How Organized Crime Groups Interact: A Theory of Differential Cooperation*

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Abstract

Interactions between organized crime groups (OCGs) are under-explored in the literature. We study the determinants of cooperative interactions among OCGs operating in Merseyside (UK) using the complete crime dataset integrated with neighborhood-level socio-economic data and sentencing outcomes. We first address the puzzle of the coexistence of stable illegal markets and OCG violence: drug markets are contendible and OCGs resort on cooperation to mitigate risks of unbounded competition. Hence, the nexus between markets and violence is mediated by the structure of inter-OCGs cooperation (or lack thereof). We find that, net of urban and socio-demographic factors, violence is consequential to cooperation failure. Second, as in illegal markets contracts are not enforceable, incentives to collaborate and profit-sharing mechanisms are distorted. We posit that OCGs select partners and collaborations to balance risks and opportunities. Relative to the former aspect, we show that cooperation is differential as it is more likely to realize between groups characterized by asymmetric control of territory. Relative to the latter, OCGs are selective in the nature of interactions, with a positive relationship between expected returns (and associated risks) and cooperation intensity. Importantly, this mechanism complements network-based strategies used by OCGs for mitigation of risks involved with partner selection.

Keywords: criminal Networks, drug Markets, urban disorganization

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1 Introduction

No person is an island, and neither are OCGs. Yet, very limited attention has been paid by criminologists to the relational patterns established among groups operating within the same locale. Debates around organized crime have focused on the nature of groups and their activities (e.g., Schelling, 1971; Smith, 1975; Reuter, 1983; Gambetta, 1993; Paoli, 2008; Varese, 2010; Campana and Varese, 2018), on their internal structure (e.g., Paoli, 2008; Densley, 2013; Catino, 2014) or the impact of organized crime (and gangs) presence on neighborhoods, cities or countries, for instance on economic development (Acemoglu et al., 2020; Pinotti, 2015; Lavezzi, 2008), neighborhood trust and state legitimacy (Blattman et al., 2021), level of violence (Cohen and Tita, 1999; Robinson et al., 2009; Huebner et al., 2016; Molzahn et al., 2012) and "ordinary" crime (Aziani et al., 2020). While these streams of research have provided key insights, they have either focused on the micro-level (internal) mechanisms or the macro-level (aggregated) impact of OCGs (and gangs) on specific settings. In this work, we bring into the picture meso-level mechanisms by focusing on inter-OCGs relational patterns. We believe that understanding such patterns is crucial in shedding light on macro-level regularities observed in the literature, particularly, the coexistence of stable illegal markets and organised violence, as well as micro-level regularities, such as the mechanisms underpinning partner selection in co-offending. In this work we will show that a meso-level (inter-group) analysis is best suited to explore the complex, dynamic, setting in which OCGs operate and are confronted with.

A (still) relatively small set of works have started to apply a relational approach to the study of violence, mostly concerning gangs operating in US cities (e.g., Papachristos, 2009; Tita and Radil, 2011; Papachristos et al., 2013; Bichler et al., 2019), following on the pioneering work by Kennedy et al. (2017) on mapping violent conflict among Boston gangs as part of Operation Ceasefire. We expand on these works on "networked violence" (Papachristos, 2009; Bichler et al., 2019; Niezink and Campana, 2022) by shifting the focus from violent relations to co-operative relations. We will show that cooperation and violence are two sides of the same coin, with violence erupting as the result of a breakdown in cooperation within the organized crime milieu.

The importance of understanding mechanisms underpinning cooperation goes well beyond the study of violence as successful – and sustained – cooperation can generate stronger, more resilient and more entrenched OCGs, with consequences for the well-being of individuals, communities and – in most serious cases – countries. While collaboration among individuals has attracted criminological attention since the early works on co-offending (Reiss Jr, 1988, Reiss Jr and Farrington, 1991; Sarnecki, 2001 is the first to apply a formal social network approach to co-offending), the quantitative study of cooperation between groups has received much more limited interest. This is surprising – and problematic – as OCGs (and gangs) are more than just the sum of their parts (as empirically shown by Papachristos, 2009). The importance of studying inter-group collaboration was already hinted at in the work by Kennedy et al. (2017), but only quantitatively explored in a handful of works: Coutinho et al. (2020) studied the impact of market overlap on collaboration between OCGs and motorcycle gangs in Alberta, Canada, and Ouellet et al. (2019) the impact of alliances on the probability of survival among Haitian street gangs operating in Montreal, Canada (we will return on these works in the next section). We build on these works to investigate the structure and determinants of collaboration among all OCGs identified by Merseyside Police (Liverpool, UK) as operating within their jurisdiction between 2015 and 2018.

This study first attempts to understand the puzzle of the *co-existence* of stable illegal markets and violence. Our starting point is that illegal markets - similarly to legal markets - are contendible, and competitive pressure and conflict may hinder participants' business. However, while in legal markets competition is framed within a stable normative setting, in illegal markets it can escalate into unbounded violence. OCG overcome the risks of unbounded competition through cooperation. Hence, cooperation in illegal markets disciplines the nexus between neighborhood (social) organization, illicit markets and violence (that is, competition). We explore the impact of inter-OCGs collaborative interactions on neighborhoods. In particular, we will show that interactions among OCGs have a systemic effect on illegal activities beyond organized crime as well as the overall level of violence in neighborhoods: more inter-OCGs collaborative interactions increase the future size (or “thickness”) of illicit markets (as measured in terms of episodes of drug dealings) in a neighborhood while a break-down in collaboration increases overall levels of violence. As cooperation both fosters economic opportunities and prevents potential conflict, we find that in unregulated competitive markets violence is a consequence of the failure of cooperation. In other words, violence and business are substitute activities, and as such, variables related to these activities are expected to move in opposite directions.

Having assessed the macro-level role of cooperation within a competitive, unregulated setting, the study then turns to understanding its micro-level properties. As in illicit markets contracts are not enforceable, incentives to collaborate and profit-sharing mechanisms are distorted: resources unlocked through collaboration can alter parties’ relative market power, thus increasing the odds of one group overthrowing the other in future interactions. Against this backdrop, we will show that collaborative interactions among OCGs follow what we term “differential cooperation”, meaning that groups with overlapping turfs can collaborate as long as there is *asymmetry* in the degree of territorial strength. Secondly, we will show that a group gets selected as a partner if such an interaction is lucrative enough, meaning if benefits outweigh the costs. Our proposed theory of “differential cooperation” links the type of criminal activities performed in a territory to the structure of inter-gang relationships. It is based on the idea that OCGs moderate the risk of cooperation by operating a careful selection of (i) partners and (ii) opportunities. Partners are picked by accounting for both a partner’s market power (as measured in terms of turf presence) and the opportunity’s risk-gain profile. In particular, less established groups are more likely to collaborate with more established groups to obtain better market access, whereas larger, more established groups may choose smaller and more peripheral partners to moderate the opposite risks of losing market shares vis-à-vis other market participants or being overthrown by an empowered partner. In this sense, ours is a theory of *differential* cooperation as it predicts that cooperation is more likely between OCGs characterized by asymmetric *market power*[1].

To address all the above, this study expands the methodological toolkit used to study organized crime (and gangs), by offering (i) a novel way of measuring turf control, (ii) a new index of cooperation aimed at capturing two critical features. First, that the effects of cooperation between OCGs can stretch well beyond neighborhoods where actual ventures are recorded, in principle affecting any areas where the joint presence of those OCGs has been documented. Second, OCG relationships are highly dynamic: new bonds can be created, and old bonds can be severed if not perpetuated. Therefore, an index of cooperation has to be able to naturally reflect movements in either direction.

We study collaboration among OCGs by leveraging police records from Merseyside Police (Liverpool) in the United Kingdom, integrated with granular census socio-demographic information. Merseyside is the fourth largest metropolitan area of the UK with a population of 1.38 million people and a surface of 645 square km[2]. Merseyside records the highest number of OCGs per million population in England and Wales (127 groups/million), more than double the national average (47 groups/million) and 25% more groups than Greater London (100 groups/million; HMICFRS, 2018:94). Crucially for this work, the force has been ranked as "outstanding" in tackling serious and organised crime, including its ability to collect intelligence on those groups (HMICFRS, 2018: 127-129, it should be noted that only 3 forces out of 43 have received the highest rating of outstanding in England and Wales). The high intensity of organized crime activity and the high level of effectiveness of police procedures make Merseyside an exceptionally suitable setting to study organised-crime related dynamics.

Finally, in this work we follow the definition of organized crime adopted by the police and based on the guidelines included in the "Organised Crime Group Map-

[1]The heterogeneity of size of OCGs is a persisting regularity and a puzzle of urban landscapes (Bouchard and Morselli, 2014). OCGs have collective identities that are tied to the occupation of geographic space, which leads to rivalry with other co-located groups (Coutinho et al., 2020; Papachristos et al., 2013)

[2]See the table *"2009 Mid-Year Estimates – Table 9 ONS"*, accessible on http://statistics.gov.uk.

ping 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." (Government, 2010: 15). This definition is in line with the one set out in the 2000 UN Protocol on Transnational Organized Crime (UN, 2000), which has become a template for definitions adopted by more than a hundred countries across the world. The UK definition of organized 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 on the concepts of organized crime and gangs, and their potential overlap, we refer to Decker and Pyrooz, 2014; Campana and Varese, 2018; Decker et al., 2022: Ch. 1).

The paper is organized as follows: in Section 2, we place our contribution within the existent literature; in Section 3, we build and empirically motivate our theory on differential cooperation. Section 4 describes all sources of data used in the analysis. In Section 5, we present the methodology and the models used in our analysis and in Section 6 the results of the empirical analysis. Section 7 concludes.

2 Background

Determinants of localized cooperation between self-organized groups of co-offenders (Organized Crime Groups: OCGs) have been explored from three separate, yet intertwined, streams of literature that are relevant to our work.

The first stream attempts to discipline the complex web of relationships taking place *between* OCGs. Work on collaboration and OCGs is scarce as studies tend to focus on collaboration *within* OCGs (see, for example, Bichler et al., 2017 and

Tita and Radil, 2011). The handful of studies on collaboration *between* OCGs systematically examined the structure and composition of co-offending activities (Malm et al., 2011) or the evolution of group boundaries and group resilience along time (Ouellet et al., 2019), a matter that can provide insights on the resilience of illicit markets more generally (Bouchard, 2007), especially in light of the limited size and reach of most OCGs (Bouchard and Morselli, 2014). Within the structural exploration of interactions between OCGs, Coutinho et al. (2020) exploit a large data set on OCGs in Canada to construct a multilevel network (Lazega et al., 2008). They use information on individuals known or suspected to be involved in organized criminal activities, the criminal collaborative ties between them, their OCG memberships, the locations in which they were active, and the illegal activities in which they were involved to determine under what conditions members of larger organized criminal groups collaborate with one another. They find that the tendency for OCG offenders to form ties across larger OCGs depends not only on spatial co-location, but also on the type of groups to which offenders are affiliated, as well as the embeddedness of those groups in spatially-situated illicit markets. In this study, illicit market overlap between groups is defined in terms of OCG members engaging in drug trafficking activities in the same geographic locations. Relevant to our study, they find that in general, *large* OCGs tend *not* to collaborate when their respective illicit (drug) markets overlap.

The finding by Coutinho et al. (2020) provides evidence of the competitive nature of illicit markets. It also suggests that cooperation (a) does take place and (b) is subject to limits and constraints. We built on these observations by conjecturing that OCGs exhibit signs of "differential cooperation", meaning that OCGs with overlapping territories can cooperate, as long as there is an *asymmetry* in the degree of their territorial embeddedness: OCGs are more likely, in general and for any territory, to establish links with OCGs characterized by a degree of territorial control *different* from their own. We speculate that this peculiar characteristic of partner selection - which survives fixed effects at neighborhood and OCG level - is hinting at two opposing forces inherent to the *contendible* nature of criminal markets: on the one hand, standard economic incentives naturally driving cooperation via division of labor and market access, and, on the other hand, a strategic endeavor adopted by OCGs to limit the influence of potential competitors thus de-escalating the risk of aggressive takeovers. Taken together, these forces are consistent with the narrative that points to the existence of a competitive market pressure (Levitt and Venkatesh, 2000) and the transitory nature of OCG relationships (Bouchard and Morselli, 2014).

The second stream of research that our work is linked to leverages the ethnic, cultural and economic heterogeneity of urban societies in exploring the determinants of intergroup violence. This literature consists of two main avenues. Both take as unit of measure the urban *neighborhood* and propose, as candidate explanations, either competition between different groups or neighborhood disorganization[3] (Hipp et al., 2009).

The first sub-stream of studies focuses on the tendency of group cohesion to foster a sense of group identity that results in competitive interactions among members of different groups[4] (Hipp et al., 2009). Such is the case for example in Jacobs and Wood (1999), Messner and Golden (1992) and O'Brien (1987). In particular, three main theories inform this type of analysis (Hipp et al., 2009): the consolidated inequality theory (Blau and Blau, 1982), which focuses on economic competition across groups; the group threat model (Blumer, 1958), which posits that the dominant group responds with violence to a narrowing of the economic gap. Lastly, the defended neighborhood model (Suttles and Suttles, 1972) predicts that members of the dominant group perceive residential ethnic transition as a challenge and respond to this perceived competition by committing intergroup violent events in an effort to "defend" their territory (Hipp et al., 2009). A feature of the studies mentioned above is that ethnic heterogeneity enters the analysis both as a feature of the neighborhood and of the subject groups under investigation. Such ambivalence can hinder a clear-cut nexus between violence and diversity as the latter

[3] In its most prevalent contemporary definition, social disorganization refers to the inability of a community to realize common values and maintain effective social controls (Mastrobuoni et al., 2014).

[4] Most studies focus on the competition among groups in the context of violent riots. For a review, see Hipp et al. (2009), with particular reference to Green et al. (1998) and Olzak et al. (1996).

might both affect social dynamics as well as structural features of the neighborhoods[5]. Crucially, our dataset features an ethnically cohesive set of individuals, but ethnically heterogeneous neighborhoods. This feature allows us to single out the structural implications of the latter on the social (criminal) dynamics under analysis.

The second sub-stream of works studying localized violence in urban environments posits that locally-contextualized violence is the consequence of a socially fractured neighborhood (Hipp et al., 2009). In this literature (Peterson et al., 2000, Sampson and Groves, 1989, Shaw and McKay, 1942), neighborhood instability (as captured by higher levels of residential instability, ethnic heterogeneity and poverty) results in weaker social interactions, a breakdown of informal social control, and consequently, higher rates of crime. This model predicates a clear-cut relationship between the degree of deprivation of a neighborhood and the amount of crime.

Within the sub-stream of literature on urban disorganization, several authors have focused on the exploration of the relationship between neighborhood violence and drug markets. In general, the assessment of the strength and direction of the interaction between these two factors is made complex by the presence of potentially many moving parts at play. For example, violence could occur in active drug markets because it facilitates the routine activities of those involved in the market (Baumer, 1994; Baumer et al., 1998; Blumstein, 1995; Blumstein, 2000; Goldstein, 1985; Johnson et al., 2000; White and Gorman, 2000) or because violence is a defining factor of players existing in the surroundings (see, for example, Pearson and Hobbs, 2001). However, while several studies have shown that the rates and counts of drug activity and violent crime are often correlated (Gainey and Payne, 2003; Goldstein, 1985; Sherman et al., 1995; Weisburd and Mazerolle, 2000), the strength and direction of correlations vary widely across geographical and institutional settings, everything equal (Durán-Martínez, 2015), with many drug markets being relatively peaceful (Reuter, 2009). In some settings, the cor-

[5]For example, ethnically-diverse neighborhoods can also possess poorer access to services, etc.

relation simply fails to hold (Lum, 2008). In other studies, it appears that drug market activity can affect levels of violence independently of social fragmentation (Martinez Jr et al., 2008), or co-move with violence as an integrated component of the daily routines and structural dynamics of drug markets (Baumer, 1994; Baumer et al., 1998; Blumstein, 1995; Blumstein, 2000; Goldstein, 1985;Johnson et al., 2000; Ousey and Lee, 2002). These partially conflicting observations hint at some missing part regulating the nexus between neighborhood organization, drug dealing and violence. In this work, we show that *after* controlling for neighborhood effects, inter-OCG dynamics explain a critical fraction of the nexus. In particular, we build a dynamic measure of inter-OCG cooperation and show that the link between localized violence and drug dealing exists and is strong *if* interacted through this novel measure. In this sense, we show the two outcomes move with opposite sign yet similar intensity, relative to variations of this measure.

The third stream of research we link to posits that OCG violence spill-overs through both time and space (Green et al., 2017), where space can entail either the geographic or social dimension, or a combination of both. Promising work has expanded on the stream of research investigating the concentration of OCG violence in urban spaces[6] (e.g., Block, 2000, Brantingham et al., 2012, Tita and Greenbaum, 2009) by jointly considering granular definitions of social layers *and* geographic proximity among candidate cofactors of violence. In particular, Papachristos et al. (2013) studies how neighborhood properties and social networks influence OCG violence. They take geolocated OCGs in Boston and Chicago as unit of measure and study violence as a function of OCGs' proximity and previous interaction. They find that adjacency of OCG turf and prior conflict between OCGs are strong predictors of subsequent OCG violence. More recently, Tita and Radil (2011) and Papachristos and Bastomski (2018) adopted a spatial autoregression approach to pin down the effect of either mechanism. They find that OCG violence is reactive to both dimensions, however, the socio-spatial dimension is dominant.

[6] We refer the reader to the review of Sierra-Arévalo and Papachristos (2017) for a thorough compendium of recent advancements in the literature on social network analysis and OCG violence.

In this paper, we take a complementary approach to Tita and Radil (2011) and Papachristos and Bastomski (2018) and explore a potential motivating factor for violence to diffuse in urban contexts populated by OCGs: failure to cooperate.

3 Organized Crime in Merseyside: Stylized Facts and Hypothesis Building

In this section, we build a theory on the mechanics of interactions between OCGs that is motivated by several empirical regularities. Unless stated otherwise, the unit of analysis[7] is the set of $C = 5,239$ crime records generated by Merseyside Police (MP) in the $M = 201$ geographical units[8] of Merseyside Metropolitan Area (U.K.) between January 2015 and March 2018 by $N = 1,211$ OCG members (OCGMs), each individual belonging to one of the $K = 134$ OCGs present in the area. Each crime record is linked to one of the $H = 384$ offenses of the England and Wales legal system, which we re-categorize in 15 macro-classes. In this section, we will focus on violence and drug-related macro-classes.

3.1 Stylized Facts: Key Features of OCG Landscape in Merseyside

1. OCGs are Heterogeneous in Size. The first regularity we present is related to the activity and size of OCGs in Merseyside. In the left panel of Figure 1 we plot the number of OCGMs per OCG, and in the right panel we plot the number of crimes per OCG. As we see, there is a high dispersion in both dimensions. We find that 67% of OCGs consist of 2 to 10 members and only 6.7% OCGs are made of more than 20 members (corresponding to 9 OCGs). This is in line with empirical

[7] We postpone to Section 4.1 a detailed description of the data, and to Section 5 the formal construction of OCG and inter-OCG relationships. Here we provide critical stylized facts on OCG members behavior which are relevant for our hypothesis building.

[8] Unless stated otherwise, geographic units correspond to *Middle Layer Super Output Areas* (MSOAs), that is small-area census units that are demographically stable, containing around $8,000$ inhabitants each. See, for a description, Section 4.1

evidence showing that opportunistic and small OCGs are the predominant form of operating unit in organized crime (Bouchard and Morselli, 2014; Niezink and Campana, 2022). Similar distributions appear in previous studies on organized crime (Bouchard and Morselli, 2014): studying a sample of incarcerated dealers in Quebec, Bouchard (2006) found that a majority of dealers were active in organizations of 2 to 10 members (60 %), and that 13.7% had more than 20 members. In an analysis of 557 drug dealing cases collected from police files in Baltimore, Eck et al. (2000) found that 35% of OCGs consisted of 2 to 10 offenders, and only 7.1% had more than 20 members. The authors conclude that "large organizations do not dominate the market, but grow out of it" (p.264) (Bouchard and Morselli, 2014). This is striking also in light of the comparably higher homogeneity of the number of crimes committed by each OCG (right panel of Figure 1). It is then important to ask why we observe a *persistent* degree of heterogeneity in the size of OCGs that is so remarkably consistent across urban landscapes around the world.

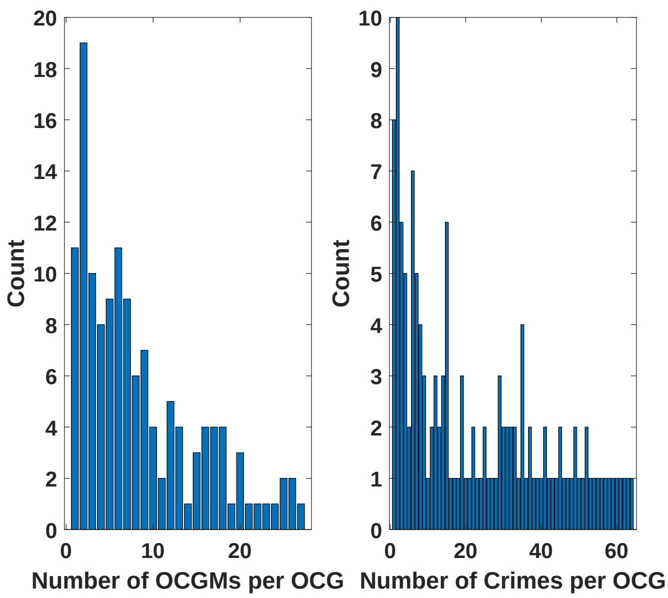

Figure 1: *(Left Panel.)* Number of members per OCG *(Right Panel.)* Number of crimes per OCG.

2. OCG Turfs Are Contendible. What are the turf dynamics in Merseyside? The second regularity is related to the dynamics of inter-OCG competition across Merseyside neighborhoods. We identify the most active and the second-most active

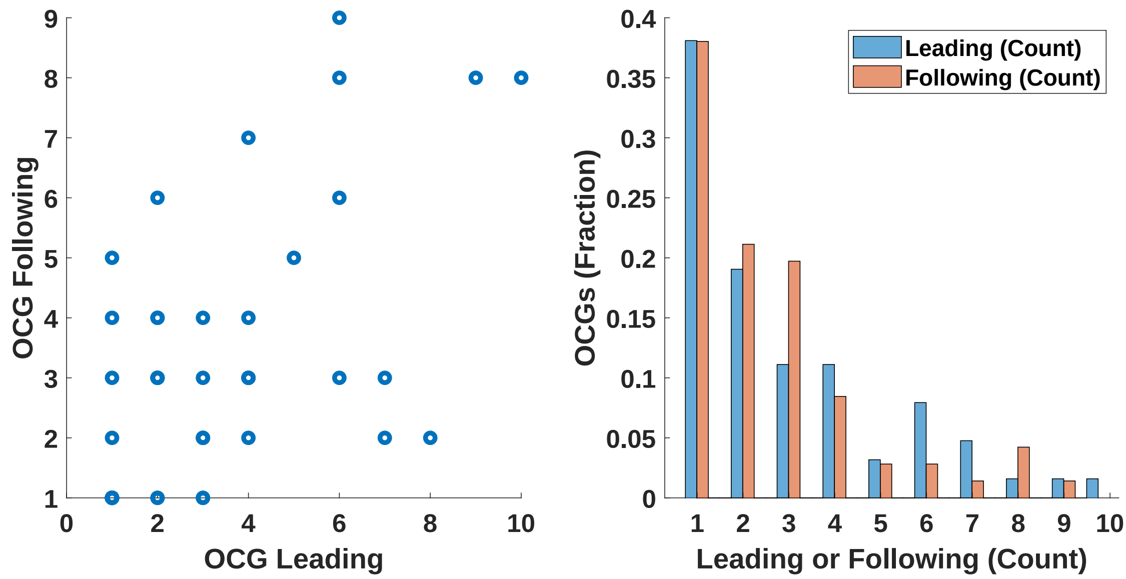

Figure 2: *(Left.)* Turf overlapping of OCGs in Merseyside. Each dot represents an OCG and it indicates the number of geographical units in which the OCG is the most (*X-axis*), and second-most active (*Y-axis*) OCG (labeled "OCG Leads" and "Following", respectively) among OCGs operating in those geographic units. *(Right.)* Proportion of OCG leaders/followers by the number of geographic units in which they lead/follow.

OCG (as measured in terms of police recorded events[9]) for each geographical unit, respectively labeled as *Leader* and *Follower* in that specific area. We then count the number of geographic units in which each OCG leads or follows. The left panel of Figure 2 shows a scatterplot counting the areas in which each OCG leads and follows.

We would expect that a fully-consolidated market structure, that is a market with no overlaps, would map into a mass of observations squeezed in the proximity of the origin along the X-axis. In other words, we would expect in general a limited number of followers, and an even smaller number of OCGs leading *and* following in a relatively large number of areas. However, the figure points to a very different scenario. Evidence from Merseyside suggests that OCGs' territories overlap frequently: the majority of OCGs are both leaders in some areas and followers in other areas. This holds regardless of the number of areas in which an OCG leads or follows. Most OCGs appear as both leading *and* following

[9] To construct the measures of OCG activity, we use all police recorded events attributed to an OCG.

regardless of the number of occupied turfs, thus suggesting a potentially fragile market segmentation/overlap characterized by a persistent push to occupy new spaces and securing market power[10].

What are the implications of this overlap? Previous research suggests that criminal markets are hostile settings characterized by intense competition among participants, resulting in substantial economic disparities (Paoli, 2014). Illicit market-driven violence implies that acquisition and control of turfs (areas) is a resource-intensive process (e.g., Papachristos et al., 2013), and turf wars are costly both in terms of lost lives and lost profits[11] (Levitt and Venkatesh, 2000). Hence, succumbing parties are likely to pay a "cost of defeat" and react accordingly, for example, by withdrawing from areas where competition is inconclusive (i.e. does not bring the OCG to a dominant position) or their market position is compromised. The right panel of Figure 2 supports this idea by plotting the distributions of areas (turfs) occupied by OCGs as either leader or follower. As expected, the fraction of OCGs occupying a dominant (i.e. the leaders) or nearly-dominant (i.e. the followers) position falls in the number of turfs, reflecting the logistic and competitive challenges typical of any competitive market. However, by comparison between these two groups, it emerges that OCGs that show high activity in multiple areas are more likely to be leading on these turfs rather than occupying a non-dominant position. This is consistent with the notion that areas are actively contended and that defeat is costly: as is not viable for OCGs to entrench in a turf in a non-dominant position, groups may either retreat or pursue market-sharing agreements, thus motivating the faster drop in the rate of following OCGs against leading OCGs as showed in the figure.

3. Stable Drug Markets and Violence Coexist. To further explore the

[10] Indeed, this observation might be mechanically driven by the artificial geographical segmentation that we used and/or a side effect of OCGs. However, in Figure 13 (Appendix B.1) we show that results of Figure 2 are robust to a more granular definition of geographic area (namely, *Lower Super Output Areas*, each containing an average of $1,600$ residents and 670 households, as opposed to the $8,000$ residents of MSOA), and OCGs size.

[11] An indirect cost is market instability. Levitt and Venkatesh (2000) documented that the negative shock induced by an OCG war translates in a fall of $20-30\%$ in both quantity and price of drugs sold during fighting (with drugs priced below marginal cost). Despite this, the OCG discussed in their work engaged in hostile activity against rival OCGs about $1/4$ of the time of the analysis.

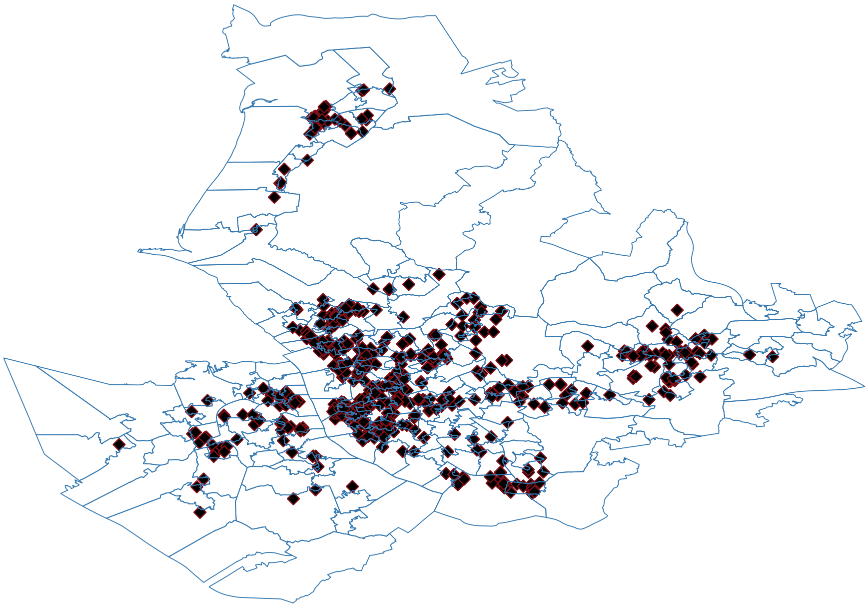

Figure 3: MSOAs of Merseyside area. *(Top Panel.)* The location of OCG violent crime. *(Bottom Panel)* OCG drug dealing. Violent crime, drug dealing of type A and type B and C are captured by black diamonds, grey circles and black circles, respectively. MSOA boundaries are captured by blue lines

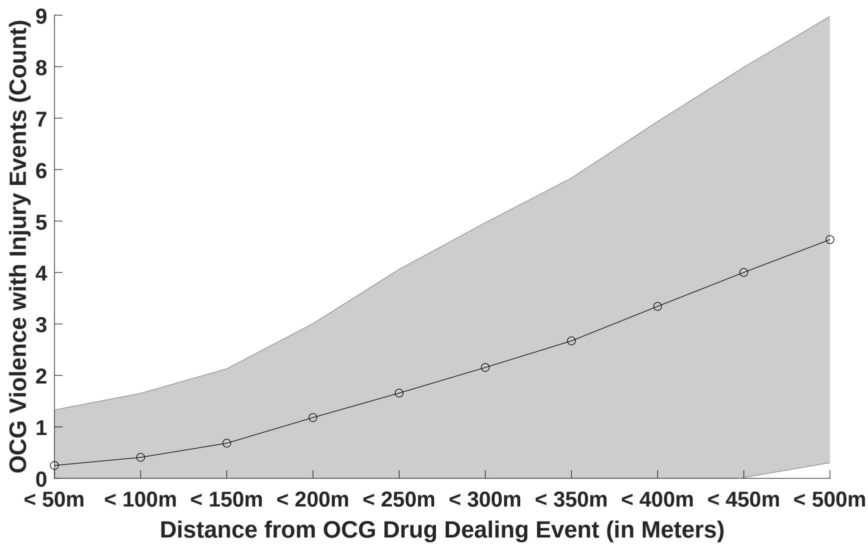

Figure 4: Average number of OCG violent crime per OCG drug dealing event taking place within 50 to 500 meters radius. Gray area represents standard errors.

consequences of territorial overlap of OCGs, we introduce a third regularity. In Figure 3 we geo-localize all the incidents of OCG violence and market activity, where market activity is proxied through drug supply crime[12]. At the incident

[12]Drug crime represents, on average, the most lucrative localized type of crime committed by OCGs (Levitt and Venkatesh, 2000) and as such it is a perfect candidate for proxying market

level, drug dealing visibly clusters in three macro areas across Merseyside, with episodes of OCG violence scattered throughout. The spatial overlap between organized drug dealing and violence is even more apparent in Figure 4, where we plot the average number of OCG-related violent events spatially surrounding an OCG-related drug supply events. We do so by computing the average number of OCG violent crimes recorded within centroids centered on each drug supply event, ranging from 50 to 500 meters radius. In the picture, non-zero levels of violence are recorded at all distances. In particular, OCG drug dealing places attract on average at least one event of violence within a 150m radius. This number smoothly increases as the radius expands. A further - more formal - way to assess the degree of clustering between OCG drug supply and violence is by computing spatial proximity based on a widely used standard method: the nearest neighbor index[13] (see Bailey et al., 1995 for a primer). To this purpose, we consider the set of drug dealing events characterized by at least one violent crime taking place within a given surrounding area (centroids) from the drug event. We construct such areas by using fixed linear distances (radius) ranging from 100 to 500 meters[14]. We then measure the spatial proximity based on the nearest neighbor index across such a subset of events. Results are reported in Table 1, where a nearest neighbor index (labeled as *N.N.I.*) below 1 indicates spatial concentration. Spatial clustering of this subset of drug-related events is confirmed for point sets built at all distance levels, with index ranging from 0.4 to 0.19.

The co-existence of a *stable* relationship between drug markets and violence in urban areas is a strong regularity. This is in line with the literature that identi-

activity Reuter (2014).

[13] Nearest neighbor methods are used to uncover potential spatial dependencies within point pattern data by comparing two types of distances: those between actual events (and their nearest neighbor) and those between events and randomly chosen points across a region. If event-to-event distances exist at higher frequencies than event-to-random point distances, then clustering is suggested (Lum, 2008). The method produces a simple index measuring the observed mean distance between an event and its nearest neighbor relative to the expected mean distance if events were randomly spread. An associated Z-score provides a sufficient statistics for testing clustering.

[14] Lum (2008) extended the method to allow for spatial dependence between heterogeneous events, in particular, drug and violence crime (with no distinction between OCG and non-OCG offenders). She confirms the clustering of drug and violence in a dataset comprising $105,477$ crime reports relative to the City of Seattle.

	< 100m	< 150m	< 200m	< 250m	< 300m	< 350m	< 400m	< 450m	< 500m
N.N.I.	0.4	0.24	0.22	0.19	0.19	0.19	0.19	0.21	0.2
Z-Score	-11.24	-18.64	-23.11	-26.42	-28.66	-29.66	-30.54	-31.04	-31.75
N	98	167	246	294	340	365	390	415	435

Table 1: Nearest Neighbor Index and Z-score for all the OCG drug dealing events that are associated with at least one OCG violence event, with the association computed at several distances. In the table, *N.N.I.* and *N* stand for the nearest neighbor index and the number of events identified by the algorithm, respectively (see also Note 13).

fies such relationship as a defining feature of "disorganized neighborhoods" (see Section 2 for references). The relationship between drug markets and violence has been explained by invoking a variety of factors[15]: offenders may be part of a subculture that uses violence to facilitate economic transactions (see, e.g., Baumer, 1994), or, violence can be an intrinsic feature of open-air drug markets, as *milieus* that bring together "people with weapons, vulnerable victims, hard cash, and opportunities to rob and assault" (Lum, 2008). In addition, enhanced police monitoring of drug markets may exacerbate existing economic compulsive violence by putting pressure on the incentive structure of market participants (Resignato, 2000), besides affecting data observation.

These theories identify a convincing nexus between *generic* violence and drug market dynamics. However, they do not address the specific incentive structure motivating OCGMs and their interactions[16]. Arguably, OCGMs behavior is a function of the structural and behavioral properties of the OCG they belong to. In other words, we can not study OCGMs behavior in isolation, that is without consideration for group-level dynamics (see, e.g., Papachristos et al., 2012; Coutinho et al., 2020 and Sierra-Arévalo and Papachristos, 2017).

Grounded on the regularities introduced above, we postulate an alternative motivating factor for OCG conflict surrounding drug markets: competition generated

[15]Several works have explored the potential foundations of the systemic relationship between drugs and violence outside an OCG context. We refer the reader to Lum (2008) for a thorough literature review.

[16]The definition of OCG notoriously eludes behavior or structure-based taxonomies (see Bouchard and Spindler, 2010 and Spindler and Bouchard, 2011 for a methodological discussion). However, OCGs and OCGMs are engaged at a higher rate in violent and drug dealing relative to the general pool of offenders, as OCGs facilitate the coordination of complex illicit economic activities through organization (Levitt and Venkatesh, 2000).

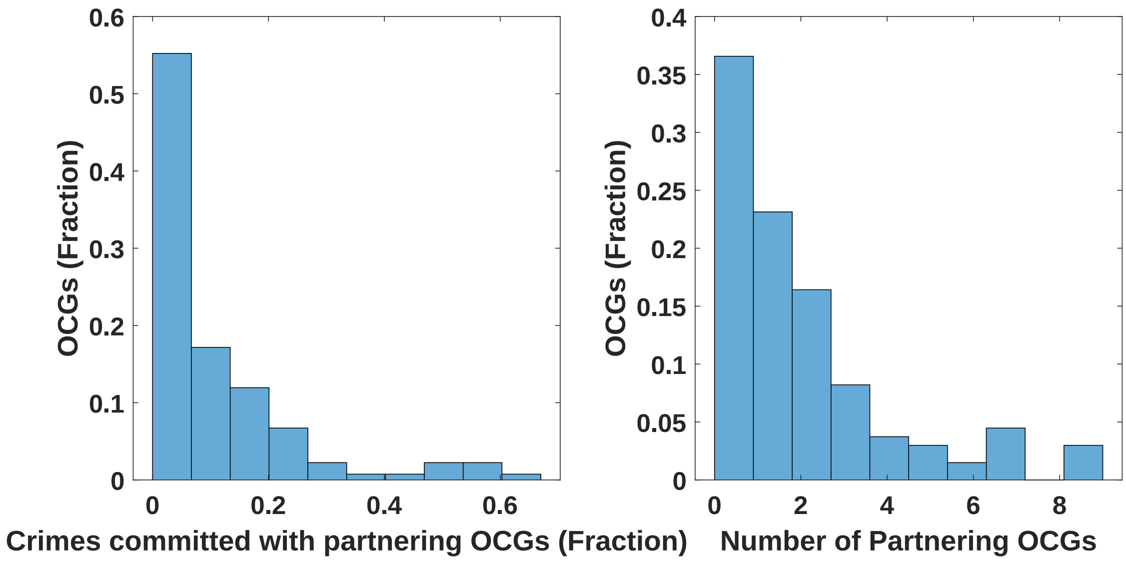

Figure 5: *(Left.)* distribution of the volume of crime committed by an OCG in partnership with other OCGs. A value of zero (respectively, one) implies that no crime (respectively, all crime) is committed in association with one or more partnering OCGs. A partnership between two different OCGs realizes when at least two OCGMs belonging to each respective OCG have been involved in a crime together. *(Right.)* distribution of new partnerships between OCGs.

by the *contestability* of markets in which OCGs are involved. Illicit markets' boundaries are elusive, and therefore, market overlaps are difficult to measure (Johnson et al., 2000 Coutinho et al., 2020; Bichler et al., 2017). However, as OCGs often deal with commodities that are spatially located (Campana and Varese, 2018; Coutinho et al., 2020), overlapping spatial OCG presence as measured by crime events can be used to proxy market overlap. Lack of formal institutions regulating illegal transactions implies that OCGs use violence to consolidate their market share, enforce control and expand their reach[17] (Reuter, 2014; Levitt and Venkatesh, 2000), thus giving rise to conflicts to secure a monopoly (i.e. the OCG "turf") and deter potential "entrants" (Dell, 2015).

4. OCGs are Heterogeneous in the Degree of Cooperation. While rivalries between OCGs have received wide attention in the literature, and there are good reasons for that also in our case, cooperative relationships between OCGs

[17]For example, Levitt and Venkatesh (2000) estimate that efficiency gains arising from a successful turf takeover amount to revenues in selling drugs $23,000 a month higher than pre-expansion. This can be imputed to the combined effect of geographical expansion (i.e. market share doubles) and increased market power.

operating in the same locale have been largely neglected (Bouchard and Morselli, 2014). Cooperation between OCGs potentially unlocks fresh resources, for example through division of labor (Fijnaut et al., 1998), collusion in price setting (Levitt and Venkatesh, 2000) or improved market access. Resources can be then invested by successful OCGs to expand operations or minimize the odds of being displaced by competing groups. Arguably, cooperation is in principle rational. However, a multiplicity of factors compatible with a conflictual landscape as the one we observe in Merseyside may hinder its realization, or restrain its reach and/or duration to short-lived opportunistic interactions.

This brings us to the fourth and last empirical regularity we consider in this work, which is a visualization of the cooperative dynamics of Merseyside. The left panel of Figure 5 depicts the distribution of the *volume* of crime committed by an OCG in partnership with other OCGs. A value of zero (respectively, one) implies that no crime (respectively, all crime) is committed in association with one or more partnering OCGs. A partnership between two different OCGs realizes if at least two OCGMs belonging to each respective OCG have been involved in a crime together. About 63% of OCGs commit crime with other OCGs, with roughly 5% of all OCGs (corresponding to 7 OCGs) committing more than 50% of their crime activities with at least one partner. Hence, we note that a sizeable fraction of crime is committed through collaborations, and volumes are heterogeneous across OCGs. In the right panel of Figure 5 we plot the distribution of new partnerships between OCGs, that is, we measure the number of OCGs any OCG collaborates with ignoring repeated interactions. We see that roughly 62% of OCGs in our data (corresponding to 87 OCGs) establish a partnership with *at least* another OCG. By looking at the subset of OCGs with at least one partner, the median and average number of partners is equal to 2.8 and 2, respectively. All of the above shows that the dynamics underpinning OCG operations in Merseyside are characterized not only by the tensions that we have discussed above, but also cooperation, with OCGs showing a rich operational profile in terms of both volume and complexity of collaboration that co-exist with a highly-conflictual environment.

3.2 Hypotheses Building

In this work, we investigate the structure and determinants of co-offending collaborations between organized crime groups (OCGs) across social, temporal and spatial dimensions with a focus on the drug-violence nexus. In so doing, we also aim to understand the puzzle of the *co-existence* of stable illegal markets and violence. Grounded on the regularities observed in Section 3.1, we break the problem into three hypotheses. Our starting point is that illegal markets - similarly to legal markets - are contendible, and competitive pressure and conflict may hinder participants' business. However, while in legal markets competition is regulated by a stable normative framework (which predates every participant), in illegal markets competition can escalate into unboundedly violent conflict[18]. OCGs overcome the risks of unbounded competition by establishing a (weak) bilateral/multilateral institutional framework, that is through cooperation. We formally hypothesize that in illegal markets a relationship between violence (that is, competition) and business exists, and that this is mediated by the extent and reach of OCG cooperation:

Hypothesis 1. *After controlling for neighborhood characteristics, a positive relationship exists between the degree of cooperation of OCGs operating in a neighborhood (either within or outside that neighborhood) and the level of illegal market activity in that neighborhood. At the same time, an inverse relationship exists between the degree of cooperation and the level of violence experienced within that neighborhood.*

Under the above hypothesis, cooperation is a *structural* feature of illegal markets because it *jointly* fosters economic opportunities and bounds conflict. Ignoring OCG cooperation leads to a spurious relationship between violence and business, consistent with the ambiguous evidence reported in Section 2. When cooperation between OCGs operating in a place fails (either in that place or elsewhere) competition dynamics kick in, and therefore it naturally follows from our theory

[18] Even in legal contexts, competition dynamics can erode the design, the implementation and the enforcement of a collaboration agreement via multiple channels, for example by putting pressure on the mechanism used for sharing the proceedings between parties: in experiments with ultimatum games, Roth et al. (1991) and Grosskopf (2003) showed that fairness in bargaining processes is vulnerable to the introduction of competition.

that in unregulated competitive markets violence is *consequential* to cooperation *failure*.

After having assessed the macro-level role of cooperation, we then turn to understanding the micro-level properties of cooperation. In legal markets, the formation of ventures is sustained by enforceable contracts, and property rights regulate surplus sharing. In principle, cooperation between OCGs is characterized by a structure of economic incentives that overlaps with the one of licit ventures[19]. However, the lack of solid institutional devices ensuring the division of surplus exacerbates the competitive pressure, and cooperation might induce "perverse incentives". For example, resources unlocked through a successful collaboration might alter the relative market power of co-offenders thus increasing the odds of one party displacing the other in future interaction, similar to what would happen in a team tournament[20].

If perverse incentives due to competition exist, they should cascade in two main dimensions of OCG cooperation mechanics: partner selection and co-offending behavior. Relative to the former, in Section 3.1 we observed a marked heterogeneity in the presence of OCGs operating in Merseyside; this is a persisting regularity of urban landscapes across countries (Bouchard and Morselli, 2014) which we expect to matter in partner selection. In particular, we expect cooperation to be *differential*, that is to realize between groups characterized by *asymmetric* control of the territory. This is because less established groups are more likely to collaborate with more established groups to obtain better market access, whereas larger, more established groups may choose smaller and more peripheral partners to moderate the opposite risks of losing market shares vis-à-vis other market participants or being overthrown by an empowered partner. Hence, rational OCGs will seek to establish agreements with partners characterized by a control of the territory which is asymmetric with respect to their own. This brings us to our second hypothesis:

[19] We refer the reader to the review of Draca and Machin (2015) for a comprehensive overview on the economic motives for crime participation in general.

[20] Formally, a team tournament is a competition where groups compete for a large award that only a small fraction will obtain and the payoff of groups is contingent upon *relative* performance (Nalbantian and Schotter, 1997).

Hypothesis 2. *Within any neighborhood, more established OCGs deflect the joint risks of defeat (by opponents) or overtake (by partners) by establishing partnerships with smaller and less established groups, whereas small groups seek to achieve access to better market opportunities enabled by larger and more established partners.*

Hypothesis 2 identifies a condition under which geographically-proximate groups can collaborate, thus expanding on the previous findings of Papachristos et al. (2013) and Coutinho et al. (2020) that pointed to a negative correlation between proximity and cooperation. It further provides a rationale for the *persisting* heterogeneity in the size of OCGs discussed in Section 3.1.

Third, if market pressure exists, net of collaboration costs, it must be that only the most lucrative activities can generate enough surplus to make the risks of repeated collaboration sustainable. This brings us to the third and last hypothesis:

Hypothesis 3. *Given the costs and risks involved in establishing partnerships, a positive relationship exists between the expected returns of an activity and the probability that a repeated collaboration (i.e. cooperation) between OCGs materializes.*

Consequently, the size of expected returns allows us to segment crime activities between those performed in a *thin*, non-structured market and those performed in a *thick*, structured market. Thin markets are environments where competition is likely to act as a leveler, meaning that market forces hinder long-lasting cooperation, whereas, in a thick market, cooperation bears *positional* and *structural* implications for involved OCGs[21].

Several works have attempted to estimate the returns to crime (see Draca and Machin, 2015 for a recent literature review) and, in particular, drug dealing (e.g.,

[21] A further dimension discriminating between these two alternative market shapes may be related to the production function used to carry over activities. We speculate in fact that different criminal activities require specific production functions of varying levels of complexity. For example, it is clear that the importation and distribution of drugs are more complex than, say, theft, and it is characterized by a production function with lower (or no) substitutability between inputs.

Reuter et al., 1990; Fagan, 1992; Hagedorn, 1994). Previous literature suggests that the returns to drug selling tend to be much greater than those of other criminal activities (Reuter et al., 1990; Levitt and Venkatesh, 2000). We then expect that drug dealing, especially hard drugs, is more likely to be akin to a thick market.

4 Data

4.1 Description of the Datasets

This study is geographically centered on Merseyside. This is the fourth most populated metropolitan county of the United Kingdom, and it is made of 22 metropolitan districts (with Liverpool city, the highest-density metropolitan district of UK, being the main one). Overall, it is endowed with a population of 1.38 million and a surface of 645 square-km of land[22]. In this work, we use three sources of administrative data.

Our first and main source is supplied by Merseyside Police (MP) and is given by all criminal reports[23] handled by MP between January 2015 and March 2018 (42 full months of data). Given our focus on incentive-driven, cooperative crime, we make only one alteration to the original dataset: we exclude all events classified by the police as domestic incidents and sexual offenses. The resulting dataset contains 375,599 reports, corresponding to 353,530 individual incidents. For each report, detailed information is provided on the nature of the crime h, time t, location m, and, if a suspect has been linked by MP to the incident, a personal identifier i for the suspect. For each suspect, MP records a vector of demographic indicators $\boldsymbol{x}_i$ containing age and ethnicity. Lastly, the report indicates whether the person has been associated by MP analysts to an OCG, in which case we refer to such individual as an organized crime group member (OCGM). Each OCGM

[22] See the table *"2009 Mid-Year Estimates – Table 9 ONS"*, accessible on http://statistics.gov.uk.

[23] In this paper we take a broad approach by including all recorded events, regardless of their criminal justice outcome: this includes events in which a person was arrested, cautioned, charged, and wanted on a warrant, as well as interviewed, suspected, or when no further action was taken.

Crime Class	All Incidents		with Individual		with OCGM		Matched
	Count	Percentage	Count	Percentage	Count	Percentage	
Arson	3,037	0.81	422	0.33	31	0.59	13.90
Burglary	44,226	11.78	6,615	5.13	671	12.81	14.96
Criminal Damage	57,985	15.45	9,481	7.36	313	5.97	16.35
Drug Possession (A)	4,056	1.08	3,990	3.10	115	2.20	98.37
Drug Possession (B/C)	15,597	4.16	15,263	11.85	711	13.57	97.86
Drug Trafficking (A)	3,029	0.81	2,974	2.31	310	5.92	98.18
Drug Trafficking (B/C)	3,844	1.02	3,462	2.69	228	4.35	90.06
Threats	32,022	8.53	13,143	10.20	276	5.27	41.04
Other	10,825	2.88	6,952	5.40	432	8.25	64.22
Robbery	4,824	1.29	1,550	1.20	130	2.48	32.13
Sexual	2,070	0.55	1,221	0.95	8	0.15	58.99
Theft or Fraud	125,882	33.54	28,451	22.08	803	15.33	22.60
Violence without Injury	7,942	2.12	3,625	2.81	171	3.26	45.64
Violence with Injury	56,550	15.07	28,598	22.20	799	15.25	50.57
Weapons Related	3,450	0.92	3,096	2.40	241	4.60	89.74
Sum	375,339	100	128,843	100	5,239	100	–

Table 2: Table of incidents for each reconstructed crime category as per Section 4.1. The table contains counts and percentage (on total number of crime incidents) for all crime incidents and counts and percentage (on total number of crime incidents attributed to OCGs) for OCG crime.

is associated with one of the $k = 1, ..., K = 134$ OCGs[24] . As a result, we have information on $62,948$ individuals, $N = 1,211$ of which have been marked as OCGM. OCG, OCGMs and their respective action set supply the main building blocks for the ensuing analysis. In some of our results, we will look at the broader distribution of crime across the entire population. Therefore, in the following, we refer to the data set of all crimes as the *full* data set and the subset of OCGM-related crime as the *restricted* data set.

Overall, the MP dataset contains a taxonomy of $H = 384$ classes of offenses[25], which we reclassify in 15 crime macro-classes. Crime classes with associated count and rate relative to total reported crime are listed in Table 2, where we also report matching rates (i.e. when a crime is linked to a suspect) and the fraction of crime linked to OCGM. In terms of reported crime, three major classes stand out: theft or fraud (35%), followed by violence with injury (15%) and criminal

[24] In our data, the relationship between OCGs and OCGMs is static, in the sense that only the last known affiliation of an OCGM is recorded.

[25] The taxonomy of crime activities of the UK legal system subdivides offenses between 10 macro-categories.

	All Individuals			OCGM		
Ethnicity	Count	Percentage	Average Age / S.D.	Count	Percentage	Average Age / S.D.
White British	46953	82.67	32	1107	93.10	28
			13			8
Non Stated	3793	6.68	34	26	2.19	32
			15			11
Any other White Background	1710	3.01	30	0	0.00	0
			11			0
Any other Black Background	634	1.12	30	19	1.60	27
			12			9
White Irish	554	0.98	31	3	0.25	27
			12			4
Any other Mixed Background	549	0.97	30	11	0.93	32
			11			10
Black African	547	0.96	31	4	0.34	36
			12			13
Any other Background	538	0.95	31	5	0.42	28
			11			4
Any other Asian Background	446	0.79	30	3	0.25	26
			11			7
Black Caribbean	288	0.51	33	6	0.50	34
			13			15
Total	56794	100.00	32	5128	100.00	26

Table 3: Demographic composition of crime incidences, for all individuals and OCGMs.

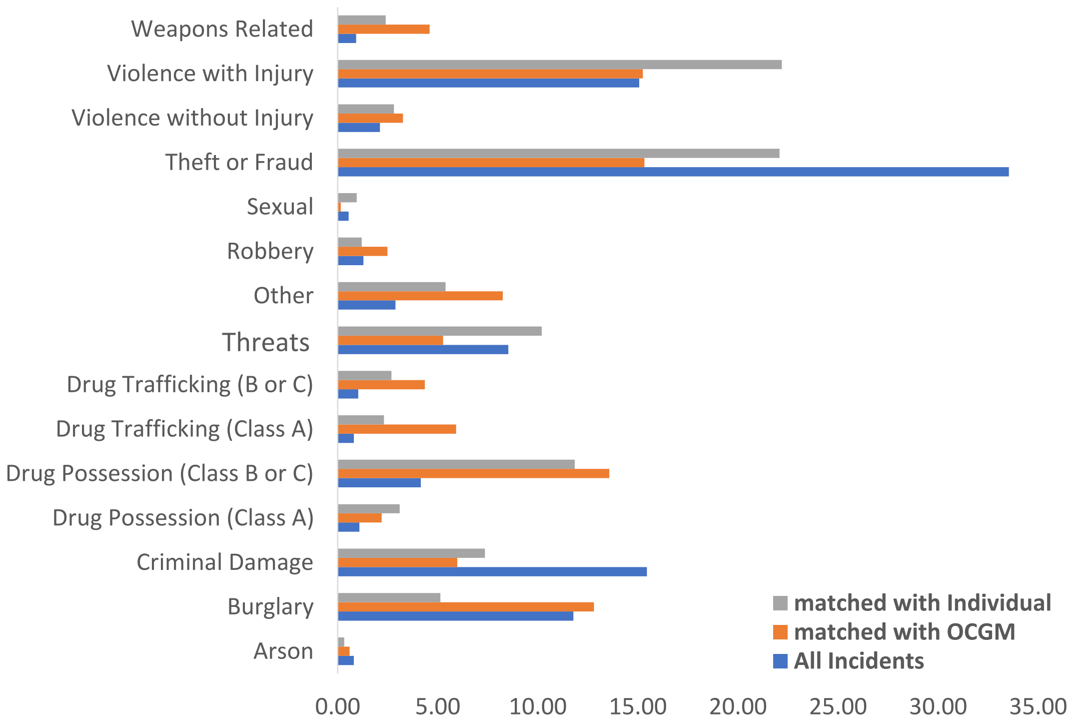

Figure 6: Volume of incidents by class of crime and matching rates for the population and OCGM-specific. Blue area represent the fraction of crime (on total crime incidents), whereas gray and orange bar represent the matching rates for the population in general and OCGMs individuals, respectively.

damage (15%). On the other hand, the matching rate is the highest for violent crime, followed by theft or fraud and drug possession (for class B or C drugs). As for other works dealing with comparable datasets (Kirchmaier et al., 2021), matching is very heterogeneous across classes, with violent crime having the highest rate. By comparing matching with the rate of crime attributed to OCGMs, we notice that OCGMs are predominantly involved in drug crime (of all types) and burglary, possibly reflecting also some crime-targeting effect of MP. Figure 6 puts the percentage incidences of Table 2 on a scale.

A theoretically interesting question raised by using arrest data is the extent to which the structure of the co-arrest network is driven by policing behavior rather than co-offending behavior (Papachristos and Bastomski, 2018). In Table 3 we report the demographic features of the MP dataset. A large literature correlates over-policing with ethnicity and status (see Papachristos and Bastomski, 2018 for a review). However, from the table we see that at least ethnically speaking, suspects are homogeneous in both the general population and OCGMs, with 83% and 93% of individuals given by white British subjects, respectively. While this allows us to moderate concerns of ethnicity-induced over-policing, we note that OCGMs and non-OCGMs are structurally diverging in another demographic dimension: OCGMs are on average 28 years old, 4 years younger than the average of the general offenders' population.

In Figure 7 we plot the frequency of crime activity for OCGMs and Non-OCGMs. Both distributions show exponential decay[26]. However, only 32% of OCMs are single-offender as opposed to 66% of Non-OCGMs, with an average number of crimes per individual of 4.19 for OCGMs and 1.99 for non-OCGMs, matching an observed regularity of OCGM behavior (see, for example, Bouchard and Spindler, 2010 and Spindler and Bouchard, 2011). The OCGMs distribution first-order stochastically dominates the Non-OCGMs one in all its support, yet, the Non-OCGM displays a longer tail, with some non-OCGM individuals committing more than 50 crimes. A divergence in the frequency of crime might be reflective of a structural divergence in the seriousness of crime in two ways. First, OCGMs might commit more serious offenses that attract more severe sanctions than the length of the data. Secondly, it is likely that OCGMs seek to stay "under-radar", favoring profit-generating activities and avoiding unnecessary volume crime.

In Figure 7 we focus on OCG activities and report crime levels and number of OCGMs per OCG, respectively. OCGs are heterogeneous in scope and size, with an average and median number of crimes of 34.48 and 16.5, respectively; and an average and median number of affiliates of 9.03 and 6 respectively. Taken together, these observations supply first-order evidence of the collaborative nature of organized crime *within* OCGs. In Section 5.1 we will supply a description of inter-OCG relationships.

The second source of data is given by a battery of 29 sociodemographic indicators which we construct from data of the UK Office for National Statistics (ONS) as

[26] In untabled analysis available on request, we make this statement precise against benchmark exponential distributions.

	Merseyside	UK
Demographic Density (per hectare)	34.698	4.1
Fraction residents under 15	0.165	0.177
Fraction residents between 15 and 24	0.137	0.131
Fraction residents between 25 and 29	0.065	0.069
Fraction residents between 30 and 44	0.189	0.206
Fraction residents between 45 and 64	0.268	0.254
Fraction residents above 64	0.176	0.163
Couples on All Family Arrangements	0.520	0.578
Lone Parent Households with Dependent Children	0.039	0.030
Born Abroad on Total	0.053	0.138
Fraction of Minorities of Non-British origin	0.075	0.202
Fraction of Residents with social Grade AB	0.181	0.230
Fraction of Residents with social Grade C1	0.314	0.309
Fraction of Residents with social Grade C2	0.197	0.206
Fraction of Residents with social Grade DE	0.308	0.255
Fraction of full-time student aged ≥ 4 at non term-time address	0.009	0.012
Fraction Unemployment	0.056	0.044
Fraction Employed in Agriculture and Manufacture	0.014	0.084
Fraction Employed in Construction, Utilities, Transport	0.171	0.189
Fraction Employed in Hospitality and Entertainment	0.062	0.085
Fraction Employed in Financial, Real Estates, Professional and Education	0.178	0.357
Fraction Employed in Public Administration, Health and other	0.065	0.077
Fraction Employed in Trade	0.068	0.146
Fraction of Agriculture and Manufacture Businesses	0.057	0.084
Fraction Construction, Utilities, Transport Businesses	0.085	0.189
Fraction Hospitality and Entertainment Businesses	0.107	0.085
Fraction Financial, Real Estates, Professional and Education Businesses	0.290	0.357
Fraction Public Administration, Health and Other Businesses	0.225	0.077
Fraction Trade Businesses	0.151	0.146

Table 4: Demographic indicators used in the analysis for Merseyside area (averaged at MSOA level) and UK.

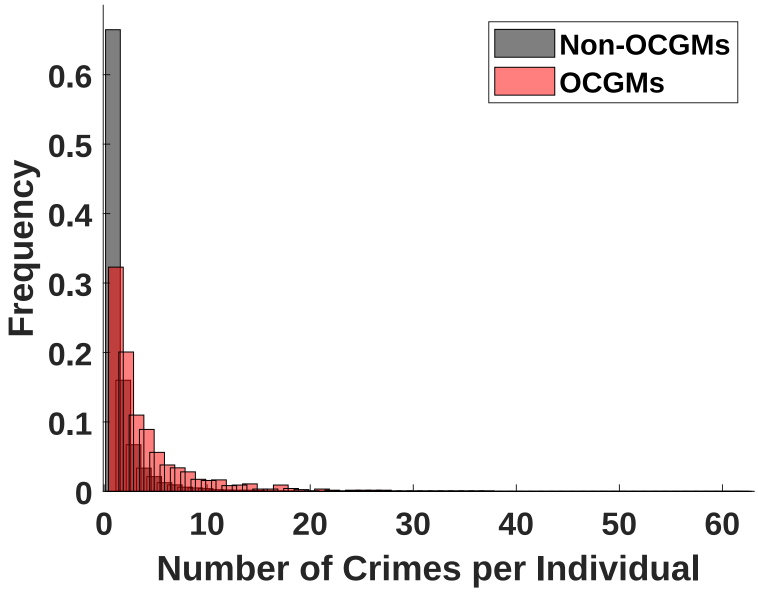

Figure 7: Frequency of crimes per individual suspect, non-OCGM and OCGM.

part of the last available national census[27]. We use the indicators to characterize the geographic unit which each incident is linked to. As the focus of this paper is on understanding the determinants of inter-OCG cooperation at neighborhood level, we use, as geographic units, the Middle Layer Super Output Area (MSOA). These are small-area census units that provide a good approximation of neighborhoods and are demographically stable, centered at around $8,000$ inhabitants each.

In Table 4 we report indicators for both Merseyside and UK averages. Relative to the whole nation, Merseyside is inhabited by an older and more ethnically cohesive population than the nation-level average, with 2.7% more of residents aged above 45 years old and -12.5% of non-UK minorities in percentage-gaps. Standard indicators correlated with social status and deprivation consistently indicate that Merseyside is poorer than the average of the UK. A higher fraction of single-parent households (+1.00%) is matched with higher unemployment (+1.20%) and lower social grade[28], with a higher presence of semi-skilled, unskilled manual workers

[27]These correspond to qualifiers contained in the following tables: *Enterprises by industry and employment size band, Population density, Usual resident population, Age structure, Living Arrangements, Economic activity, Approximated Social Grade, Length of residence in the UK, Lone parent households with dependent children, Ethnic group by sex by age.*

[28]Our measure of social grade corresponds to the *NRS Social Grade*. This classification distinguishes households in five groups, from A (Upper middle class) to E (Non-working), depending on the occupation of the head of the household.

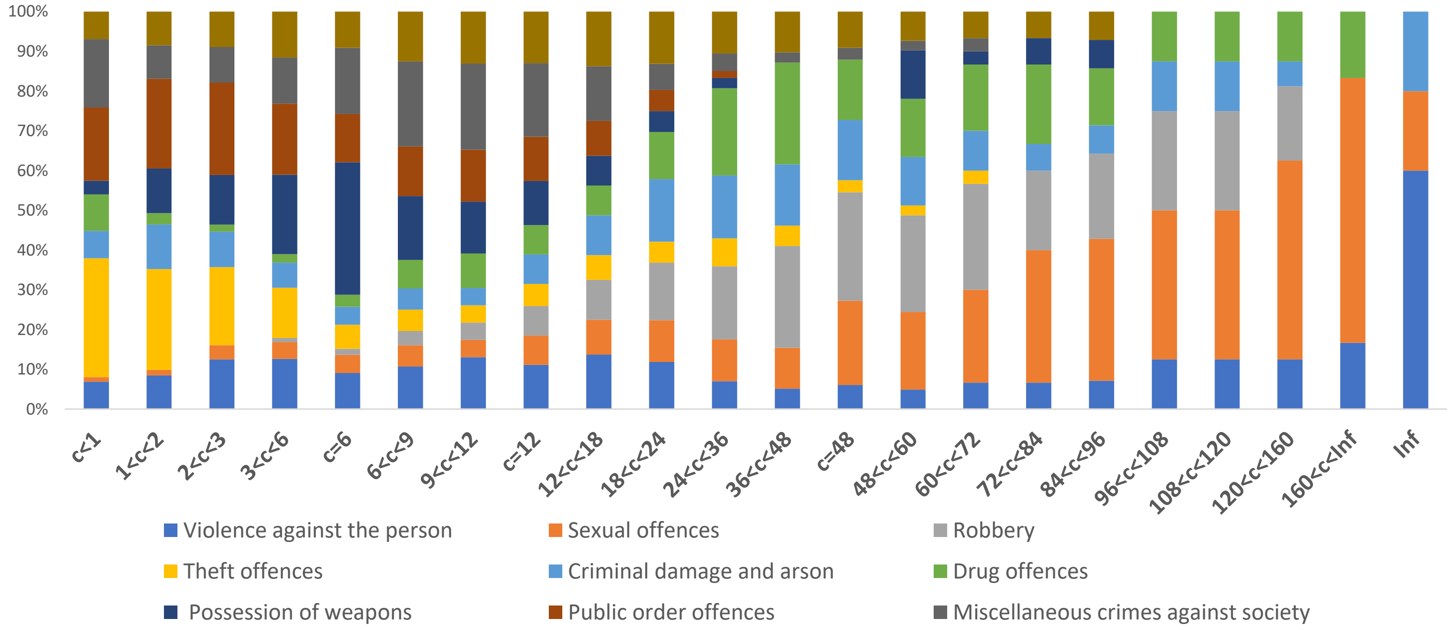

Figure 8: Sentence lengths (in months) by type of crime as categorized by Criminal Justice Statistics Quarterly for all convictions ordered between Q1:2015 and Q1:2018. In the table, c and *Inf* stand for the months of the sentence length and "Life Sentence", respectively.

and unemployed (+5.30%).

While most of our work attempts to explain crime as understood in terms of count of crime events (frequency of crime, see Section 5 for details), for testing Hypothesis 3 we complement counting with a measure of crime intensity (severity). This is obtained by means of the third and last source of data, which we refer to as the "sanction dataset", a collection of all 175,824 court orders for England and Wales as provided by Criminal Justice Statistics Quarterly UK for the period matching the MP dataset (January 2015 to March 2018). This data is used to proxy the severity ("intensity") of individual crimes (See Section 5). Each court order contains, as inputs, the offense[29] and a set of demographic indicators $\boldsymbol{x}_i$ given by gender, ethnicity and age of the indicted person i. The output of an order is a battery of 94 binary variables detailing the order actual outcome. We select all orders for which an indicted person has been found guilty of the offense

[29] As explained in Section 5, the matching between sentence length and crime activity is at offense level as opposed to offense group, hence our reclassification is neutral to our measure of intensity of crime activity.

and sentenced to custody. We use custody as opposed to fines due to the broader inclusiveness of the former measure (e.g., homicide is sentenced with mandatory custody and not a fine). [30].

In Figure 10 we report actual sentence lengths (in months) aggregated through the 10 macro-categories of crime of the UK judicial system. We discretize the distribution of actual sentences' lengths using the 21 bins adopted by the Criminal Justice Statistics Quarterly. Each bin collects all sentences with a length within the boundaries of that bin, standardized by the total number of sentences in that specific bin. Different crime macro-categories are represented in each bin. However, the relative prevalence of some classes (such as weapons-related crime) strongly correlates with the length of the sentence[31].

5 Methodology

Notation. In the following, bold notation describes matrices and vectors; $\boldsymbol{I}_n$ is the identity matrix of dimension n and $\mathbf{1}_n$ is the $n \times 1$ vector of ones. We frequently use component-wise notation for functions and matrix or vector multiplication. For example, vector $\boldsymbol{x} \equiv \{x_i\}_{i=1}^n$, $\boldsymbol{x}^a$ denotes the vector $\{x_i^a\}_{i=1}^n$, and $\log \boldsymbol{x}$ denotes the vector of natural log $\{\log x_i\}_{i=1}^n$. The presence (respectively, the absence) of a subscript t attached to x_t indicates that the variable dynamically evolves across periods $t = 1, 2, ...$ (respectively, the variable is static). For empirical variables (i.e. variables constructed using the dataset), the presence (respectively, the absence) of t implies that the variable has been constructed with the data realized in period

[30]In the literature, various measures of crime harm have been proposed, chiefly, with the purpose of measuring the seriousness of crime, thus enabling a comprehensive risk assessment of suspects to improve resource allocation and accountability (Sherman et al., 2016). Building on court records, the Australian National Offence Index (Andersson, 2003), the Canadian Crime Survey Index (Canada, 2022) or the New Zealand Justice Sector Seriousness Score (Sullivan and Su-Wuen, 2012) associate a score to offenses based upon realized court charges. Being output-based measures, the score is a function of a crime seriousness as well as other factors such as the history of the offender (Sullivan and Su-Wuen, 2012). Sherman et al. (2016) construct an "history-neutral" index based upon starting "point of UK sentencing guidelines. This abstraction supplies researchers with a *harm* index, that is a *victim*-centered score which is neutral relative to offender identity and crime history.

[31]In Appendix A.1 we take a complementary angle and report the distribution of sentence lengths for each of the macro-classes above.

t (respectively, with data across *all* available periods $t = 0, ..., T$).

5.1 Metricizing OCG Activity and Collaborations

5.1.1 Construction of OCGM and OCG networks

In this work, we conceptualize the interactions between OCGs and OCGMs as a multi-layer dynamic network (Coutinho et al., 2020). A dynamic network[32] is a set of periods $t = 1, 2, ..., T$, nodes $i = 1, 2, ..., N$ and edges $a_{i,j,h,m,t}$, whereby edges connect nodes to each-other. Formally, $a_{i,j,h,m,t} > 0$ is an edge directed from node i to node j in period t corresponding to a crime of class h. If nodes i and j are not connected in period t, $a_{i,j,h,m,t} = 0$. A network is *undirected* if $a_{i,j,h,m,t} = a_{j,i,h,m,t}$. Algebraically, a sufficient statistics for describing a dynamic network at time t is given by the $N \times N$ *adjacency matrix* $\boldsymbol{A}_t$ with elements $a_{i,j,h,m,t}$. In the following, we will interchangeably use "adjacency matrix" and"network".

In our paper, we construct two inter-related networks. The first network characterizes the interactions between OCGMs . Let $\mathcal{N}$ be the set of OCGMs recorded in the MP dataset, ordered by an MP-issued numerical IDs. Each individual $i \in \mathcal{N}$ is endowed with a set of static *features*, such as gender, ethnicity or, critical for our work, the OCG they belong to, $k_i = 1, ..., K$, collected by vector $\boldsymbol{x}_i$, which is an element of a matrix $\boldsymbol{X} = \{\boldsymbol{x}_1, ..., \boldsymbol{x}_N\}$. The building block of our network is given by the *crime matrix* $\boldsymbol{C} = [\boldsymbol{o}, \boldsymbol{t}, \boldsymbol{c}, \boldsymbol{m}]$ of dimension $T \times (N + 3)$. Each row vector of the matrix is a *crime record*, $\boldsymbol{c}_t = [\boldsymbol{o}_t,\ t,\ c_t\ m_t]$, organized as follows: the $1 \times N$ vector $\boldsymbol{o}_t$ has generic element $o_{t,i}$ picking value 1 if OCGM i has been associated to crime $\boldsymbol{c}_t$ and 0 otherwise, the scalar t is a numerical timestamp uniquely associated to the crime record, h_t is a numerical indicator uniquely associated to one of the $H = 384$ crime offenses of the UK justice system (see also Section 4.1) and lastly, m_t is one of the $M = 201$ neighborhoods where the crime has been committed. For convenience, we exploit the 1:1 relationship between timestamps and records and refer to each period[33] t as the *crime* t.

[32]For a literature review of network approaches in OCG studies, see Papachristos (2014).

[33]Indeed, in the analysis, periods/crimes are conveniently aggregated depending on the task

To describe connections between suspects, we define the generic edge $a_{i,j,h,m,t}$ such as

$$a_{i,j,h,m,t} = \Phi\left(o_{t,i}, o_{t,j}, h_t, m_t, \boldsymbol{x}_i, \boldsymbol{x}_j\right), \tag{1}$$

where $\Phi(\cdot)$ is a generic *interaction* function which potentially depends on the (possibly disjoint) presence of actor i and j in crime record $\boldsymbol{c}_t$, the nature of the offense h_t, the location where the crime has been committed m_t, and the individual characteristics of i and j (our approach is a generalization of Papachristos et al., 2015b). We refer to matrix $\boldsymbol{A}_{h,m,t}$ as the *OCGM network*. Edges are *undirected* if $a_{i,j,h,m,t} = a_{j,i,h,m,t}$, in which case, $\boldsymbol{A}_{h,m,t}$ is a symmetric matrix. We will specialize the weights $a_{i,j,h,m,t}$ of the matrix $\boldsymbol{A}_{h,m,t}$ and the temporal structure in Sections 5.1.2 and 5.2, respectively.

Second, we define the interactions between OCGs, where we indicate a generic OCG with $k \in \mathcal{K}$. These are captured by the $K \times K$ adjacency matrix $\boldsymbol{G}_{h,m,t}$ with the generic element $g_{p,q,h,m,t}$ defined as the sum of co-offenses of typology h of OCGMs belonging to OCGs p and q in location m and period t. Formally,

$$g_{p,q,h,m,t} \equiv \left(\sum_{i:k_i=p} \sum_{j:k_j=q} a_{i,j,h,m,t} \right) \Big/ 2, \tag{2}$$

so that an edge between OCG p and q exists if *at least* two OCGMs respectively associated to p and q have co-offended together in a crime type h. Notice that if $\boldsymbol{A}_{h,m,t}$ is symmetric, also $\boldsymbol{G}_{h,m,t}$ is. We refer to $\boldsymbol{G}_{h,m,t}$ as the *OCG network*: this is the building block of our models.

An Example of OCG Network. Figure 9 exemplifies the various dimensions and abstractions involved in the network construction process for a network where we suppressed the temporal, crime-type and spatial dimensions for simplicity. In this example, the police identified suspects $i = 1, ..., 6$ such that $i = 1, 2, 3$ belong to OCG 1 (colored for convenience in red) and suspect $i = 5, 6$ belong to OCG 2 (colored in green). Importantly, we assume that suspect $i = 4$ does not belong to any OCG. From the graph, it appears that nodes $i = 1$ and $i = 2$

at hand (see Section 5.2 for details).

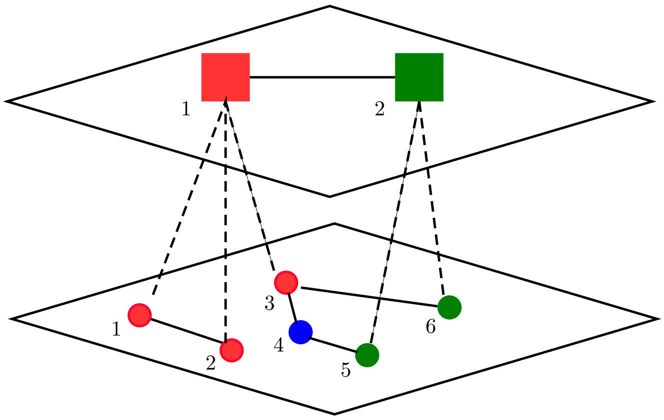

Figure 9: A representation of the network structure adopted in this paper. The lower plane represents the space of interaction between OCGMs as observed *within* any period t. In this example, suspects $i = 1, ..., 6$ are identified such that $i = 1, 2, 3$ belong to OCG 1 (colored for convenience in red) and suspect $i = 5, 6$ belong to OCG 2 (colored in green). Suspect $i = 4$ is assumed not to belong to any OCG and is present on the plane only for convenience. Nodes $i = 1$ and $i = 2$ collaborated in at least a crime, and so did nodes $i = 4$ and $i = 5$, and nodes $i = 3, 4, 6$. Edges $a_{3,6}$ and its equivalent $a_{6,3}$ connect OCGMs belonging to different OCGs. In the upper plane, we represent OCG 1 and OCG 2. For these two OCGs, it holds that $g_{1,2} = g_{2,1} > 0$ as a consequence of $a_{3,6} = a_{6,3} > 0$

collaborated in at least a crime, and so did nodes $i = 4$ and $i = 5$, and nodes $i = 3, 4, 6$. This will be reflected by edges $a_{1,2}, a_{2,1}, a_{3,4}, a_{4,3}, a_{4,5}, a_{5,4}$ and $a_{3,6}, a_{6,3}$ taking positive values, which will be stored accordingly in the OCG network $\boldsymbol{A}$. Crucially, of all these edges, only $a_{3,6}$ and its equivalent $a_{6,3}$ are the ones that connect OCGMs belonging to different OCGs. In the upper plane, we represent OCG 1 and OCG 2. For these two OCGs, it holds that $g_{1,2} = g_{2,1} > 0$ as a consequence of $a_{3,6} = a_{6,3} > 0$. Therefore, the OCG network $\mathbf{G}$ will contain only two positive entries, corresponding to cells $g_{1,2}$ and $g_{2,1}$.

To appreciate the complexity of empirical OCGM interactions, in Figure 10 we plot both OCG and OCGM networks as extracted from the MP dataset. On the Left Panel, where the OCGM network is plotted, we observe a core of densely interconnected OCGMs surrounded by isolated OCGMs[34]. Reassuringly, the embeddedness of OCGMs is a broadly observed regularity in the literature of urban crime (see, in particular Papachristos et al., 2013; Green et al., 2017; Tita and

[34]In untabled results available upon request we show with several metrics that embeddedness is even stronger when placing OCGMs within the entire population of offenders.

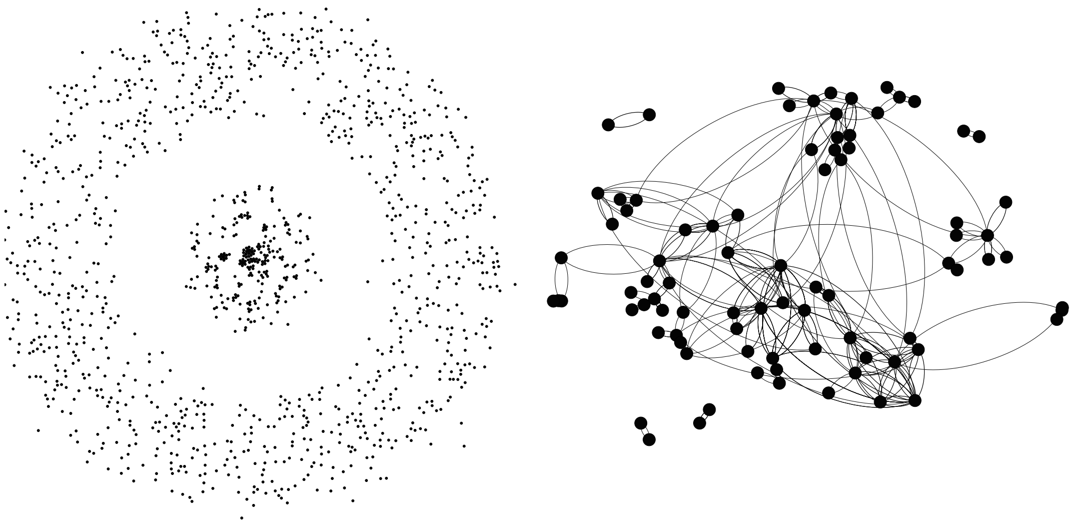

Figure 10: (*Left Panel.*) The empirical OCGM network as constructed from the MP dataset such that a node (respectively, an edge) corresponds to an OCGM (respectively, at least one co-offense). (*Right Panel.*) The empirical OCG network such that a node (respectively, an edge) corresponds to an OCG (respectively, at least one co-offense jointly committed by members of two OCGs).

Greenbaum, 2009 and the review of Papachristos, 2014) which transcends individual relationships carrying over to various notions of agglomeration, with particular relevance of a geographical one: inter-neighborhood flows (Bastomski et al., 2017 Papachristos and Bastomski, 2018). Our notion of agglomeration, the OCG, is primarily a social one. As such, in addition to the geographical dimension, the OCG network can be shaped by the partially coordinated design of individual actors, reflecting hierarchies, conflicts and market structure (see also Stylized Fact 4 in Section 3.1). On the right panel of Figure 10 we plot the OCG network. Out of the $K = 134$ OCGs, 85 of them (corresponding to roughly the 63%, see also Section 3.1) have at least one interaction with another OCG, with an average of 4.5 interactions across all OCGs. Differently from the OCGM network, the OCG network is concentrated, as it composed by a total of only 5 components[35], thus signaling a rich woven of interactions, with only 8 OCGs engaging in mutually-exclusive partnerships.

[35] A component is a subnetwork in which each pair of nodes is connected with each other via a path of edges Jackson (2010).

5.1.2 Measuring the Frequency and Intensity of Crime Relationships

Given any pair of OCGMs i and j respectively belonging to OCGs p and q, inter-OCGM and inter-OCG edges $a_{i,j,h,m,t}$ and $g_{p,q,h,m,t}$ can be characterized in various ways depending on available data and scope. Typically, $a_{i,j,h,m,t}$ is a binary variable picking a value of 1 if two subjects have been suspected co-offending together in *at least* one occasion, either as evidenced in crime reports (see, for example, Lindquist and Zenou, 2014, Papachristos et al., 2015b or Lindquist and Zenou, 2019), intel (Coutinho et al., 2020; Papachristos et al., 2012) or self-reporting[36] (Liu et al., 2012), or 0 if no interaction is observed. Formally, in this classical approach, a link $a_{i,j,h,m,t}$ is defined as

$$a_{i,j,h,m,t} = 1 \quad \text{if} \quad \sum_{t=0}^{T} (o_{t,i} \cdot o_{t,j}) > 0 \quad \text{s.t.} \quad l_t = m \text{ and } w_t = h, \tag{3}$$

such that $a_{i,j,h,m,t} = 1$ only if both OCGMs co-offended in at least a crime $\boldsymbol{c}_t$ involving crime type h in area m. Indeed, all networks constructed on (3) are *static*, so that $\boldsymbol{A}_{h,m,t} = \boldsymbol{A}_{h,m}$ and, by using (2), $\boldsymbol{G}_{h,m,t} = \boldsymbol{G}_{h,m}$. This approach produces weight structures that we call *binary* networks $\boldsymbol{A}^B_{h,m}$ and $\boldsymbol{G}^B_{h,m}$. We expand on this by characterizing $\boldsymbol{A}$ (and $\boldsymbol{G}$) with two alternative weight structures: a count structure and an intensity structure.

Count networks. The count structure is straightforward: a *count* OCGM network, indicated by $\boldsymbol{A}^C_{h,m,t_0,t_1}$ contains, as an element a^C_{i,j,h,m,t_0,t_1}, the count of co-offenses of type h of i and j occurring in area m between periods t_0 and t_1 (included), such that

$$a^C_{i,j,h,m,t_0,t_1} \equiv \sum_{t=t_0}^{t_1} (o_{t,i} \cdot o_{t,j}) \quad \text{s.t.} \quad l_t = m \text{ and } w_t = h. \tag{4}$$

Notice that element $a^C_{i,i,h,m,t}$ contains the sum of *all* crimes of type h committed by i in area m between periods t_0 and t_1.

[36]Taking an opposite perspective, several papers used similar sources of information to obtain networks of OCG *rivalries*, for example, by means of intel (Papachristos, 2009; Tita and Radil, 2011) or through records of fatal and non-fatal gun violence between OCGMs (Papachristos et al., 2013 and Green et al., 2017.

The count matrix $\boldsymbol{A}^C_{h,m,t_0,t_1}$ generates, through (2), the *count* OCG network $\boldsymbol{G}^C_{h,m,t_0,t_1}$, in which each entry g^C_{p,q,h,m,t_0,t_1} represents the *sum* of type h crimes jointly committed by OCGMs belonging to p and q between periods t_0 and t_1 in area m. Lastly, we can use $\boldsymbol{G}^C_{h,m,t_0,t_1}$ to normalize[37] the count network $\boldsymbol{A}^C_{h,m,t_0,t_1}$ to generate what we refer to as the *joint OCG-normalized* OCGM network, $\boldsymbol{A}^J_{h,m,t_0,t_1}$, such that each entry is equal to $a^J_{i,j,h,m,t_0,t_1} \equiv a^C_{i,j,h,m,t_0,t_1}/g^C_{p,q,h,m,t_0,t_1}$. Importantly, the OCG network associated to $\boldsymbol{A}^J_{h,m,t_0,t_1}$ is the *binary* network $\boldsymbol{G}^B_{h,m,t_0,t_1}$.

Intensity networks. Binary and count-based networks allow to isolate the geometrical features of interaction and supply intuitive metrics to understand the frequency of OCG co-operations; as such, they are instrumental for testing Hypotheses 1 and 2. However, as evidenced by our discussion of court orders (see Figure 8 in Section 4.1) even within a given class of felonies, the severity of a crime and the associated sentence length can vary widely across offenses, hinting at heterogeneity in the severity, expected penalty and *motivation* of underlying actions (Ratcliffe, 2015; Ignatans and Pease, 2016; Sherman et al., 2016; Ashby, 2018). Such heterogeneity is key for uncovering the rationale of OCG cooperation, as we do in Hypothesis 3.

To construct a salient measure of crime intensity, we note that the starting point of the framework leading to Hypothesis 3 is that co-offenders are incentive-driven (Becker, 1968, Clarke and Felson, 1993, Ouellet et al., 2022). Incentives imply that an action is performed if *expected* personal returns stemming from the offense, that is personal benefits times the probability of realization *given* the personal characteristics of the offender as included in the vector $\boldsymbol{x}_i$, outweigh expected personal costs[38]. In other words, for any crime typology h committed by OCGM

[37] In the literature, it is typical to normalize the *binary* network $\boldsymbol{A}^B_{h,m,t}$ by replacing each entry $a^B_{i,j,h,m,t}$ with $a^B_{i,j,h,m,t}/\sum_{j\in\mathcal{N}} a_{i,j,h,m,t}$. An important difference between the binary network $\boldsymbol{A}^B_{h,m,t}$ and its row-normalized analogue lies in the type of peer influence each matrix describes. It can be shown that the former structure is apt to describe a local-aggregate type of influence (i.e. a model where individuals are influenced by the sum of their peers' behaviors) whereas the latter describes local-average influence (see (Lindquist and Zenou, 2019) for a derivation and discussion of the relevant literature).

[38] Our approach is in line with rational choice theory, which predicates that offenders are decision-makers who engage in a cost-benefit analysis of the anticipated risks and rewards of engaging in a criminal act (Becker, 1968, Clarke and Felson, 1993).

i, a crime is performed if

$$E\left[\text{returns of } h \mid \boldsymbol{x}_i\right] \geq E\left[\text{sanction of } h \mid \boldsymbol{x}_i\right] + E\left[\text{other costs of } h \mid \boldsymbol{x}_i\right].$$

Conditioning costs and benefits to personal features $\boldsymbol{x}_i$ is important. For example, the sanction (and therefore, the motivation) associated with drug dealing of class B or C drugs might vary widely depending on the age of the indicted person. From the above equation, only the first element of the right-hand side (i.e. the sanction if caught and indicted) is known to the researcher under the assumption that (rational) OCGMs are aware of the sanction that action h might attract. Therefore, we take the expected sanction *given* the offender's personal characteristics as a *lower bound* for the expected returns of committing a crime, net of any other cost[39]. In this perspective, any felony recorded in the MP dataset maps into an action which has to be *at least as* rewarding as the connected sanction.

Therefore, our intensity (or returns) score seeks to adapt to the profile of offenders to maximize the fit with the actual cost-benefit analysis of decision-makers. This is achieved by computing, for each crime type $h = 1, .., H$ and each combination of the characteristics in vector $\boldsymbol{x}_i$ as determined from the MP dataset, an indicator $e(h, \boldsymbol{x})$ that uses the data of the sentence dataset as follows:

$$e(h, \boldsymbol{x}) \equiv \frac{E\left[\text{sanction of } h \mid \boldsymbol{x}\right]}{\kappa}. \tag{5}$$

In the above formula, the numerator of $e(\cdot)$ is the expected sentence length (in months) given characteristics in $\boldsymbol{x}$ as computed from the sentence dataset, in which we impose[40] that life sentences are transformed to a 30 years sentence (equivalent to 320 months). The denominator κ standardizes the indicator in a 0 to 1 range.

[39]Other costs may include, for example, opportunity costs that vary widely between individuals of different age or educational background (Draca and Machin, 2015). Indeed, our bound might not hold in general, as certain crimes are not driven by a rational evaluation. However, this concern is moderated by the fact that our offenders are OCGMs, who show to qualitatively differ from non-OCGMs in several dimensions, and all sex and domestic offenses have been removed from our dataset (see Section 4.1).

[40]Indeed, *any* order-preserving arbitrary transformation is valid up to life sentences, and the relatively small number of life sentences (59, equivalent to less than 1.5% of all sentences) moderates scaling concerns.

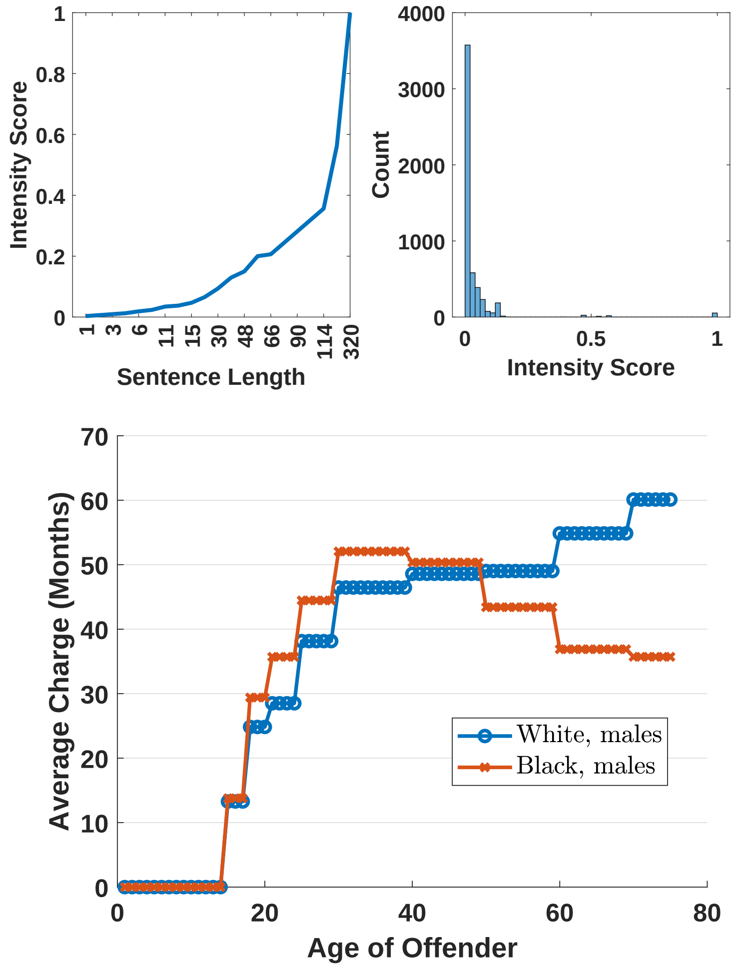

Figure 11: (*Top Left Panel.*) The intensity score as constructed in (5), where the sentence length is measured in months. (*Top Right Panel.*) Empirical distribution of the intensity score for all OCG crimes. (*Bottom Panel.*) The intensity score (5) for the offense class *"Trafficking of Drugs"* computed for all male profiles of age $0-80$ of white and black ethnicity, respectively.

As a result, the indicator $e(\cdot)$ maps every crime h of the U.K. judicial system into an index which is conditional to the features $\boldsymbol{x}_i$ of each suspect i as recorded in the MP dataset. The indicator constructed in (5) is plotted in Figure 11, On the upper left side of the figure we show the theoretical construction, whereas on the upper right side, we plot its empirical counterpart on all crimes recorded in the dataset. Importantly, we notice that most crime is concentrated within an index value of $0.01-0.3$. However, more than 2.5% records attract index values above 0.5. This confirms that at the local level crime shares features of heterogeneity we discussed, at national level, in Section 4.1. To show the flexibility of our score in capturing potential variability of crime costs (and returns) across individuals,

OCGM Network	$\Longleftrightarrow$	OCG Network
$\boldsymbol{A}^B_{h,m,t_0,t_1}$		$-$
$\boldsymbol{A}^C_{h,m,t_0,t_1}$		$\boldsymbol{G}^C_{h,m,t_0,t_1}$
$\boldsymbol{A}^J_{h,m,t_0,t_1}$		$\boldsymbol{G}^B_{h,m,t_0,t_1}$
$\bar{\boldsymbol{A}}^C_{h,m,t_0,t_1}$		$\bar{\boldsymbol{G}}^C_{h,m,t_0,t_1}$

Table 5: The relationship between network structures used in the paper. For any pair of OCGs i and j respectively belonging to OCGs p and q, each entry of a binary network $\boldsymbol{A}^B_{h,m,t_0,t_1}$ assesses whether one or more crime h relationships exist between i and j within periods t_0 and t_1 in neighborhood m. $\boldsymbol{A}^C_{h,m,t_0,t_1}$ and $\boldsymbol{G}^C_{h,m,t_0,t_1}$ respectively count all crime co-offenses between i and j and p and q. Each entry g^C_{p,q,h,m,t_0,t_1} of the count network $\boldsymbol{G}^C_{h,m,t_0,t_1}$ contains the count of offenses jointly committed by OCGMs belonging to p and q. Each entry a^J_{i,j,h,m,t_0,t_1} of the joint OCG-normalized OCGM network $\boldsymbol{A}^J_{h,m,t_0,t_1}$ corresponds to $a^C_{i,j,h,m,t_0,t_1}/g^C_{p,q,h,m,t_0,t_1}$. Lastly, each element $\bar{a}^C_{i,j,h,m,t_0,t_1}$ of matrix $\bar{A}^C_{h,m,t_0,t_1}$ corresponds to the sum of the intensity of co-offenses committed by OCGMs i and j, whereas each element $\bar{g}^C_{p,q,h,m,t_0,t_1}$ of matrix $\bar{G}^C_{h,m,t_0,t_1}$ corresponds to the sum of the intensity of co-offenses committed by OCGMs belonging to OCG p and q.

in the bottom panel of the figure we plot the (month-adjusted) intensity score (5) for the offense class *"Trafficking of Drugs"* for all male profiles of age $10-80$ of white and black ethnicity, respectively.

Secondly, we construct two further weight matrices, $\bar{\boldsymbol{A}}^C$ and $\bar{\boldsymbol{G}}^C$ which we refer to as the OCGM and the OCG cumulative *intensity* networks, respectively (see also Table 5 for a mapping between the various classes of networks). To obtain the new weights, define $\bar{\boldsymbol{A}}_{h,m,t_0,t_1}$ as a matrix with generic element $\bar{a}_{i,j,h,m,t_0,t_1}$, such that

$$\bar{a}^C_{i,j,h,m,t_0,t_1} \equiv \sum_{t=t_0}^{t_1}(o_{t,i} \cdot o_{t,j} \cdot e(h_t,\ \boldsymbol{x}_i)) \quad \text{s.t.} \quad l_t = m. \tag{6}$$

Hence, the matrix $\bar{\boldsymbol{A}}^C_{h,m,t_0,t_1}$ is a (potentially) *asymmetric* matrix collecting in each cell (i,j) the sum of returns obtained by the offender i in crimes committed with co-offender j between periods t_0 and t_1 included. Through (2) we immediately obtain network $\bar{\boldsymbol{G}}^C_{h,m,t_0,t_1}$, an asymmetric matrix collecting in each cell (p,q) the sum of returns obtained by OCG p in crimes committed with OCG q.

5.1.3 Measuring OCG Cooperation across Neighborhoods

To address Hypothesis 1, we construct an index of cooperation capable of reflecting two regularities of OCG interaction discussed in Section 3.1. The index rests on the assumption that within any time period t short enough, OCG relationships between any pair of OCGs p and q are generally uniform, that is we do not expect p and q to simultaneously cooperate *and* fight with each other. The first regularity we consider is that OCG turfs may extend across multiple neighborhoods and overlap with each other (see also the left pane of Figure 2). As a result, given a pair of OCGs p and q active in both neighborhoods l and m, with observed collaborations in l but not in m, we want our cooperation index to pick up collaboration in both neighborhoods l and m: in fact, the lack of observed co-offenses in m might be by design (i.e. OCGs decide not to co-offend in that specific area) or by the failure of the police to record joint offenses. Second, since market pressure is generally high, the OCG landscape is highly dynamic (see the right pane of Figure 2), a feature that we expect to shape the structure of collaborations: new bonds can be created, and old bonds can be severed if not perpetuated. Therefore, we want our index to be able to capture both directions of collaboration dynamics.

We construct the index based upon the dynamic binary OCG network $\boldsymbol{G}^B_{t_0,t_1}$ rather than a cumulative or intensive-based network. This choice is pragmatic, as it equips us with a straightforward interpretation of variations of the index. Our index is time-dependent, that is it rises whenever new collaborations are formed, and falls if existing collaborations are not perpetuated, relative to the total number of OCGs operating in any given neighborhood m in the time interval dictated by t_0 and t_1. The most general form of the index is defined as a measure I_{h,m,t_0,t_1}, such that

$$I_{h,m,t_0,t_1} \equiv \frac{\left(\sum_{p\neq q,\ g_{p,p,h,m,t_0,t_1}=1} \sum_{q\neq p,\ g_{q,q,h,m,t_0,t_1}=1} \sum_{l=1}^{M} g^B_{p,q,h,l,t_0,t_1}\right)/2}{\Gamma_{h,m,t_0,t_1}}, \tag{7}$$

where the numerator simply counts the number of edges established, across Merseyside, during any interval t_0 to t_1 between OCGs that are both active in neighbor-

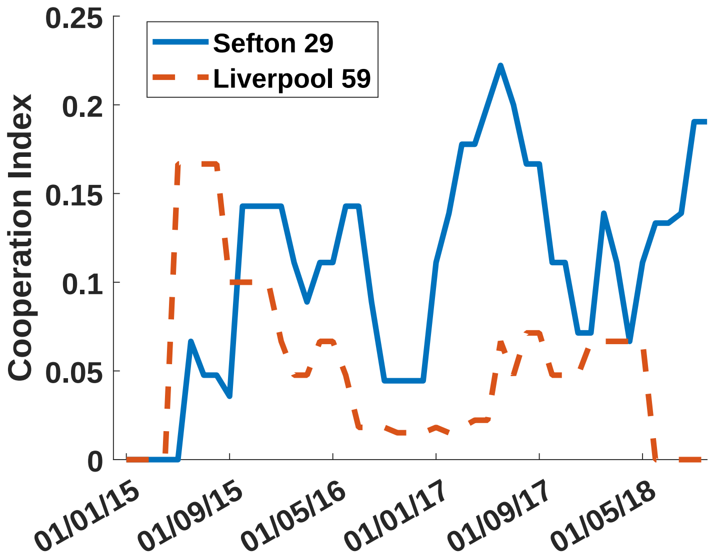

Figure 12: The cooperation index as defined in 7 constructed for two MSOA of Merseyside using a 12 months rolling window. Data is merged via summation at monthly level $z = 1, ..., 42$, and for each month z, the cooperation index is generated with a time interval is given by the past 12 months of crime data.

hood m. Importantly, edges can realize in *any* of the $l = 1, ..., 201$ neighborhoods of Merseyside. The denominator, $\Gamma_{h,m,t}$, is given by the *maximum* number of possible collaborations between OCGs operating in neighborhood m during interval t_0 to t_1, and it is indeed equal to the number of OCGs active in neighborhood m times all possible OCGs operating in m they may have created edges with,

$$\Gamma_{h,m,t_0,t_1} \equiv \frac{\left(\sum_{p=1}^{K} g^{B}_{p,p,h,m,t_0,t_1}\right) \times \left(\sum_{p=1}^{K} g^{B}_{p,p,h,m,t_0,t_1} - 1\right)}{2}.$$

where we further divide by two to capture the indirect nature of links (i.e. a connection between OCG a and b equals a connection between b and a). In the paper, rather than using the general per-crime index, we will mainly use a version of it that aggregates across all $h = 1, ..., H$ typologies of crime, I_{m,t_0,t_1}. Importantly, the index varies widely across neighborhoods and/or time periods, reflecting the dynamic nature of OCG interactions. We show this in Figure 12, where we plot the cooperative index as constructed in (7), for two randomly selected neighborhoods of Merseyside. In the figure, data is aggregated both in the time and the crime-type dimensions. Data is aggregated at the monthly level, $z = 1, ..., 42$, and for each month z, a cooperation index $I_{m,z-12,z-1}$ is generated where the time interval is given by the past 12 months of crime data, meaning that two OCG p and q operating in the neighborhood m are flagged as collaborating if they co-offended in at least a crime h in the past 12 months.

5.1.4 Quantifying the Asymmetry of OCG Turf Control within Neighborhoods: Divergence Index and Differential Cooperation

Hypothesis 2 rests on the idea that illicit markets are contendible, and that competitive pressure coped with lack of enforceable contracts generate deterrence violence and affects incentives to cooperate (see also Brantingham et al., 2012 and the literature therein). OCGs moderate potential pitfalls of cooperation by fostering *asymmetric* relationships which give rise to the notion of differential cooperation, for which larger/stronger OCGs favor interacting with smaller/weaker OCGs, whereby smaller OCGs are keen to collaborate with larger groups to elude potential costs (such as deterrence violence) and gain better market access. We now build a metric to measure the degree of asymmetry of turf control of OCGs within any given neighborhood m, a so-called *divergence index*. The idea behind the divergence index is that we proxy turf control with territorial presence, as measured in terms of the mass of crime committed by an OCG in any given area weighted for the total amount of crime committed in the same area. First, for each neighborhood[41] $m = 1, ..., 201$ we define C_{m,t_0,t_1} as the total sum of crimes committed in the neighborhood m from period t_0 to period t_1 included. Then, we can obtain the number of crimes committed by OCG p *without* the contribution of q in neighborhood m, which we call b_{p,q,m,t_0,t_1}, as follows

$$b^C_{p,q,m,t_0,t_1} \equiv \sum_{h=1}^{H} \left(g^C_{p,p,h,m,t_0,t_1} - g^C_{p,q,h,m,t_0,t_1} \right), \tag{8}$$

which we conveniently collect in the matrix $\boldsymbol{B}^C_{m,t_0,t_1}$ in which each diagonal element is equal to 0. Lastly, we compute, for each OCG p and q, and neighborhood m,

[41] We refer the reader to Section 4.1 for the details on the construction of neighborhoods and some descriptive statistics.

the divergence index. This is given by the fraction of crime committed by OCGMs belonging to p *not* involving members of OCG q on the total number of offenses in neighborhood m,

$$r_{p,q,h,m} \equiv \frac{b^{C}_{p,q,m,0,T}}{C_{m,0,T}}, \tag{9}$$

which we collect in matrix $\boldsymbol{R}_m$. This latter matrix supplies the synthetic notion of turf control, which we will operationalize in models described in Section 5.2.2. Notice that differently from previous metrics discussed above, our measure of turf control is static[42].

5.2 Models of OCG Interaction

We articulate this section in various subsections, discussing the testing strategy behind each hypothesis.

5.2.1 Testing Hypothesis 1: Cooperation and the Neighborhood

In Hypothesis 1 we explore the causal nexus between the intensity of OCG cooperation and the activities performed in neighborhoods. More precisely, we take a granular approach and study the fluctuation in the amount of crime of class h observed in a neighborhood m as a function of changes to the cooperation index $I(\cdot)$ as defined in Section 5.1.3. We do so through the following dynamic Poisson

[42]Indeed, a core idea of our work (see Section 3.1) is that turfs are contendible and potentially unstable (Brantingham et al., 2012), however in the current framework we focus on OCG dynamics *given* a fixed notion of geographic bound (the turf), and we leave the topic of turf formation and its geographic evolution to future analysis, referring the reader to the work of Brantingham et al. (2012) and their literature review.

panel model[43]

$$\log\left(E\left[C_{h,m,z}\right]\right) = \alpha_{h,m} + \delta_{1,h} I_{m,z-b,z-a} + \boldsymbol{\tau}_z \cdot \boldsymbol{v}_{h,z}. \tag{10}$$

In the model above, crime data is aggregated at the monthly level, such that it supplies us with $z = 1, ..., 42$ snapshots for each of the $m = 1, ..., 201$ neighborhoods. On the left-hand side of (10) we have the count of crime C of class h committed in the neighborhood m within any month z. On the right-hand side, our variable of interest is the cooperation index I, which maps cooperation into a scale from 0 to 1 for each neighborhood m using networks constructed within a moving time interval of length $[a, b]$. An index of 0 implies that during the time window, OCGs operating in neighborhood m did not engage in co-offenses anywhere in Merseyside, whereas an index of 1 signifies that all OCGs active in m during the interval $[a, b]$ engaged in at least a co-offense somewhere in Merseyside. We select a and b to capture a full year of cooperation[44]. Furthermore, we circumvent issues of simultaneity by imposing a lag of one month to the window between dependent and independent variables. Hence, we pick $a = 1$ and $b = 12$.

As our analysis is at neighborhood level, neighborhood fixed effects α_m are included to control for all time-invariant geographic specificities. Lastly, vector $\boldsymbol{\tau}$ incorporates a battery of 62 month-year time dummies to single out all time-specific dependencies.

[43] More precisely, we use a Poisson fixed effect model with robust standard errors estimated with a standard Sandwich linearized estimator. We favor this combination over negative binomial models (Hausman et al., 1984) because the former does not impose conditional independence, it is fully robust to any distributional misspecification, and it allows any kind of serial correlation under clustering of errors (Wooldridge, 1999). We further perform a Ramsey's REST test for the model misspecification to confirm that the model is well-specified (available upon request). The Ramsey Regression Equation Specification Error Test (RESET) test is a general specification test for the linear regression model that tests whether non-linear combinations of the fitted values help explain the dependent variable.

[44] As a robustness check, in untabled analysis available upon request we tested alternative time frames obtaining similar results (in qualitative terms).

5.2.2 Testing Hypothesis 2: Selecting Partners

Hypothesis 2 focuses on partner selection. To investigate this matter, we reduce the structure of OCG collaborations to the binary OCG network $\boldsymbol{G}^B$ (see Section 5.1.1 for its construction) and construct a dyadic logit regression model where the outcome of interest, $P(g^B_{p,q,m})$, is the probability that OCGs p and q establish *at least* a collaboration in neighborhood m. We relate the outcome to each OCG's turf presence by means of the following model:

$$\frac{P(g^B_{p,q,m})}{1 - P(g^B_{p,q,m})} = \beta_0 + \beta_1 \left|r_{p,q,m} - r_{q,p,m}\right| + \beta_2 \left(r_{p,q,m} + r_{q,p,m}\right) + \beta_3 \left|\text{age}_p - \text{age}_q\right|. \quad (11)$$

Coefficient β_1 quantifies the effect of the divergence index r, which measures the *differences* in turf control as metricized in terms of the fraction of crime committed by p and q with no involvement of OCGMs belonging to the other OCG (see Section 5.1.4 for the definition of the divergence index r). Since the probability of a link might be influenced by p and/or q attaining a certain level of territorial activity rather than because of each OCG *relative* control of the turf, we also include β_2. The coefficient β_3 measures the difference in the mean age of OCGMs belonging to p and q and it is used to capture the demographic-related aspects of homophily.

The estimation of dyadic regressions is problematic as observations are not independent of each other since the same OCG may appear in potentially multiple dyads[45]. Provided that regressors are exogenous, logit yields consistent coefficients, but standard errors are inconsistent. For this reason, we correct the dyadic correlation of errors and any potential heteroscedasticity through the method developed[46] by Fafchamps and Gubert (2007). Furthermore, we cluster observations at neighborhood level.

[45] In other words, not only the probability of an edge between p and q is affected by all partnering choices of p, but also by the choices of q relative to all other OCGs. Formally, $E\left[u_{p,q}, u_{p,k}\right] \neq 0$ for all p, $E\left[u_{p,q}, u_{q,k}\right] \neq 0$ for all q as well as $E\left[u_{p,q}, u_{k,p}\right] \neq 0$ and $E\left[u_{p,q}, u_{k,q}\right] \neq 0$. Failing to account for dependence of this type will, typically, result in standard errors which are too small and consequently more Type I errors in inference than is desired (see, for an analytic review of contemporary dyadic regression methods, (Graham, 2020)).

[46] Practically, the correction is implemented using the script available on Marcel Fafchamps's website.

5.2.3 Testing Hypothesis 3: Selecting Deals

Lastly, we turn to the study of the *intensity* of collaborations. Hypothesis 3 conceptualizes a relationship between the expected utility of crime typologies and the *strength* of cooperation between OCGs. This expands and complements our previous analysis and the literature that investigates the nexus between partner selection and crime typologies (see, for example, Coutinho et al., 2020 and the works cited therein). In this literature, the structure of OCG collaborations is usually reduced to the binary OCG network $\boldsymbol{G}^B$ we deployed above. As edge formation between any of two actors i and j is hardly an independent process but rather a function of the edge formation behavior and characteristics of *all* actors in a given population, models of network formation are usually estimated through binary exponential random graph models (ERGMs), which expand traditional logit models by allowing for correlation in tie formation. The basic idea behind ERGMs is to specify a vector of sufficient network statistics $\boldsymbol{S}(\boldsymbol{G}^B)$ and OCG-specific covariates $\boldsymbol{X}$ and formulate the probability of observing the network as depending on the count with all networks endowed with the same sufficient statistics being drawn with equal probability conditional on OCG-specific covariates. Coefficients are then estimated to maximize the likelihood of obtaining the observed network. Formally, the ERGM specifies the probability $P(\cdot)$ of observing a network $\boldsymbol{G}^B$ endowed with network attributes $\boldsymbol{S}$ conditional on covariates $\boldsymbol{X}$ such as[47]

$$P_\gamma(\boldsymbol{G}^B|\boldsymbol{X}) = \frac{\exp(\boldsymbol{\gamma} \cdot \boldsymbol{S}_{\boldsymbol{X}}(\boldsymbol{G}^B))}{\sum_{\boldsymbol{G}^B} \exp(\boldsymbol{\gamma} \cdot \boldsymbol{S}_{\boldsymbol{X}}(\boldsymbol{G}^B))} \tag{12}$$

where the denominator is a normalizing constant computed on all possible networks and $\boldsymbol{\gamma}$ is the vector of parameters to be estimated. Since the computation of the normalizing constant is computationally impossible due to the size of the set of interactions, Markov chain Monte-Carlo (MCMC) methods are routinely implemented[48].

[47] It is easy to show that when the sufficient statistics $\boldsymbol{S}(\boldsymbol{G}^B)$ is given by only edges, or in other words, edges are independent, the ERGM coincides with a logit model with dependant variable corresponding to $\boldsymbol{G}^B$dependent

[48] The idea behind MCMC methods is to create a Markov chain on the set of nodes in $\boldsymbol{G}^B$, where the equilibrium distribution equals $P_\beta(\boldsymbol{G}^B|\boldsymbol{X})$. Once the equilibrium distribution is

In order to capture the *strength* of cooperation between OCGs, we drop from the $H = 384$ offenses of the U.K. legal system all activities related to the consumption of drugs (about 15% of observations) and merge the remaining offenses in $\bar{h} = 1, ..., 6$ macro-classes of crime activities. Then, we replace, as measure of analysis, $\boldsymbol{G}^B$ with the count network $\boldsymbol{G}^C$ defined as

$$\boldsymbol{G}^C \equiv \sum_{t=0}^{T} \sum_{\bar{h}=1}^{6} \sum_{m=1}^{M} \boldsymbol{G}^C_{h,m,0,T},$$

effectively moving away from the binary framework. For estimating the model, we adopt the *valued* ERGM approach pioneered[49] by Krivitsky (2012). Valued ERGMs extend standard ERGMs by also modelling whether a covariate increases or decreases the (potentially non-binary) value of an edge (i.e. the strength of collaboration) between network actors (Krivitsky, 2012), thus allowing us to discriminate between episodic co-offending and repeated cooperation. As the space of potential interaction in valued ERGMs is potentially infinite[50], a reference distribution has to be specified (Krivitsky, 2012). Similar to other works (see, for example, Ouellet et al., 2022) we impose a Poisson distribution[51]. We briefly describe OCG-specific covariates $\boldsymbol{X}$ and network attributes $\boldsymbol{S}_{\boldsymbol{X}}$ below. These are also collected in Table 6.

OCG-Specific Covariates. We deploy two broad classes of OCG-specific covariates. First, it is in an established regularity of the literature on peer effects in crime networks (e.g. Papachristos et al., 2015a, Liu et al., 2012) that demographic homophily is an important driver of inter-OCG cohesion. To control for that, first,

reached through the iterative procedure, random draws can be computed for the J observations of $\boldsymbol{G}^B$ necessary to maximize an approximate log-likelihood function attached to (12). See (Pavel N. Krivitsky et al., 2022) for a description and various implementation examples of the methodology.

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

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

[51] The Poisson distribution is a conservative modelling choice for social network processes as it presumes a simple random network formation protocol as opposed, for instance, a preferential attachment protocol (which would require us to engage in several ad-hoc assumptions), and it is equivalent to a binomial distribution for networks large enough (see, for an analytic taxonomy of random networks and candidate formation protocols, Jackson, 2010). We calibrate the Poisson distribution parameter λ to achieve a best-fit with the observed edge distribution, such that $\lambda = 1.55$.

Typology	Covariates	Notes
Return from Crime	Total Returns from Crime (excl. drug consumption)	Sum of returns from all crime activities
	Drug Trafficking per OCGM	Drug Trafficking of Class A, B and C
	Acquisitive Crime per OCGM	Theft, Fraud, Burglary and Robbery
	Violence with Injury per OCGM	-
	Violence without Injury per OCGM	-
	Threats per OCGM	-
	Weapons per OCGM	-
Demographics	Age	Average age of OCMs
Structural	Density	Sum of collaborations per OCG
	Triadic Closures	Sum of triadic closures per OCG

Table 6: The covariates used in testing Model 12.

we include OCGM age, expressed in terms of absolute deviations from the OCG average age (similar to models in (11)). Second, we include a binary variable to capture the match (or lack thereof) between the median OCG ethnicity. Both variables are computed for all possible pairs of OCGs.

The second and main class of OCG-specific covariates is given by the cumulative returns to crime (as defined in Section 5.1.2) standardized, for each OCG, by the number of OCGMs. We separately study models including the total returns of crime and a breakdown of returns for various crime activities. This strategy allows us to inspect the existence of a general link between profitability and cooperation as per Hypothesis 3, as well as further investigate structural differences between various types of crime activities. Using crime intensity as opposed to crime counts enables a comparison between various classes of crime, holding returns constant. In other words, it allows us to inspect the relevance and magnitude of specific crime activities *given* returns[52]. To do so, we compute, for each OCG, the per-capita return of each crime macro-class $\bar{h}$[53] (see Table 6). Then, for each crime-intensity covariate X and OCGs p and q, we use, as regressor, both absolute deviation $|X_p - X_q|$ and sum $X_p + X_q$. The combination of the two allows us to consider

[52]This is particularly relevant in light of the heterogeneity, in terms of harm and revenue, of crime activities *within* any crime class (see Section 4.1), such that the qualitative and organizational implications of an additional unit of crime depends on the specific offense.

[53]Formally, given N_k the number of OCGMs populating OCG k, this procedure is equivalent to computing, for each OCG k, the value $\bar{g}^C_{k,k,\bar{h},0,T}$ of network $\bar{\boldsymbol{G}}^C$ as defined in Section 5.1.2.

both the implications of the gap between the p and q crime activity and their total combined magnitude.

Structural Covariates. Similar to Ouellet et al. (2019), we control for two measures of network connectivity: the number of OCG collaborations and the number of triadic closures each OCG is involved in. The first covariate indicates the expected number of collaborations between any of the OCGs given the observed number of collaborations across the entire network. This term is equivalent to the intercept of standard logit models (Krivitsky, 2012). Triadic closures provide a measure of transitivity (Ouellet et al., 2019), which occur every time that the collaboration intensity between an OCG and two separate OCGs stimulates the probability that also these two OCGs collaborate[54].

6 Results

In this section we present the results of estimations for models (10), (11) and (12).

Cooperation and the Neighborhood. Table 7 presents estimates of model (10) for two selected classes of crime, Drug Dealing (class A) and Violence with Injury[55]. Coefficients are reported on a month-neighborhood basis. Hypothesis 1 is built around the idea that violence and business are substitute activities, and as such, variables related to these activities are expected to move in opposite directions. This is verified in Column (3) and (6), where we see that a 1% increase in the cooperation index is jointly associated with a 1.4% increase in the monthly neighborhood levels of OCG crime related to drug dealing of class A substances and a 1.5% decrease in crime of violence with injury, crucially controlling for all time-invariant neighborhood's characteristics (Neighborhood Fixed Effects) and

[54] Formally, given three OCGs p, q, b, a triadic closure $T_{p,q,b,t}$ can be defined as $T_{p,b,q,t} \equiv \phi\left(g^C_{p,q,t}, g^C_{p,b,t}, g^C_{q,b,t}\right)$, whereby $T_{p,b,q,t} > 0$ means that the triadic closure exists at time t. In our analysis, triadic closures are operationalized to capture *transitivity* of collaborations between OCGs, that is, the likelihood that if $g^C_{p,q,t} > 0$ and $g^C_{p,b,t} > 0$, also $g^C_{q,b,t} > 0$.

[55] In Appendix B.2 (Table 11) we report results for the analysis of the model of Column (3) and (6) (Table 7) for all classes of crime. Interestingly, only *Threats* and *Weapons* are significantly associated with variations in the cooperative index, with a negative association (similar to Violence with Injury) and a positive association, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Drug Dealing (class A)			Violence with Injury		
Cooperation Index	0.011**	0.012***	0.014***	-0.01	-0.010**	-0.015**
	(-0.01)	(0.00)	(0.00)	(-0.01)	(0.00)	(0.00)
Constant	-3.48***	-	-	-2.37***	-	-
	(-0.23)	-	-	(-0.08)	-	-
Time F.E.	N	Y	Y	N	Y	Y
Neighborhood F.E.	N	N	Y	N	N	Y
Observations	6,792	3,639	2,283	6,792	3,639	2,283
AIC	2,000.02	1,444.69	1,457.72	4,285.27	3,429.42	3,406.32
BIC	2,020.50	1,450.89	1,550.71	4,305.74	3,435.97	3,504.57

Table 7: Estimation of models in (10). Coefficients are computed on a month-neighborhood basis. The estimated 62 month-year time F.E and the 200 neighborhood F.E are omitted from the table. *AIC* and *BIC* stand for Aikake Information criterion and Bayesian Information Criterion, respectively. Robust standard errors are in parenthesis. Symbols *,** and *** represent statistical significance at $0.1, 0.05$ and 0.01 level, respectively.

a large battery of time-variant effects (Time Fixed Effects). Jointly taken, these results robustly support Hypothesis 1, which is the core pillar of our work.

While coefficients are reassuringly stable across all models (1)-(3) and (4)-(6), by looking at selection information criteria (AIC and BIC) as well as significance of coefficients, we further highlight that spatial and time-related features also affect violence (consistently with, for example, Papachristos, 2009 and Green et al., 2017).

Selecting Partners. Table 8 presents the results for the estimation of model (11), where we establish a theoretical nexus between OCG presence and control on turf and the likelihood of establishing partnerships with other OCGs. Estimates are in log-odds. From the baseline model, we make three observations. First, by looking at the magnitude and sign of the intercept and the covariate *age*, we obtain two reassuring regularities observed in the behavior of OCGMs across the world (see, e.g. Bouchard and Morselli, 2014, Bouchard, 2006). The first regularity is that on average, the baseline probability for two OCGs to establish a collaboration is rather low, about 1.2% after conversion from log-odds. The second regularity is that gangs are demographically cohesive, so that a one-year

	(1)	(2)
Turf Presence (abs diff)	3.581^{***}	8.670^{**}
	(-0.52)	(-4.05)
Turf Presence (sum)	-	-4.87
	-	(-3.98)
Age (abs diff)	-0.044^{**}	-0.044^{**}
	(-0.02)	(-0.02)
Constant	-4.350^{***}	-4.059^{***}
	(-0.20)	(-0.30)
Observations	24,932	24,932
Groups	183	183

Table 8: Estimation of models in (11). Coefficients are reported in log-odds. Standard errors are corrected for dyadic correlation of errors (Fafchamps and Gubert, 2007). Symbols *,** and *** represent statistical significance at $0.1, 0.05$ and 0.01 level, respectively. Observations are grouped at neighborhood (MSOA) level.

increment in the age gap between two gangs roughly halves the probability for the two OCGs to establish collaboration. The second observation we make is that divergences in turf control, as expressed by variable *Turf Presence (sum)* are strongly and positively associated with the probability of collaborating at least once, thus verifying our theory of differential cooperation (Hypothesis 2). From Column (2) we note that this result survives the introduction of covariate *Turf Presence (sum)*, which measures the combined effect of (disjoint) turf presence of the OCGs. Importantly, this latter regressor is not significant, showing that OCG size (of either OCG) taken in isolation from the structure of other OCGs operating in the same territory is not a factor for inter-OCG edge formation (cooperative link). Hence, it is the *relative* size/presence that matters for edge formation (i.e., cooperation). Specifically, a 10% increase in the gap of turf control increases the probability of establishing at least one link between the two OCGs by about 13% (in terms of average marginal effects).

Selecting Crime Activity. Table 9 contains a battery of estimations based upon model (12), where, differently from other models estimated in this paper, variables of crime activity measure the intensity of crime (per OCGM) rather than the count of offenses. Estimates are in log-odds. Column 1 contains only sociodemographic characterizers for OCGs, i.e., age (expressed in absolute difference) and ethnicity (expressed by a dummy with value 1 if two OCGs share the median ethnicity and zero otherwise). We also include regressor *Nonzero* to capture potential anomalies in the behavior of OCGs characterized by a zero-inflated distribution, and regressor *Density* which measures the average number of collaborations in the structure (that is the intercept). Reassuringly, we observe that the effect of the age covariate is robust and closely matching its effect in model (11). At the same time, median ethnicity bears no implication on the number of collaborations. This is also reassuring in light of the high ethnic homogeneity of Merseyside OCGs as discussed in Section 4.1.

Column 2 and 4 add to the analysis the total intensity of crime per OCGM, both in terms of absolute deviations and the combined level of activity across OCGs. From Column 2, an increment of 1 unit of per-OCGM crime intensity throughout the period raises the odds of cooperation by roughly 3.78 times after conversion from log, whereas a comparable increment in the gap of crime intensity reduces the odds of collaboration by about double this magnitude, roughly by $1/\exp(1.883) = 6.57$. Taken together, these two observations are in line with Hypothesis 3: (repeated) cooperation is more likely when stakes (as measured in terms of severity of realized crime) are higher. Relative to Column 2, Column 4 additionally tests, through covariate *Triadic Closure*, the existence of network-based strategic effects. OCGs are 1.80 times more likely to cooperate with an OCG if any of their partners is already collaborating with that OCG. At the same time, it is important to remark that the result discussed for Column (3) survives the introduction of strategic motifs, albeit with marginally smaller magnitude. This means that the two effects are *coexistent* within the set of motivations guiding OCG cooperation.

Columns 3 and 5 modify the models of Column 2 and 4 by disaggregating crime into the six macro-classes discussed in Table 6. Relative to the previous results, we make three observations. First, the coefficient of *Density* (i.e. the intersect) is now significant and consistent with the results of model (11): the odds of collaborating with other OCGs are 0.43 times those of not collaborating. Therefore, OCG networks are more fragmented and less prone to aggregation than other social

	(1)	(2)	(3)	(4)	(5)
Total Crime (sum)		1.330***		0.965***	
		(0.194)		(0.144)	
Total Crime (abs diff)		-1.883***		-1.507***	
		(0.394)		(0.351)	
Drug Trafficking (sum)			10.845***		9.207***
			(1.898)		(1.749)
Drug Trafficking (abs diff)			-13.154***		-12.166***
			(3.539)		(3.535)
Acquisitive Crime (sum)			6.506***		5.272***
			(1.493)		(1.424)
Acquisitive Crime (abs diff)			-3.829		-3.246
			(2.027)		(1.928)
Violence with Injury (sum)			1.623***		1.310***
			(0.243)		(0.209)
Violence with Injury (abs diff)			-2.288***		-2.010***
			(0.475)		(0.454)
Violence without Injury (sum)			12.505		12.077
			(7.750)		(7.383)
Violence without Injury (abs diff)			-28.779**		-25.715**
			(10.142)		(9.661)
Threats (sum)			24.343		22.355
			(15.927)		(14.023)
Threats (abs diff)			-36.026		-33.435
			(21.235)		(19.357)
Weapons (sum)			11.787**		8.790*
			(4.313)		(4.027)
Weapons (abs diff)			-4.874		-3.653
			(6.285)		(6.335)
Age (abs diff)	-0.043**	-0.040**	-0.042**	-0.036**	-0.035*
	(0.013)	(0.015)	(0.014)	(0.013)	(0.014)
Ethnicity (match)	0.076	0.115	0.162	0.069	0.125
	(0.033)	(0.282)	(0.307)	(0.256)	(0.256)
Nonzero	-3.853***	-3.632***	-3.354***	-3.793***	-3.527***
	(0.211)	(0.211)	(0.217)	(0.200)	(0.204)
Density	0.188	-0.209	-0.836***	-0.269	-0.778***
	(0.138)	(0.160)	(0.246)	(0.156)	(0.224)
Triadic Closure				0.590***	0.499***
				(0.100)	(0.101)
Observations	3,570	3,570	3,570	3,570	3,570
AIC	-6,027.1	-6,019.0	-6,031.8	-6,048.0	-6,060.8
BIC	-6,008.6	-5,988.1	-5,939.1	-6,010.9	-5,961.9

Table 9: Estimation of models in (12) where crime-related covariates are standardized by OCG size. Coefficients are reported in log-odds. Given two generic *OCGs* p and q, *sum* $= x_p + x_q$, *abs diff* $= |x_p - x_q|$ and *match* $= 1$ for $x_p = x_q$ and 0 otherwise. *AIC* and *BIC* stand for Aikake Information criterion and Bayesian Information Criterion, respectively. Symbols *,** and *** represent statistical significance at $0.1, 0.05$ and 0.01 level, respectively.

structures[56]. Second, by looking at sign of coefficients, it appears that the effects on cooperation of aggregate crime intensity carry over to the disaggregated analysis, meaning that *for given levels of intensity*, Hypothesis 3 qualitatively holds for all classes of crime. Third, crime typologies diverge in significance and magnitude of effects. In particular, the sum coefficient is not significant for crimes of Violence without Injury and Threats. This might imply that these classes might be fundamentally different from other classes, e.g. by possessing a too-weak risk-reward profile. Such would be the case if activities under these two categories do not generate enough profit to induce the incentive structure and profit-sharing concerns at the basis of our theory on differential cooperation. On the other hand, in order for our theory to hold under this interpretation, we would need cooperation to be strongly associated with activities characterized, on average, by a high risk-reward profile. We verify this by looking at the magnitude of statistically significant crime covariates. In this sense, the crime activity characterized by the highest magnitude (both in terms of sum and absolute difference) is the drug trade, followed by violence with injury.

7 Conclusions

The study of cooperation among self-organised crime groups of offenders (OCGs) using formal network models is largely unexplored, yet understanding such mechanisms is key to understanding regularities in illegal markets, and their players, as well as adverse outcomes in urban areas, such as the level of violence affecting neighborhoods. We maintained the importance of a meso-level analysis focusing on inter-OCGs relational patterns to unpack macro-level empirical regularities, such as the coexistence of stable illegal markets and violence, as well as shedding light on mechanisms driving partner selection in co-offending.

In this work, we offered a theoretical and quantitative exploration of the structure and determinants underpinning cooperation among OCGs across social, temporal

[56] We refer the reader to Jackson (2010) for an extensive taxonomy of human networks and their statistical properties.

and spatial dimensions and its impact on local communities, especially through the drug-violence nexus. We did so by leveraging a granular large-scale crime dataset from Merseyside in the United Kingdom (2015-2018), integrated with neighborhood-level socio-economic data from the UK Office for National Statistics and sentence outcomes from Criminal Justice Statistics Quarterly UK. Merseyside is a particularly suitable setting with a population of 1.38 million people, the highest number of OCGs per million population in England and Wales – more than double the national average – and a police force judged "outstanding" in their ability to collect evidence on OCGs.

We proposed a theory of differential cooperation between OCGs. We posited that in illegal markets, where enforceable contracts are not available and surplus sharing is not regulated by property rights, OCGs are faced with the risk of unbounded competition that can translate into violence. They strategically respond to their weak institutional environment through bilateral/multilateral cooperation. However, the lack of property rights and a stable institutional framework can generate perverse incentives. For example, a successful joint endeavour can lead to perverse outcomes, e.g. by generating resources that may be used by an OCG against their partners. We maintained that OCGs address this criticality by establishing collaborations through a mechanism we termed differential cooperation.

More precisely, we found evidence that cooperation is differential as it is realized between groups characterized by asymmetric control of their territory (turf). Within any neighborhood, we show that more established OCGs deflect the joint risk of defeat (by opponents) or overtake (by partners) by establishing cooperation with smaller and less established groups, whereas small groups seek to achieve access to better market opportunities enabled by larger and more established partners. In particular, a 10% increase in the gap of turf control increases by about 13% the probability of establishing at least one link between the two OCGs on average.

Secondly, in the context of risks generated by the perverse incentives of cooperation, we found that there exists a positive relationship between the expected returns (and associated risks) of an activity and the probability of repeated cooperation. We found evidence of a strong relationship between (accumulated) crime intensity and the propensity for OCGs to collaborate, transversally across all classes of crime. This is consistent with the idea that cooperation is possible only when the reward profile of a potential collaboration is strong enough to out weight its potential risks, thus reflecting strategic opportunism from OCGs. In particular, an increment of 1 unit of per-OCGM crime intensity throughout the period of the analysis raises the odds of cooperation by a factor of 3. This phenomenon coexists with (and is not substituted by) significant network effects in three-way cooperation as captured by triadic closure: two OCGs that intensively collaborate with the same common partner are more likely to establish a direct collaboration between them - plausibly, a further strategy to decrease risk when selecting partners, particularly in a context characterized by low trust (Campana and Varese, 2013).

Our theory of differential cooperation is nested within the idea that the unbounded competition typical of illicit markets (i.e. violence) and business are substitute activities and, as such, variables related to these activities are expected to move in opposite directions. In other words, OCGs overcome the risk of unbounded competition through cooperation. Indeed, we found that a 1% increase in inter-OCG cooperation is jointly associated with a 1.4% increase in the monthly neighborhood levels of OCGs' drug dealing of hard drugs (class A substances) and a 1.5% decrease in violence with injury. This shows that group-level (meso-level) decisions have a structural impact on the characteristics of illegal markets and levels of violence in a neighborhood. It also goes to show that in unregulated competitive markets, violence is consequential to cooperation failure.

Our work points to four policy implications. Firstly, it highlights the importance of considering self-organised groups of offenders as strategic entities when developing interventions aiming at curbing their activities as well as broader illegal markets. It is particularly important to understand how groups select their partners and opportunities in their local areas to improve the efficacy of interventions. Secondly, our work suggests that interventions aimed at curbing OCG-related violence need to take into account the structure of cooperation among the OCGs active in an area as cooperation and violence are two sides of the same coin, with violence likely to erupt as a result of breakdown in cooperation within the OCG milieu. Thirdly, our findings stress the importance of group-level relational mapping if we are to understand the workings of illicit markets as well as adverse dynamics at the community (urban area) level. Finally, this work has also offered a novel way of measuring turf control and a new index of cooperation that analysts might find useful when developing evidence-based interventions and, crucially, tracking the subsequent short- and medium-term consequences (including those unintended) of such interventions.

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APPENDIX

A Data Particularities

A.1 Court Orders

	$c < 1$	$1 < c < 2$	$2 < c < 3$	$3 < c < 6$	$c = 6$	$6 < c < 9$	$9 < c < 12$	$c = 12$
Violence against the person	0.06	0.06	0.07	0.12	0.06	0.06	0.03	0.06
Sexual offences	0.01	0.01	0.02	0.04	0.03	0.03	0.01	0.04
Robbery	0	0	0	0.01	0.01	0.02	0.01	0.04
Theft offences	0.26	0.18	0.11	0.12	0.04	0.03	0.01	0.03
Criminal damage and arson	0.06	0.08	0.05	0.06	0.03	0.03	0.01	0.04
Drug offences	0.08	0.02	0.01	0.02	0.02	0.04	0.02	0.04
Possession of weapons	0.03	0.08	0.07	0.19	0.22	0.09	0.03	0.06
Public order offences	0.16	0.16	0.13	0.17	0.08	0.07	0.03	0.06
Misc. crimes against society	0.15	0.06	0.05	0.11	0.11	0.12	0.05	0.1
Fraud offences	0.06	0.06	0.05	0.11	0.06	0.07	0.03	0.07
	$12 < c < 18$	$18 < c < 24$	$24 < c < 36$	$36 < c < 48$	$c = 48$	$48 < c < 60$	$60 < c < 72$	$72 < c < 84$
Violence against the person	0.11	0.09	0.08	0.02	0.02	0.02	0.02	0.01
Sexual offences	0.07	0.08	0.12	0.04	0.07	0.08	0.07	0.05
Robbery	0.08	0.11	0.21	0.1	0.09	0.1	0.08	0.03
Theft offences	0.05	0.04	0.08	0.02	0.01	0.01	0.01	0
Criminal damage and arson	0.08	0.12	0.18	0.06	0.05	0.05	0.03	0.01
Drug offences	0.06	0.09	0.25	0.1	0.05	0.06	0.05	0.03
Possession of weapons	0.06	0.04	0.03	0	0	0.05	0.01	0.01
Public order offences	0.07	0.04	0.02	0	0	0	0	0
Misc. crimes against society	0.11	0.05	0.05	0.01	0.01	0.01	0.01	0
Fraud offences	0.11	0.1	0.12	0.04	0.03	0.03	0.02	0.01
	$84 < c < 96$	$96 < c < 108$	$108 < c < 120$	$120 < c < 160$	$160 < c < \infty$	∞		
Violence against the person	0.01	0.01	0.01	0.02	0.01	0.03		
Sexual offences	0.05	0.03	0.03	0.08	0.04	0.01		
Robbery	0.03	0.02	0.02	0.03	0	0		
Theft offences	0	0	0	0	0	0		
Criminal damage and arson	0.01	0.01	0.01	0.01	0	0.01		
Drug offences	0.02	0.01	0.01	0.02	0.01	0		
Possession of weapons	0.01	0	0	0	0	0		
Public order offences	0	0	0	0	0	0		
Misc. crimes against society	0	0	0	0	0	0		
Fraud offences	0.01	0	0	0	0	0		

Table 10: Distribution of sentences length for UK Convictions, with crimes grouped by divisions used by the Criminal Justice Statistics Quarterly, UK.

B Further Tests

B.1 Turf Overlapping and Turnover at higher granularity

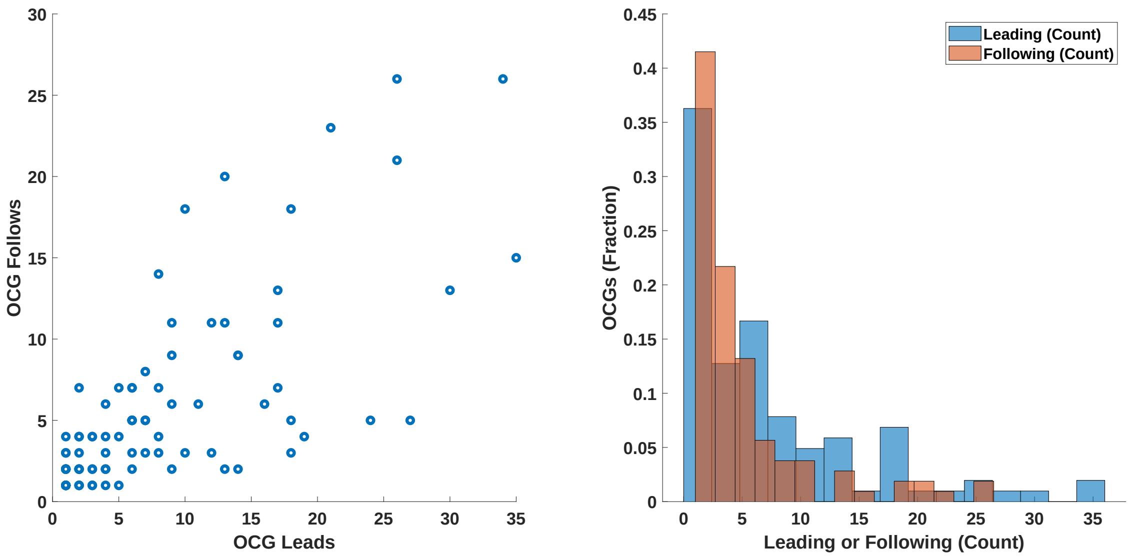

Figure 13: *(Left.)* Turf overlapping of OCGs in Merseyside. Each dot represents an OCG and it indicates the number of LSOA in which the OCG is the most (*X-axis*, and second-most active (*Y-axis*) OCG (labeled "OCG Leads" and "Following", respectively) among OCGs operating in those geographic units. *(Right.)* Proportion of OCG leaders/followers by the number of geographic units in which they lead/follow, respectively given by blue and red bins (red bins are offset for readability).

B.2 Effects of Cooperation on Classes of Crime

BURGL	DAMAGE	POSS. (A)	POSS. (B,C)	TRAFF. (A)	TRAFF. (B,C)	
0.002	-0.005	-0.000	0.006	0.014**	0.008	
(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	
THREATS	OTHER	ROBBERY	THEFT, FRAUD	VIO W/O IN	VIO W. IN	WEAPONS
-0.033**	-0.003	-0.005	-0.001	-0.009	-0.015**	0.012*
(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)

Table 11: Estimation of models in (10) where the dependent variable is the Cooperative Index as defined in the main text. Coefficients are converted to percentages from incidence rate ratios. All estimations run with time and location fixed effects included. The estimated 62 month-year time F.E and the 200 neighborhood F.E are omitted from the table. Robust standard errors are in parenthesis. Symbols *,** and *** represent statistical significance at $0.1, 0.05$ and 0.01 level, respectively.