Opportunistic Organized Crime Groups: Theory and Evidence from the Merseyside, U.K.

Supplementary materials

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A Data

A.1 Crime Data

This study is geographically centered on Merseyside. Merseyside 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[1]. In this work, we use three sources of administrative data.

Our source is supplied by Merseyside Police (MP) and is given by all criminal reports[2] handled by MP between January 2015 and March 2018 (42 full months

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

[2]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.

of data). Given our focus on incentive-driven 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 is associated with one of the $k = 1, ..., K = 134$ OCGs[3] . As a result, we have information on $56,794$ 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 OCG data set.

Overall, the MP dataset contains a taxonomy of $H = 384$ classes of offenses, which we reclassify in 15 crime macro-classes following the U.K. judiciary system. Crime classes with associated count and rate relative to total reported crime are listed in Table 1, 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 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 (**?**), 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 1 puts the percentage incidences of Table 1 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 2 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

[3] 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.

2[2]*Crime Class	All Incidents		with Individual		with OCGM		2[2]*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 1: Table of incidents for each reconstructed crime category as per Section A.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.

	All Individuals			OCGM		
Ethnicity	Count	Percentage	Average Age / S.D.	Count	Percentage	Average Age / S.D.
White British	46,953	82.67	32	1,107	93.10	28
			13			8
Non Stated	3,793	6.68	34	26	2.19	32
			15			11
Any other White Background	1,710	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	56,794	100.00	32	5,128	100.00	26

Table 2: Demographic composition of crime incidences, for all individuals and OCGMs.

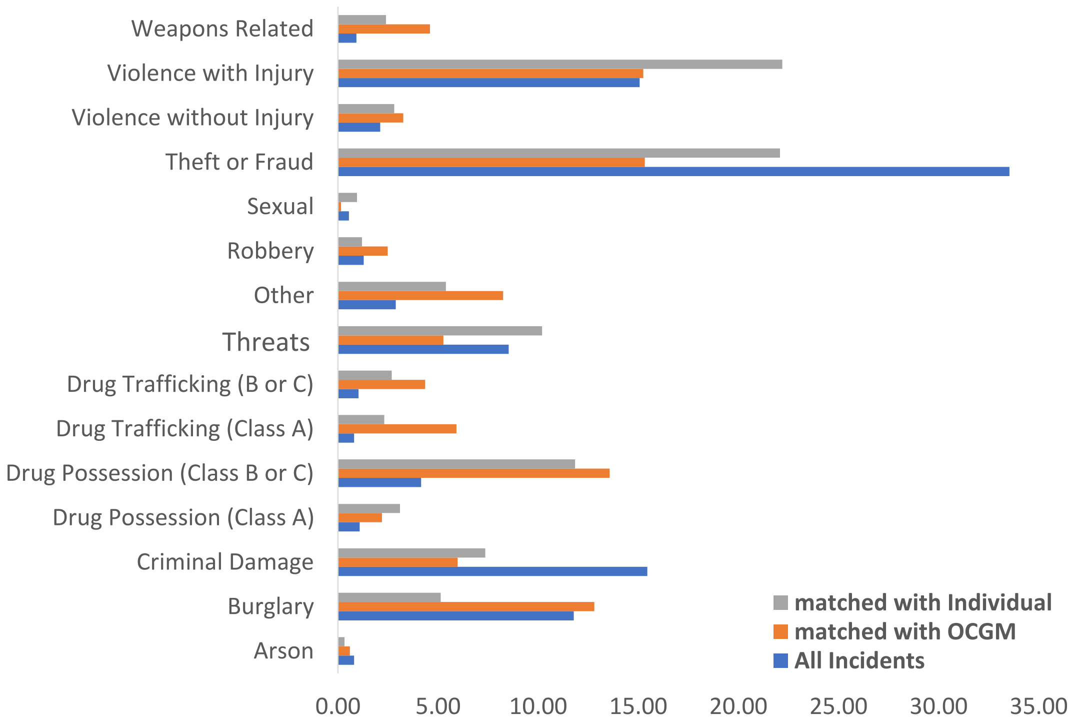

Figure 1: Volume of incidents by class of crime and matching rates for the population and OCGM-specific. Blue area represent the fraction of crime (on total crime incidents), whereas gray and orange bar represent the matching rates for the population in general and OCGMs individuals, respectively.

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 2 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.

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

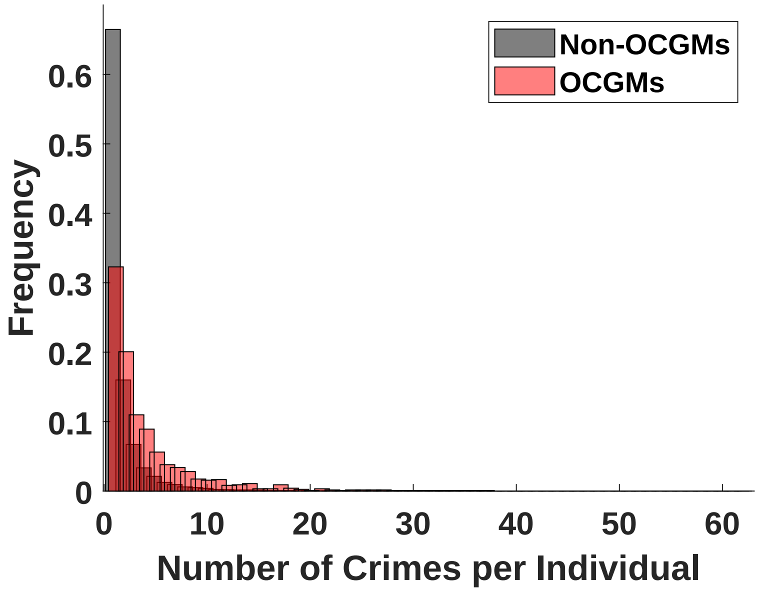

Figure 2: Frequency of crimes per individual suspect, non-OCGM and OCGM.

A.2 Geographic Data

As the focus of this paper is on understanding the determinants of inter-OCG interaction at neighborhood level, we project crimes (and OCGs) onto a geographical layer. As geographic unit of analysis we decide to use the Middle Layer Super Output Area (MSOA). These are small-area U.K. census units that provide a good approximation of neighborhoods and are demographically stable, centered at around $8,000$ inhabitants each. In Table 3 we report MSOA-averaged demographic indicators for Merseyside and compare them to 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[4], with a higher presence of semi-skilled, unskilled manual workers and unemployed (+5.30%).

[4] 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.

B Exploring the Nexus between Drugs and OCG-related Violence

The co-existence of a *stable* relationship between drug markets and violence in urban areas is a widely-addressed regularity in the criminological literature on social norms (and lack thereof) of neighborhoods (see Lum, 2011 for references). Merseyside is no exception. In Figure 3 we geo-localize all the incidents of OCG violence and market activity, where market activity is proxied through drug supply crime[5]. At the incident 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[6] (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[7]. We then measure the spatial proximity based on the nearest neighbor index across such a subset of events. Results are reported in Table 4, where a nearest neighbor index (labeled as *N.N.I.*) below 1 indicates spatial concentration.

[5]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 activity Reuter (2014).

[6] 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.

[7]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.

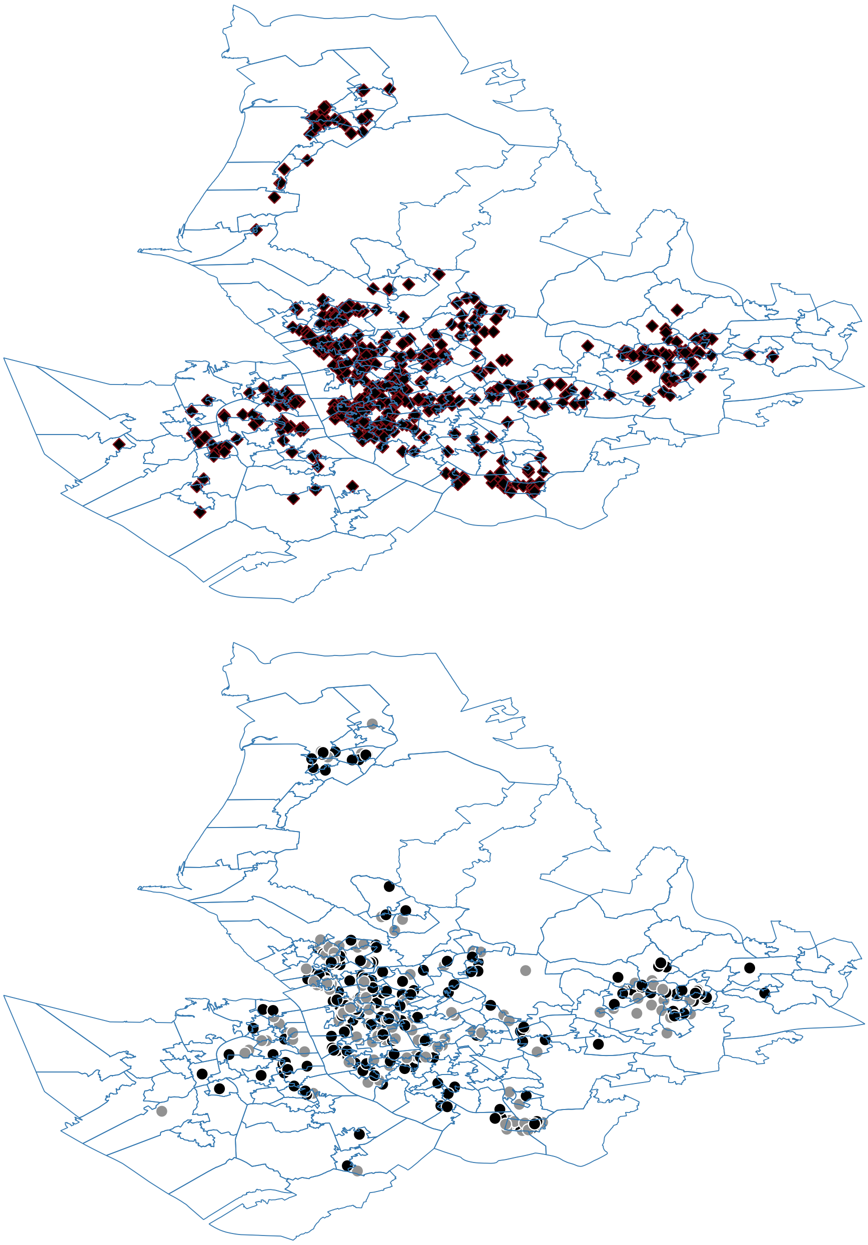

Figure 3: MSOAs of Merseyside area. *(Top Panel.)* The location of OCG violent crime. *(Bottom Panel)* OCG drug dealing. Violent crime, drug dealing of type A and type B and C are captured by black diamonds, grey circles and black circles, respectively. MSOA boundaries are captured by blue lines

Spatial clustering of this subset of drug-related events is confirmed for point sets

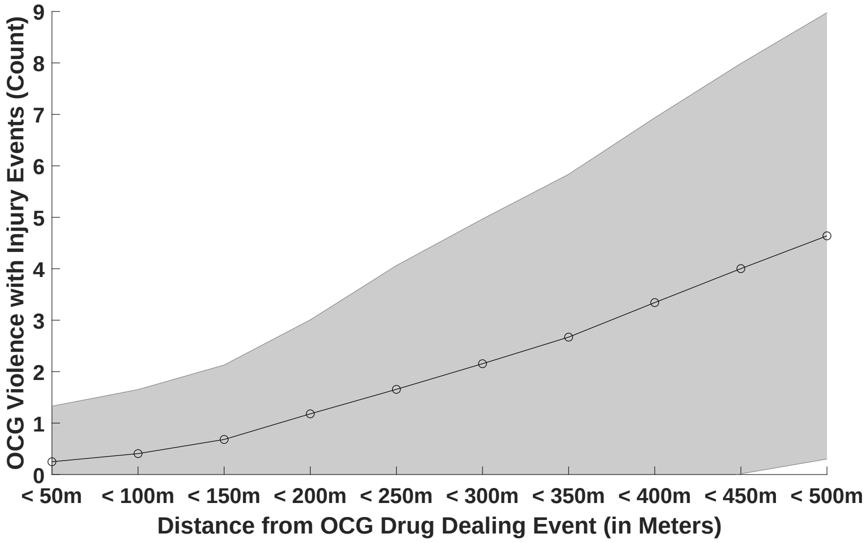

Figure 4: Average number of OCG violent crime per OCG drug dealing event taking place within 50 to 500 meters radius. Gray area represents standard errors.

built at all distance levels, with index ranging from 0.4 to 0.19.

The relationship between drug dealing and violence has been explained by invoking a variety of neighborhood-centered factors[8]: 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. In this work we provided an alternative yet complementary channel which not only motivates the existence of such positive relationship, but also logically and empirically extends the argument to a relationship between drug dealing and OCG presence and mobility.

C Estimation

To show that claims from Figure 1 in the main text relative to OCG-related violence $C^{V,ocg}$, OCG concentration N_m and OCG radius of action $\bar{N}_m$ are not fol-

[8]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.

	< 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 4: 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 6).

lowing from a mechanical artifact caused by the fixed aggregation strategy used to build the figure (i.e. homogeneously-sized bins, each containing $m = 10$ neighborhoods each), as a robustness check, in this section we propose a simple data-driven classification method. Let

$$\begin{aligned} C^{V,ocg} &= g_V(C^D) \\ N &= g_N(C^D) \\ \bar{N} &= g_{\bar{N}}(C^D) \end{aligned} \tag{1}$$

be three, possibly non-linear and discontinuous functions describing the relationship between drug dealing events C^D_m recorded on the various areas of Merseyside $m = 1, ...M$ and the variables depicted in Figure 1 in the main text. To minimize structure on the shape of the target functions, we take an agnostic approach and estimate g_V, g_N, $g_{\bar{N}}$ using regression trees (Breiman, 2017).

A regression tree[9] is fully non-parametric method that implements a recursive, binary partitioning procedure to split the data into groups of observations that are as homogeneous as possible in terms of the dependent variable (Kelly and Gráda, 2000). The procedure goes through the explanatory variable C^D and tries a split at each level. It chooses the split that partitions the data into subsets where variance of the target variable is minimized. For instance, consider the estimation of $g_V(\cdot)$ such that the target variable is $V^{g,ocg}$. Suppose that a level of $C^D = 10$ is identified by the algorithm as providing the best split across the surrounding values, such that neighborhoods characterized by fewer cases of drug dealing show an obstensibly lower count of OCG-related violence events $C^{V,ocg}$ than neighborhoods with $C^D > 10$. The procedure is then repeated for each of the two new subgroups (nodes) of data, with the algorithm again searching through the support to find the best partition in each case. This partitioning process continues until splitting become non informative (in terms of variance reduction) and/or

[9]Regression trees generalize fixed effects of parametric estimations to allow them to depend on values of the support C^D. In the limit, as the squares grow infinitesimally small, the tree reports a perfect reconstruction of the underlying function $g(\cdot)$.

the resulting splits contains a scarce number of neighborhoods. Practically, we constrain the branching process to allow for a maximum of 5 end nodes[10].

Results of the estimation of (1) are reported in Figure 5. In every graphs, each circle rapresents an observation across one of the three domains considered in (1). The top pane characterizes (C_m^D, C_m^V), whereas the central and the bottom pane show empirical relationships (C_m^D, N_m), $(C_m^D, \bar{N}_m)$, respectively. In each figure, we superimpose the predictions (red diamonds) as well as the optimal splits as identified by the regression tree. We can see that across the three dimensions considered, the regression tree identifies four partitions. Partitions are reported in table XX.

[10]We run the estimations using the R package *rpart* (Therneau et al., 2015), which we manipulate only in the dimension of the maximum tree depth, set to generate a maximum of 5 end-nodes. Alternative parametrizations (available upon request) provide similar results.

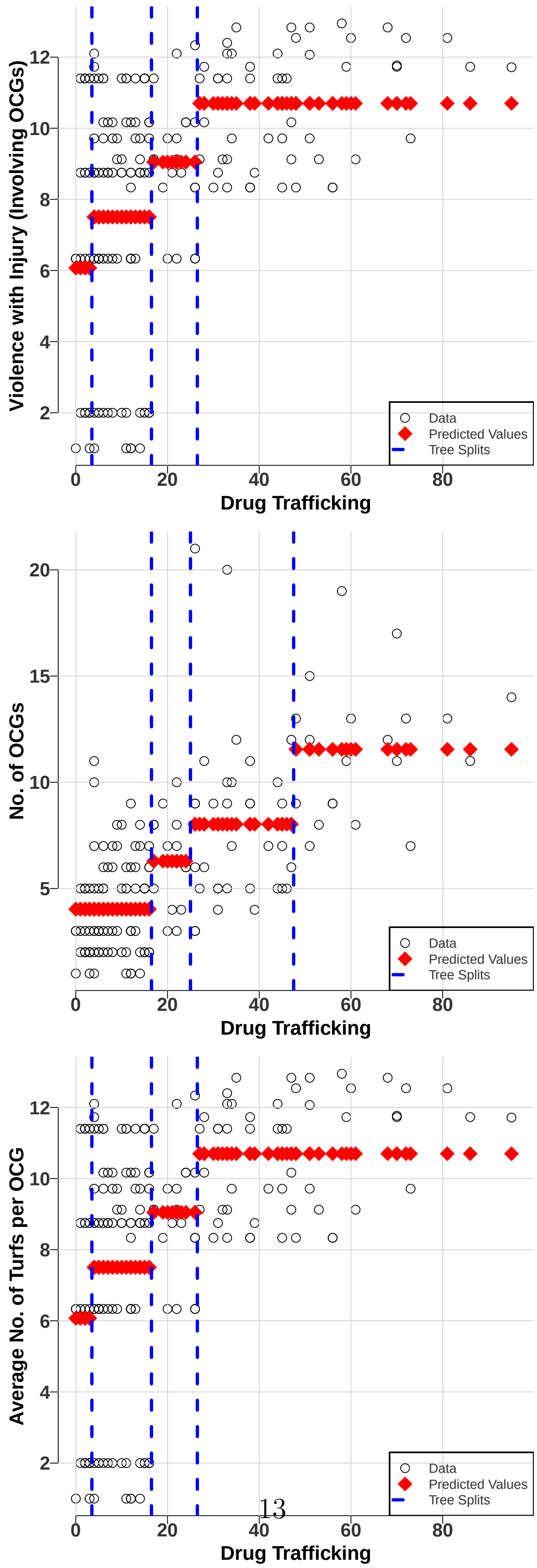

Figure 5: Prediction outcomes of the regression trees in (1).

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