.001$ (two-tailed)

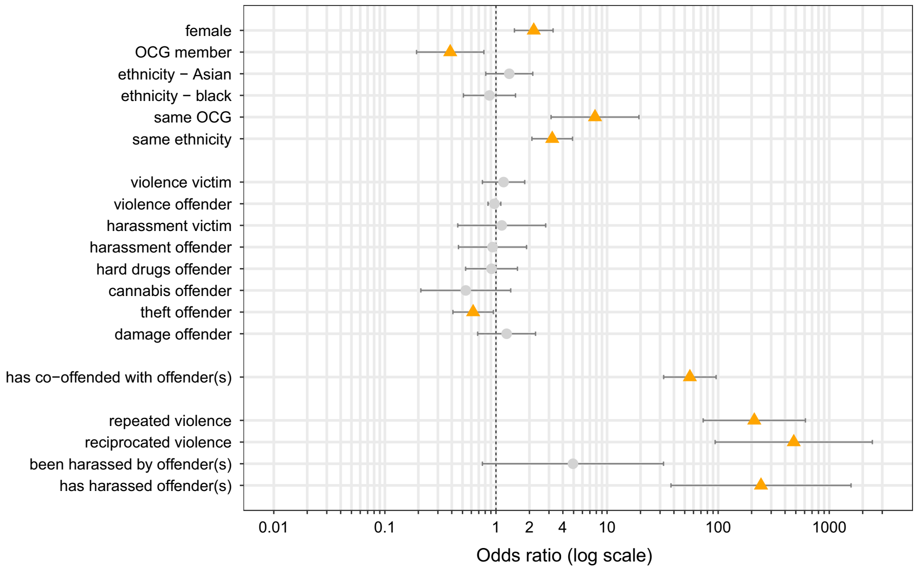

Fig. 4 Odds ratios with 95% confidence intervals for victim characteristics effects in Model 3, estimated on the OCG-instigated violent events (gray dots indicate non-significant effects)

Thirdly, violence is the result of criminal activities turning sour. It is clear from our analysis that, if you operate in the OC milieu, the risk of violent victimization is far more likely to come from people you know and who you have worked with. Finally, while belonging to an OCG appears to decrease one's risk of being selected as victim of violence in general, it increases the risk of being attacked by your fellow group members. Again, violence comes from very close to home.

Further, we explored the gender dimension of OC-instigated violence and found that women who are active in the OC milieu are more susceptible to violent victimization than men. This result adds to the very limited evidence currently available on women in organized crime. However, further investigation is much needed to better understand the role of and threats to women within the OC milieu, as well as the extent to which certain mechanisms (such as harassment-based ones) are gender-specific.

As with all the analyses based on police records, our work suffers from some limitations. An important one is that our evidence only shows events that have come to the attention of the police, therefore our results might be impacted by missing data in a non-negligible way (for example, assaults might have not been detected or, even more so, episodes of harassment). This is a common issue for covert network analysis. With this caveat in mind, we still consider such data an invaluable – and difficult to substitute – source of information (in line with the literature discussed in Sect. "Networked Violence"). Secondly, the results are not immediately generalizable beyond Thames Valley; however, they resonate with findings from other settings. A replication of this event-based study in other locales characterised by both low and high levels of violence would be invaluable for ascertaining which patterns are general and which are setting-specific. Alas, this would help shed further light on the extent to which certain mechanisms, particularly the harassment-based ones, are generalizable beyond TVP. Thirdly, this study focuses on the choice of an offender or a group of offenders to target a specific victim. The exact time between events (e.g., time until retaliation) and the formation of offender groups are two very interesting processes that merit attention in future studies. In particular, the topic of actor-oriented modeling of group formation and group action is an underexplored but important area of methodological research.

Finally, we believe that our findings might have important policy implications for police and other agencies trying to curb the emergence and persistence of violence in a given area. We believe our approach can help them better understand the mechanisms underpinning the emergence of violence and the risk factors associated to both individuals *and* relationships. Our work has shown the importance of taking relationships into account when developing red flags. It is not just individuals that matter, but even more so the relationships they develop. Red flags (and risk factors) should therefore not only be based on individual characteristics but also relational ones. Secondly, we highlighted the importance of a number of mechanisms, including the key role played by harassment in the emergence of future violence. Focusing on harassment can help police forces and other agencies de-escalate conflicts and – crucially – identify at an early stage relationships that are more likely to turn sour.

Appendix A: Robustness checks

As robustness checks, to further control for the potential effects of intimate partner violence, we have run our analysis estimating Model 3 only on the violence events that involved male offenders and a male victim (Table 5). Since none of the victims in these events were previously harassed by their offender(s), we excluded the corresponding effect from the model. We find that the results are largely consistent with those in Model 3 (see the second column of Table 5). We have also estimated Model 3 with a different choice of time Δt for defining the time window during which offenders are active in the OC milieu. For this model, we found the parameter estimates to be exactly the same as those reported for Model 3.

Table 5 Model 3 results for only the events with both a male victim and male offender(s) and the original Model 3 results

	Male-only events		Model 3	
	par.	s.e.	par.	s.e.
Female			0.78***	0.20
OCG member	− 0.90***	0.38	− 0.95**	0.36
Ethnicity - Asian	0.68	0.28	0.28	0.25
Ethnicity - black	0.32	0.31	− 0.14	0.28
Same OCG	1.96***	0.49	2.05***	0.46
Same ethnicity	1.53***	0.25	1.17***	0.22
Has been				
Violence victim	0.22	0.22	0.16	0.22
Violence offender	0.01	0.07	− 0.03	0.07
Harassment victim	0.25	0.48	0.12	0.46
Harassment offender	0.12	0.38	− 0.07	0.36
Hard drugs offender	− 0.22	0.33	− 0.09	0.27
Cannabis offender	− 0.90	0.52	− 0.63	0.48
Theft offender	− 0.16	0.23	− 0.47*	0.21
Damage offender	0.15	0.35	0.22	0.31
Has co-offended on				
Any activity	3.27***	0.34	4.02***	0.28
Repeated violence	4.54***	0.61	5.35***	0.54
Reciprocated violence	6.31***	0.92	6.17***	0.83
Been harassed by offender(s)			1.60	0.96
Has harassed offender(s)	4.02**	1.45	5.49***	0.95
Number of events	112		156	

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed)

Acknowledgements We are grateful to the Editor and three anonymous Referees for their very insightful comments. We are also extremely grateful to Thames Valley Police for sharing their data with us. In particular, we wish to express our sincere gratitude to Superintendent Marc Tarbit and Data Analyst Alastair Nall for their crucial support.

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