Endogenous Property Rights over Drug Markets: Theory and Evidence from the Merseyside, U.K.

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Profit-seeking defines the behavior of urban Organized Criminal Groups (OCGs) globally. While OCGs operate within broad illicit networks, most high-level crimes are concentrated in small geographic areas. Using detailed empirical data from Merseyside, U.K., we document how OCG activity, violence, and territorial control are distributed across the region, revealing a strong correlation between profitability (e.g., drug trafficking) and the concentration of violent episodes between OCGs. We propose a theoretical model that rationalizes these empirical observations by examining how OCGs strategically select areas based on profitability and the presence of other OCGs. Our model predicts that OCGs will establish property rights over areas even if there are no institutions to designate them. Specifically, when the frequency of OCG activity is sufficiently high, each OCG establishes a property right over one area. When the frequency of OCG activity reduces, some OCGs violently collide in the most profitable areas while others establish property rights over the middle-ranked areas in terms of profitability. These theoretical results match some empirical evidence from Merseyside, U.K., where we find that the average streak over an area of the city is larger for areas with low and medium profitability than for areas with high profitability. Performing some comparative statics, we also give policy recommendations. Indeed, our model predicts that when the lower the frequency of OCG activity, the higher the violence and the concentration levels over the most profitable areas. Thus, police interventions aimed at reducing the frequency of OCG activity might produce negative externalities.

Criminal property rights | Territorial violence | Dynamic game theory modeling | . . .

Organized Crime Groups are exerting increasing pressure on cities all over the world. While it is impossible to learn what goes through the minds of each criminal group, it is possible to study the incentives these groups have in expanding their activities in different parts of a city and in engaging in violent confrontations with rivals across the territories.

[literature on OCG or substitute]

In this paper, we match the observed behavior of organized criminal groups in Merseyside, U.K. with a theory of dynamic territory occupation. We first present some empirical facts regarding Merseyside and then show that these results can be rationalized with the help of a theoretical model. In our empirical analysis of OCG activity across Merseyside, we utilize three key indicators for each territory: the number of OCGs operating in the area, the level of OCG-related violence, and the average streak in terms of days, determined by the number of crimes an OCG commits in an area before another OCG commits one crim in that area. We rank territories based on the number of drug trafficking crimes reported by Merseyside Police (standard measure of profitability XXX). We find that OCGs concentration and violence is larger in areas that are more remunerative in terms of drug trafficking. However, while OCGs' concentration is well spread across the other areas, violence rapidly declines in non-top-tier drug trafficking areas. Most interestingly, the mean streak on an area is higher for medium-low profitable areas than in high profitable ones. This result indicates that OCGs establish property rights over medium-low profitable areas rather than on those highly profitable.

Significance Statement

While gathering empirical aggregate evidence on illegal activities by organized criminal groups is straightforward, it is hard to gather information at the individual level and thus study such groups' incentives to behave the way they do. In our work, we first provide empirical evidence on the behavior of organized criminal groups in Merseyside, and we rationalize such behaviors with a simple theoretical model. Our model gives us an understanding of how criminal entities might self-regulate when institutions for establishing rights are missing. We show that criminal groups establish rights over low-profitable areas rather than high-profitable ones. Comparative statics show that reducing activity levels from criminal groups might hide negative effects such as increasing violence in most profitable areas.

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[something about empirical findings, e.g., the fact that areas that are actually the calmest might be the one with a higher control by OCG]

These findings can be rationalized with a model where OCGs occasionally move out of their turfs to run operations in different areas of the cities. OCGs either remain idle or search for an area to run operations, with each area ranked by profitability. If two OCGs arrive in the same area, the last arrived incurs a travel cost and leaves, reflecting the investment needed to secure a new area (1). OCGs act opportunistically, exploring areas based on profitability and their belief that the area is unoccupied. With our model, we can prove how OCGs form property rights over territories in the absence of other regulatory institutions. The main insight of our theoretical model states that as the frequency of activity of OCGs reduces, OCGs establish property rights over the medium-ranked areas but have occasional violent confrontations for the control of the most profitable areas.

Rather than focusing on the spacial diffusion of crime through time (2–4, ?), our approach has the advantage of being able to capture the incentives behind OCGs' decision making process. Thanks to our approach, we can study OCGs incentives of trying to exploit a given area in relationship to the profitability of such area and to the beliefs of that OCG. On the other hand, in contrast with more typical models of criminal behavior (???) we consider a dynamic model.... Thanks to the features of our model, we can also derive some policy implications, e.g., by changing the level of OCGs activity. Shocks to OCG activity, such as increased police raids, can have ambiguous effects, potentially escalating violence over the most profitable areas as OCGs become more incentivized to target these zones when their activity decreases elsewhere. Our findings highlight the complex and evolving relationship between places, OCG activities, and exploration drivers, with poorly designed policies potentially leading to unintended urban instability and intensified violence in high-profit areas.

There is a long-standing economic literature on the appropriation of goods in the absence of formal institutions to enforce possession. Early works in this area examined economies where property rights are not initially defined but can be enforced through the allocation of scarce resources (5, 6). More recent studies have incorporated time into these models, exploring the evolution of property rights over time (7–9). While various studies have shown that anarchic competition can lead to the emergence of property rights as a solution to conflicts over goods (10, 11), there remains debate on whether such allocations are efficient. On the one hand, efficiency may be achieved when agents have sufficient information (12, 13), but on the other hand, efficiency might not be granted, in the presence of asymmetric information (14–16).

Since, in our model, agents (i.e., OCG) cannot defend a resource (i.e., an area) once they exploited it, the competition happens in a so called state of amorphy rather than in one of anarchy (5). In our model, property rights emerge as norms between OCGs that might not try to exploit an area of the city if other OCGs repeatedly exploit such area through time. This approach better suits the dynamics of OCGs' conflict over city areas (17, 18). Due to this difference, our results differ from models of property rights formation under anarchic competition (5, 14) in that in those models property rights are always formed over all resources, while in our case, depending on the activity level of OCGs, it might be that these agents do no establish property rights over some areas.

The narrative of our paper parallels evolutionary models across different disciplines such as biology (19), sociology (20, 21), anthropology (22), or economics (23, 24). In these models, the competition for resources is usually modeled assuming that agents are repeatedly randomly matched from a population to play a game, while in our model, agents are matched (i.e., they have a violent collision) only if they meet in the same resource. We study the conditions under which agents violently collide or rather establish property rights over resources. Finally, some papers in the literature on dynamic models have studied the problem of agents appropriating or exploiting different kinds of resources (25, 26). We study a dynamic model where myopic agents only recall the most recent period in which they attempted to exploit a resource. By doing so, agents that exploit the most profitable resource might differ depending on the activity level of the agents themselves.

Materials and Methods

Data. We illustrate the complex relationship between organized crime and places by leveraging on a granular dataset collecting all OCG-related crime for a large area of U.K, Merseyside. Merseyside is the fourth most populated metropolitan county of the U.K. (1.38 million individuals) in a surface of 645km^2 of land, with Liverpool city (the highest-density metropolitan district of U.K.) being its main area. Importantly for our work, Merseyside features the highest number of OCGs per million of inhabitants of U.K. (i.e. $N = 134$ groups). This rate is twice as high as the national average and a quarter higher than Greater London. The unit of analysis for this study is a cross section all crime activities recorded in the $M = 180$ areas of Merseyside county between 1/1/2015 and 4/30/2018.

Our notion of area coincides with the *Middle Layer Super Output Areas* (MSOAs), demographically stable small-area census units containing around 8,000 inhabitants each. We characterize MSOAs through a novel dataset given by the complete set of crime reports involving at least one identified offender handled by Merseyside police (MP) on their jurisdiction. This is the most comprehensive source of crime data available for Merseyside*. The dataset contains 128,843 incidents in relation to which at least one individual (out of a population of $K = 62,948$ offenders) has been arrested, cautioned, charged as well as interviewed or suspected. Each incident is geo-tagged and linked to one offense category from the taxonomy of 384 items of the English criminal law. Each offender i linked to the incident is characterized with two critical pieces of information: a personal reference number, and, in case the individual has been associated to an OCG by the MP analysts, the unique OCG reference number. The dataset has two limitations: first, it does not contain information about victims, if any. Second, only the most recent available information for each item is stored, as generated and imputed in the course of the judiciary process. As a result, individual offenders can be linked to at most one OCG, corresponding to analysts' most recent inference, up to March 2018.

Methods. We represent OCGs by means of the sum of crime activities carried out by their associates, and map these

*MP is the primary source of Merseyside data for commercial and non-commercial crime data providers (e.g. *Databank of U.K. Police*, *Economic Policy Centre*).

quantities into geographic areas. Formally, given any OCG $n \in N$, and area $m \in M$, define C_m^ℓ as the count of crimes of type ℓ committed in area m. Similarly, let $C_{m,n}^{\ell,ocg}$ and $C_m^{\ell,ocg}$ be[†] the count of crimes of type ℓ committed by associates of OCG n in area m and the sum of count of OCG-related crimes of type ℓ committed in area m, respectively. In the following will specialize ℓ to crimes of serious violence[‡], $\ell = \mathrm{V}$ and drug trafficking[§], $\ell = \mathrm{D}$.

Then, given $\phi(x)$ a simple indicator function taking value 1 for $x > 0$ and 0 otherwise, we define

$$N_m = \sum_{\ell=1}^{L} \sum_{n=1}^{N} \phi\left(C_{m,n}^{\ell,ocg}\right) \qquad [1]$$

as the total number of OCGs operating in an area i.

For each territory of Merseyside, we produce three indicators relative to OCGs operating in that specific territory: (i) a simple count of the number of OCGs (ii) the amount of recorded OCG-related violence; (iii) the average number of days intercurring between the arrest of individuals belonging to *different* OCGs, our measure of territorial control. To explore the opportunistic nature of OCGs, we then rank areas according to a simple measure of profitability, namely, the number of drug related crimes recorded by Merseyside Police (MP) on its territory.

Figure 1 collects the three indicators, where for convenience, areas have been grouped in ten equally-sized bins, and the $25 - 75$ percentile range has been plotted for each bin. Indicators (i), (ii), and (iii) are drawn in blue, red, and black color, respectively. We make two observations. First, we note that the concentration of OCGs on territories (as measured in counts of distinct OCGs) and the amount of OCG-related violence correlate positively, with both concentration and violence increasing in the value of the underlying areas. While the increasing concentration is possibly hinting at the opportunistic nature of OCG decision-making (with more OCGs being active in more profitable areas) the higher levels of violence consistently observed in areas characterized by higher drug trafficking may be a signal of the competitive nature of interaction across OCGs.

Second, we measure the mean streaks in an area as the consecutive streak of crimes of one OCG in an area before another OCG commits a crime in the same area. We notice that this indicator is higher for areas with a lower profitability value than for areas with a higher level of profitability. We are able rationalize this finding with our model of property rights. Intuitively, when OCG are active enough, the risk of violent collisions in highly profitable areas is high, and hence, some OCG might decide to focus on areas with lower profitability to avoid the risk of colliding with other OCGs in the most profitable areas. According to this finding, even in absence

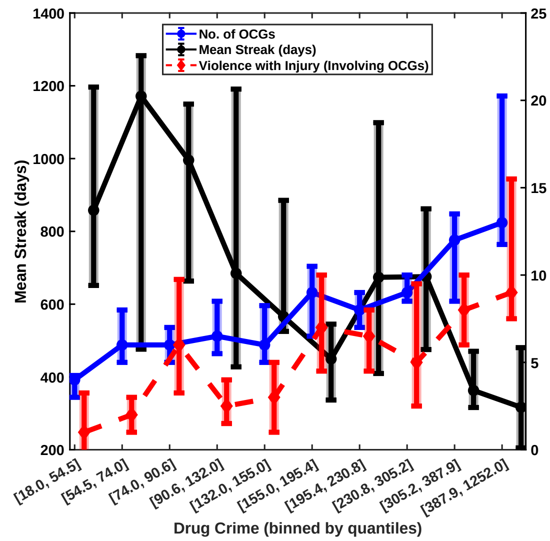

Fig. 1. In this figure areas are ranked and filed into ten tiers built upon the number of drug dealing events recorded within each area.*(Left Axis.)* Episodes of OCG-induced serious violence. *(Right Axis.)* Average number of OCGs and Average number of turfs per OCG, respectively plotted in blue and black.

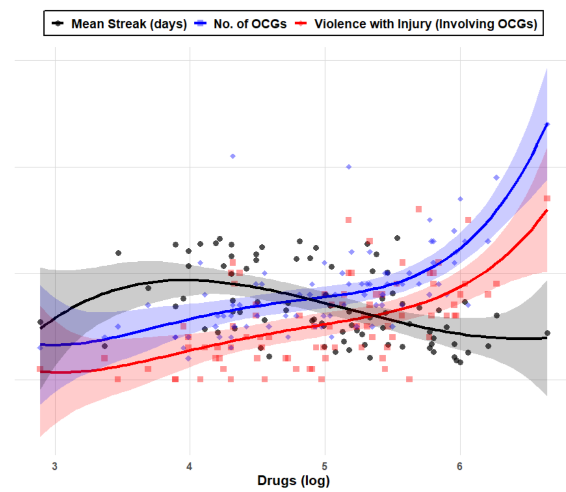

Fig. 2. In this figure areas are ranked and filed into ten tiers built upon the number of drug dealing events recorded within each area.*(Left Axis.)* Episodes of OCG-induced serious violence. *(Right Axis.)* Average number of OCGs and Average number of turfs per OCG, respectively plotted in blue and black.

of economics institutions, it is like OCG establish criminal property rights over low profitable areas but not over highly profitable ones because of the risk of violent collision over these areas. All findings are formalized in the model section. Results in Figure 1 are confirmed in Figure 2.

In the following, we will argue that the two apparently separate facts observed in the Merseyside snapshot can jointly descend from a scenario where OCGs opportunistically condition actions (particularly, the selection of areas from which to run operations) to the environment they face. Importantly, we will show that this scenario is not a knife-edge case. However, alternative states of the world are possible. Particularly, an environment where criminal groups establish property rights

[†] Formally, given any offender $k \in K$, $C_m^\ell \equiv \sum_{k=1}^{K} C_{k,m}^\ell$ and $C_{m,n}^{\ell,ocg} = \sum_{k=1}^{K} \left(g_{k,n} C_{k,m}^\ell\right)$, where $g_{k,n}$ takes value of 1 if individual k has been associated to OCG n and 0 otherwise. Last, define $C_m^{\ell,ocg} \equiv \sum_{n=1}^{N} C_{m,n}^{\ell,ocg}$.

[‡] This corresponds to offenses associated to the class *Violence With Injury*, particularly, *Wounding with Intent to do Grievous Bodily Harm* (36.3%), *Assault Occasioning Actual Body Harm* (34.9%) and *Murder* or *Attempted Murder* (17.3%).

[§] In the U.K. system, trafficking is defined as dealing, selling or sharing of controlled substances. These are split in Class A and Class B drugs. Class A refers to hard drugs such as crack cocaine, cocaine, MDMA, heroin, LSD, mushrooms, methadone and methamphetamine (crystal meth), whereas Class B refer to soft drugs such as Amphetamines, barbiturates, natural and synthetic cannabis and cathinones as well as codeine, ketamine, anabolic steroids and benzodiazepines. Trafficking is roughly split between 60% and 40%, between Class A and class B, respectively.

over each area rather than only on certain areas, and, reversely, an environment characterized by a high degree of inter-OCG conflict and turmoil.

Model

While the empirical evidence from Merseyside highlights clear patterns in organized criminal group behaviors, such as the concentration of violence in high-value areas, these observations alone do not fully explain the underlying decision-making processes of these groups. In order to better understand how and why organized criminal groups decide to exploit certain areas and engage in conflicts, we turn to a theoretical framework. By modeling the interaction between organized criminal groups as a dynamic game, we can explore the strategic considerations that drive territorial concentration and violence. This model allows us to predict how changes in external conditions, such as increased police presence, may influence criminal behavior and potentially exacerbate territorial disputes. Thus, the theoretical model not only complements the empirical findings but also provides a deeper insight into the strategic nature of these interactions.

We provide the statement and the intuition of our theoretical results in the main text, leaving all the formal proofs in the supplementary materials.

The simple model with 3 OCGs and 3 areas. We start by considering a simple model with $N = 3$ OCGs and $M = 3$ areas, denoted $1, 2$, and 3. We assume that each OCG has a separate turf and that OCGs can be either in their turf or exploiting an area. Time is continuous: OCGs leave their turf at an exponential rate η and stop exploiting an area at another exponential rate 1. OCGs benefit u_1, u_2, and u_3 from exploiting the three areas. An OCG cannot exploit an area if it is already occupied by another OCG. If two OCGs meet in the same area, the last to arrive incurs a cost c (e.g., a *collision* cost, as we propose below, or a traveling cost as in (1)) and leaves the area. We assume that $u_1 > u_2 > u_3 > c$.

Let p^m be the stationary state probability that area m is free. We assume that p^m is common knowledge (i.e. that OCGs will be able to learn it). Importantly, OCGs observe each other only if they meet in an area. i.e., when an OCG exploits an area and the other OCG arrives there and finds it occupied (it is the arriving OCG that sees that the area is occupied, and hence, leaves it). Consequently, at any point in time, the information set of OCGs consists of *i)* the time t_i^m when area m was last seen and *ii)* the state z_i^m in which it was left at that time. For example, for the area m^* last exploited by OCG i, $z_i^{m^*} = 0$ and $t_i^{m^*}$ is the time when OCG i left it. For an area m which was find occupied in a search attempt at time t_i^m, we set $z_i^m = 1$. Given this information, the probability that area m is free at time t, given the information that OCG i has at this time, is

$$q_i^m(t) = p^m \left(1 - e^{-\frac{t-t_i^m}{1-p^m}}\right) + (1 - z_i^m)\, e^{-\frac{t-t_i^m}{1-p^m}}. \qquad [2]$$

This probability quantifies the belief that OCG i holds on area m being free. Given these pieces of information, OCGs play their strategy.

A strategy for an OCG is a rule that, whenever an OCG leaves the turf, given the information set, assigns a permutation of the three areas. This permutation will be the order in which the OCGs will search which area is free between the three areas. In principle, an OCG could also decide not to visit one or all of the three areas, but as we will see, this is never the case. The first problem we analyze is that of finding the optimal exploration strategy s that OCG i should use, given the information encoded in her beliefs q_i^m.

Lemma 1 *The optimal search strategy ranks areas in order of decreasing $u_m - c/q_i^m$.*

In other words, OCGs will always prioritize areas that provide the best profits relative to the likelihood that they will find those areas free. If they find a more valuable area occupied, they will lower their priority and try again later, moving on to less valuable areas in the meantime.

Notice that, when in the search of a free area at time t area m is found occupied (i.e. $z_i^m = 1$), by Eq. (2) the new belief of OCG i on area m is $q_i^m \to 0$. This is equivalent to moving area m to the bottom of the search list. The maximum of $u_m - \frac{1}{q_i^m} c$ determines the area that i will try next. If she finds it occupied she updates her belief q_i^m, and chooses a new area. When η is *high* a simple prediction can be made.

Lemma 2 *If $\eta > \frac{u_1-u_3}{c}$, each OCG only exploits one area.*

The intuition behind such a result is quite simple. If η (the frequency with which OCGs move out of their turfs) is larger than the difference between the highest and the lowest profitable area (discounted by the travel cost), this means that when each OCG is exploiting one area, even the group exploiting the worst area (i.e., 3) will not have incentive to deviate from her behavior. If that group does not have such an incentive, neither will the other groups exploiting better areas than 3. This result shows that when groups leave their turfs frequently enough, they tend to 'specialize' in different areas, focusing on the area they can control without much competition. Essentially, the more active the groups, the less likely they are to collide in the same area. According to this result, for η as large, we should observe a relatively low concentration of OCGs in each area, low levels of violence in each area, and high streaks in each area, as each OCG exploits only one area. In other words, each OCG establishes *property rights* in one area.

More generally, it can be shown that criminal groups' behavior depends on the level of η. We provide a detailed analysis in the supplementary materials (Lemma A.1 and A.2) and an intuition here. For middle values of η, i.e., $\max\{\frac{u_1-u_2}{c}; \frac{u_2-u_3}{c}\} < \eta < \frac{u_1-u_3}{c}$, criminal groups do not establish property rights over the best area, but over the middle one. This scenario happens because when η is lower than $\frac{u_1-u_3}{c}$, but still higher than $\max\{\frac{u_1-u_2}{c}; \frac{u_2-u_3}{c}\}$, if one OCG always exploits area 2, the other two OCGs will never try to exploit that area since the probability of finding it occupied is too high. However, the other two OCgs will compete for the exploitation of area 1. Indeed, since the frequency of activity of OCGs is relatively small and since one OCG exploits area 2, one OCG will always find the right belief to try to exploit area 1. Moreover, given that two OCGs sometimes meet in area 1, one of the two OCG will occasionally exploit area 3, either because she finds area 1 occupied or because her beliefs of finding it occupied is too high. Lastly, if $\eta < \max\{\frac{u_1-u_2}{c}; \frac{u_2-u_3}{c}\}$, the frequency of activity of OCGs is so small that each OCG can find the right belief to start from area 1, and hence, no property rights are established over areas.

Different levels of η implies different concentration values over areas. Specifically, the lower η and the higher the concentration levels on area 1 since more OCGs will try to exploit such an area. In the following statement, we do a comparative statics exercise, studying the different concentration levels of the areas when η varies. Let us call $O_m(\eta)$ a function that gives for each value of η the concentration level of area m. For simplicity let us call $\underline{\eta} = \max\{\frac{u_1-u_2}{c}; \frac{u_2-u_3}{c}\}$ and $\overline{\eta} = \frac{u_1-u_3}{c}$.

Proposition 1

- *If* $\eta > \overline{\eta}$, $O_1(\eta) = O_2(\eta) = O_3(\eta)$;
- *If* $\eta < \overline{\eta}$, $O_3(\eta) < O_2(\eta) < O_1(\eta)$.

When $\eta > \overline{\eta}$, criminal groups form property rights over areas, and hence, the concentration level of each area is equal to the frequency with which criminal groups leave their turfs (i.e., $\frac{\eta}{1+\eta}$). When $\underline{\eta} < \eta < \overline{\eta}$, one OCG specializes in area 2, but the other two occasionally collide on 1. In such a case, the OCG that lastly exploited area 1 always starts from area 1 (see Lemma A.1), while the last OCG exploiting area 3 might start from area 1 or 3 depending on her belief. Hence, it must be that the concentration level of area 1 is higher than $\frac{\eta}{1+\eta}$, the one in area 2 is exactly $\frac{\eta}{1+\eta}$ and the one in area 3 is lower than $\frac{\eta}{1+\eta}$. For area 3, the concentration level has to be lower than $\frac{\eta}{1+\eta}$ since the last OCG exploiting that area occasionally goes to area 1, and the last OCG exploiting area 1 goes to area 3 only when 1 is occupied. The intuition follows for $\eta < \underline{\eta}$. In Figure 3, we qualitatively depict concentration levels for areas given $\underline{\eta} < \eta < \overline{\eta}$ to theoretically replicate those in Figure 1. It is evident from comparing the two figures that $\underline{\eta} < \eta < \overline{\eta}$ seems to be an appropriate measure of criminal groups' activities in Merseyside, U.K..

Imagine that when an OCG enters an already occupied area, we record this event as *violence* happening in an area. In the next statement, we focus on the frequency of violence. Similar to the previous case, we call $V_m(\eta)$ a function that gives for each value of η the violence frequency of area m.

Proposition 2

- *If* $\eta > \overline{\eta}$, $V_1(\eta) = V_3(\eta) = V_3(\eta) = 0$;
- *If* $\underline{\eta} < \eta < \overline{\eta}$, $V_1(\eta) > 0$ *while* $V_2(\eta) = V_3(\eta) = 0$;
- *If* $\eta < \underline{\eta}$, $V_1(\eta) > V_2(\eta) > 0$ *and* $V_3(\eta) = 0$.

The intuition for the violence is quite similar to the one for concentration levels. Indeed, when $\eta > \overline{\eta}$, each criminal group establishes property rights over one area, and hence, there is no violence. As the frequency of activity of criminal groups decreases, property rights become less appealing (specially, in the most profitable area), while trying to exploit area 1, even if that means a violent encounter with another OCG, becomes more appealing, and hence, violence in area 1 increases. Specifically, if η becomes slower than $\underline{\eta}$, all OCG will try to exploit area 1 in turn and there is no property right established over area 2. Due to this outcome, the OCGs that cannot exploit area 1 occasionally meet in area 2 since the expected profit for exploiting this area is always higher than the one for exploiting area 3 in absence of property rights over areas.

Again, we qualitatively depict violence frequencies in Figure 3 for $\underline{\eta} < \eta < \overline{\eta}$. The model's predictions mirror the empirical findings in Figure 1, where OCG concentration increases with the profitability of an area. In particular, our model predicts that as the probability of meeting rivals decreases, OCGs will increasingly target the most valuable territories, a pattern clearly visible in both figures. Specifically, the model rationalizes the empirical observation that violence is concentrated in the most profitable areas, while OCG establish property rights over the middle ranked ones.

To complete the matching between our empirical and theoretical findings, let us now focus on the expected mean streak in each area. Such a variable captures whether an OCG returns to that area ones the OCG have already exploited the area. We collect our results in the following proposition. Let us call $R_m(\eta)$ a function that gives for each value of η, the expected mean streak in the area m.

Proposition 3

- *If* $\eta > \overline{\eta}$, $R_1(\eta) = R_2(\eta) = R_3(\eta)$;
- *If* $\underline{\eta} < \eta < \overline{\eta}$, $R_2(\eta) > R_1(\eta) > R_3(\eta)$;
- *If* $\eta < \underline{\eta}$, $R_1(\eta) > R_2(\eta) \geq R_3(\eta)$.

The intuition behind the result of Proposition 3 follows the one for Proposition 1. When η is large enough, OCGs establish rights over all the three areas, and thus, always return to the same area. This result happens because when the probability of OCGs moving out of their turf is high enough, the probability of a meeting between two OCGs, and hence, a cost for a collision is so high that OCGs find it more appealing to always exploit the same area. Due to this outcome, the streak will be the same for all areas. When η takes middle values, OCGs only establish property rights over the middle ranked area and occasionally collide in the higher ranked area. Due to this outcome, the streak observed in the most profitable area is lower than the one observed in the middle ranked one. Moreover, given that the last OCG exploiting area 1 will always try to exploit that area, but the last OCG exploiting area 3 could occasionally start from area 1, it must also be that the streak in area 1 is higher than the one in area 3.

Similarly, when η is really low, the probability that the last OCG exploiting area 1 goes back to that area is one, while the same cannot be said for the other two areas. Therefore, the streak observed in the most profitable area must be larger than the ones observed in the other areas. The intuition for this results comes from the fact that when OCGs move rarely out of their turf, there is always an incentive to try to exploit the most profitable area since the probability of meeting other OCGs is relatively low. Again, we qualitatively depict the results of Proposition 3 in Figure 3. Similarly to the previous results, $\underline{\eta} < \eta < \overline{\eta}$ fits particularly well the data observed in the Merseyside, U.K..

Interestingly, we observe one main difference between our data and our theoretical predictions for the mean streaks. Indeed, in the data the mean streak for lower profitable areas are higher than those for higher profitable ones. While this fact might seem as inconsistent with our theoretical findings, it is actually due to the way we can proxy the streaks in the real world. Indeed, in the model the streaks are measured as the number of times that the same OCG goes back to an area after she visited the area the previous time she went out of her turf. In the data, since we cannot retrieve this measure, we proxied it by the number of crimes an OCG commits in an area before another OCG commits a crim in that area. The fact that this number is higher for lower and middle ranked areas in terms of profitability is consistent with our theory, according to which the last OCG visiting area 1 (the most profitable) always goes back to area 1 but never goes to 3, while the last visiting area 3 might go to area 1 the next time she goes out of her turf. At the same time, this prediction does not contradict our theoretical result according to which, the frequency of times when an OCG goes back to the most profitable area after having exploited it is higher than the frequency of times an OCG goes back to the lowest profitable area after having exploited it.

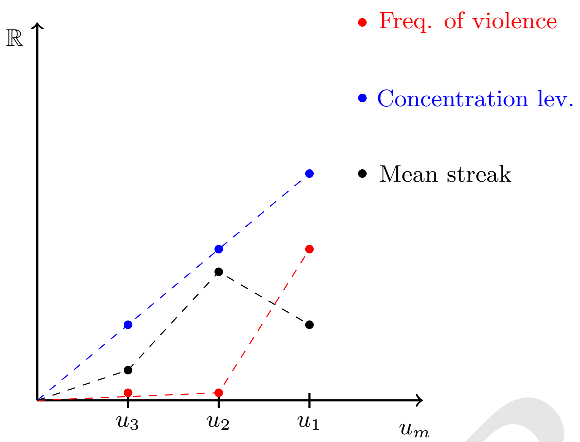

Fig. 3. Qualitative representation of violence frequencies, concentration levels and mean streaks as a function of u_m, having fixed $\underline{\eta} < \eta < \overline{\eta}$. On the y axes we depict the predicted violence frequency (red) and the predicted concentration level (blue).

In summary, the model predicts that as criminal groups leave their turfs less frequently, they are more willing to compete for the most valuable areas, as they expect these areas to be available for longer periods. This explains why we might see higher levels of violence in high profitable areas when criminal groups are less active overall. When the frequency with which criminal groups leave their turfs falls between these extremes, the strategy becomes more complex. Criminal groups still prefer the most valuable area but might not always succeed in claiming it, leading to occasional violence to establish control over the area, especially when the difference in value between areas is smaller.

While Proposition 3 might not offer insights for policy makers, as it is not clear whether is preferable or not to have a single OCG or multiple OCGs exploiting an area, Proposition 1 and 2 may suggest a further implication for policy makers interested in reducing crimes and violence in the streets of a city. Indeed, by studying the behavior of $O_m(\cdot)$ and $V_m(\cdot)$ for limit values of η, we observe some discontinuities which may seem counter intuitive without the help of our model. Let us first analyze the concentration levels.

Corollary 1 *Consider* $O_1(\eta)$*, and* $O_3(\eta)$*.*

$$\lim_{\eta\to\underline{\eta}^-} O_1(\eta) > \lim_{\eta\to\underline{\eta}^+} O_1(\eta), \ \textit{and} \ \lim_{\eta\to\underline{\eta}^-} O_3(\eta) < \lim_{\eta\to\underline{\eta}^+} O_3(\eta)$$

$$\lim_{\eta\to\overline{\eta}^-} O_1(\eta) > \lim_{\eta\to\overline{\eta}^+} O_1(\eta), \ \textit{and} \ \lim_{\eta\to\overline{\eta}^-} O_3(\eta) < \lim_{\eta\to\overline{\eta}^+} O_3(\eta)$$

The result of this statement follows from Proposition 1. This result implies that as the activity level of criminal groups (η) decreases, the concentration levels of the most profitable area increase, while the concentration levels of the least profitable one decreases.

Corollary 2 *Consider* $V_1(\eta)$*, and* $V_2(\eta)$*.*

$$\lim_{\eta\to\overline{\eta}^-} V_1(\eta) > \lim_{\eta\to\overline{\eta}^+} V_1(\eta)$$

$$\lim_{\eta\to\underline{\eta}^-} V_1(\eta) > \lim_{\eta\to\underline{\eta}^+} V_1(\eta), \ \textit{and} \ \lim_{\eta\to\underline{\eta}^-} V_2(\eta) > \lim_{\eta\to\underline{\eta}^+} V_2(\eta)$$

Similarly to the previous statement, the intuition follows from Proposition 2. Corollary 2 implies that as the criminal groups' activity (η) decreases, violence over the most profitable area increase. This result follow from the fact that, if $\eta < \overline{\eta}$, OCGs find it more and more desirable to aim for area 1, and hence, they increase the probability of colliding in that area. Similarly for area 2, when $\eta < \underline{\eta}$, then OCGs occasionally fight over that area, while for $\eta > \underline{\eta}$ OCGs always establish property rights over it. Hence, a decrease in OCGs' activity is not always beneficial for all the areas. We further discuss the implications of these results in the discussion.

Simulations with more than 3 OCGs and areas. In this subsection, we test the robustness of our results to specifications with more than 3 OCGs and locations. Since it become computationally hard to formalize results in closed forms for more than 3 OCGs, we simulate the results for these kinds of specifications. We use Matlab to compute the results of the simulations.[¶]

We choose 10 OCGs and 10 areas. We chose these numbers to reflect a diverse range of OCGs competing for control over a finite number of areas, which mirrors the complex dynamics observed in real-world organized crime networks. By varying the parameters of our model, we can test the robustness of our theoretical predictions across different scales.

We set the areas values in descending order, according to the theoretical model. Let U be the set of areas' values; in our simulations $U = \{173; 125; 100; 76; 63; 51; 42; 35; 29; 26\}$. We chose the values of u_j and u_{j+1} such that $u_j - u_{j+1}$ differ for all areas. In such a way, thresholds for η as defined in previous sections do not overlap. We set $c = 5$ fixed for every simulation, and we compute the results for $\eta \in \{0, 1, \dots, 35\}$. We depict the results for different values of η in the supplementary materials; in the main paper, we show the results for $\eta = 10$, which corresponds to a middle value of η for 10 areas and OCGs comparable to $\underline{\eta} < \eta < \overline{\eta}$.

Note that $\frac{u_1 - u_{10}}{c} = \frac{173-26}{5} \approx 30$. Hence, by Lemma 2, we should expect that for $\eta > 30$, each OCG exploits one area, namely, OCGs establish property rights over all areas. Such results are visible in Figure X and Y in the supplementary materials. Given that $\frac{u_9 - u_{10}}{c} = \frac{29-26}{5} = 0.6$, coherently with Lemma A.2, we should expect that for $\eta < 0.6$, OCGs establish no property rights, meaning they continuously fight for exploiting the most profitable areas. Again, a similar pattern arises in Figure X and Y in the supplementary material.

[¶] A detailed description of the code and procedures used in the simulations can be found at this [Github or similar repository].

Finally, for values between 0.6 and 36, we should expect OCGs to establish property rights over middle-ranked areas while fighting for the most profitable ones. We depict the results of the simulations for $\eta = 10$ in Figure 4, but again, the general pattern can be seen also in Figure X and Y in the supplementary material.

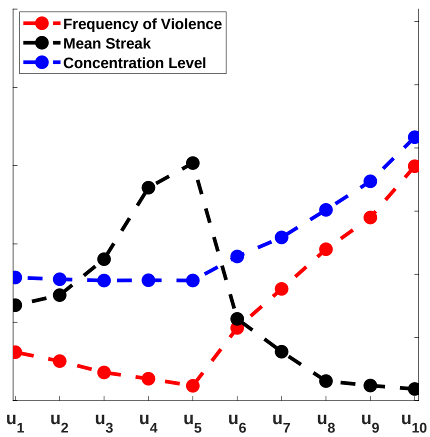

Fig. 4. This figure shows, for each area, the average frequency of violence, the average OCG concentration level, and the average streak per period as obtained from the simulation of the model with setup given by $N = 10$ OCGs, $M = 10$ areas, $\eta = 10$ and $T = 80,000$.

Coherently with Figure 1 and Figure 3, Figure 4 displays low levels of occupation and violence for low and medium ranked areas but higher values of occupation and violence for higher ranked areas. Moreover, as predicted by our theoretical model, the average number of streaks per area is low at the extremes (i.e., low high profitability) but high in the middle. This pattern confirms our previous result that when the frequency of activity of OCGs reduces, the groups establish property rights over middle ranked areas while they engage in violent collisions in higher ranked areas. Note that to measure the mean streak for the simulations, we count how many times an area is exploited by the same incumbent. Again, for this value, it is consistent with our theory to observe lower values for the highest profitable areas rather than for the lowest ones since OCGs that lastly exploited the highest profitable areas will never start their search from the lowest profitable areas but OCGs who lastly exploited the lowest profitable areas might start from the highest or from the lowest ones.

Discussion

The importance of our model goes beyond the ability to study organized criminal groups as strategic agents. Indeed, our model allows us to study the organized crime space as a dynamic environment where organized criminal groups make choices in order to maximize the exploitation of the areas. Importantly, our results allow us to study the movement of criminal activities across different areas of a city and the expansion of violence across these areas. Particularly, our results highlight important trade-offs that policy makers interested in fighting criminal activity should be aware of. Policies that focus on the reduction of criminal activities should consider possible negative side effects provoked by such a reduction. Ultimately, policy makers should decide whether to prioritize the reduction of criminal gangs activities over the episodes of violence in most profitable areas, as well as frequency of occupation of such areas.

Indeed, our results predict that it is not possible to reduce criminal activity of OCGs without increasing violence and occupation levels in the areas that are considered the most profitable by criminal groups. Suppose that a policy maker could control the frequency η with which OCGs go out of their turf to try to exploit the other areas of a city. The policy maker could, for example, increase the police activity across the city (or in particular areas), and hence, make it less appealing for OCGs to go out of their turfs. In such a case, we can rely on the results in Corollary 1 and 2 to predict OCGs behavior. Our results highlight two discontinuity points for η, namely, the frequency with which organized criminal groups leave their turfs.

Specifically, if $\eta > \overline{\eta}$, the violence levels are expected to be considerably low, but the occupation level to be high for all areas. Thus, reducing the value of η might be beneficial as long as $\eta > \overline{\eta}$. Indeed, when $\eta < \overline{\eta}$, not only the occupation levels in the most profitable areas but also the violence registered in such areas. Hence, reducing criminal activity too much could result in negative externalities for the people living in the most profitable areas. Even more importantly, when starting from a situation of $\underline{\eta} < \eta < \overline{\eta}$, if η reduces within that range, the effects ar beneficial for all areas, but if η reduces any further below $\underline{\eta}$, we observe negative side effects for both the most profitable areas and the middle ranked areas in terms of profitability. Indeed, as our results predict, when the criminal activity is sufficiently infrequent, OCGs establish no property rights over areas, meaning that violence levels expand to the middle ranked areas in terms of profitability.

These externalities arise once we consider OCGs' choices in our dynamic environment. Indeed, as OCGs' incentives to leave their turf decrease, so it does the relative probability of meeting other OCGs in the most profitable areas. Hence, when the OCGs activity decreases, the relative appeal of the most profitable areas increases, making it more likely for OCGs to try to exploit such areas when they leave their turfs. Therefore, even if the activities of OCGs decrease in absolute values, these activities will concentrate more around the most profitable areas, and hence, the occupation levels of such areas will increase. Furthermore, since OCGs might try to exploit the most profitable areas at the same time, also violence levels in such areas will increase.

To conclude, our model, predicts that the negative externalities from reducing η are worse when starting from a situation in which OCGs activity is not so frequent (i.e., $\underline{\eta} < \eta < \overline{\eta}$). Indeed, in such a case, the increase in violence levels spreads from the most profitable areas to the middle ranked ones. Therefore, given that our empirical results better fit with a parametrization of our model such that η assumes such values, if policy makers are interested in reducing criminal activities in the Merseyside, UK, they should consider also the negative effects that could hit both most profitable areas and middle ranked ones.

Data Archival. PNAS must be able to archive the data essential to a published article. Where such archiving is not possible, deposition of data in public databases, such as GenBank, ArrayExpress, Protein Data Bank, Unidata, and others outlined in the Information for Authors, is acceptable.

Materials and Methods

Please describe your materials and methods here. This can be more than one paragraph, and may contain subsections and equations as required.

Subsection for Method. Example text for subsection.

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