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A NETWORK APPROACH

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**SWEEPING UP GANGS: THE EFFECTS OF TOUGH-ON-CRIME
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ABSTRACT: Worldwide, gang proliferation is fought mostly with tough punishment strategies such as sweeps. In this paper, I study their causal effect on crime for arrested individuals and known peers following a difference-in-differences strategy. I also take advantage of the network structure I retrieved to assess peer effects and identify key players. I perform such an analysis with novel administrative data from the Metropolitan Area of Barcelona, where Latin gangs expanded rapidly and where a stark policy change occurred. Results show significant reductions in crimes of arrested individuals and their peers, particularly in crimes against the person. The areas of the sweeps benefit from improvements in crime, health and education. I further conduct an innovative counterfactual policy exercise comparing sweep outcomes with theoretically predicted crime reductions when removing key players. This exercise indicates that sweeps could have achieved a 50% larger reduction in criminal activity had key players been removed. In this way, a network analysis provides insights on how to improve policy design.

JEL Codes: C31, H56, K14, K42, Z18

Keywords: Crime, Networks, Peer effects, Police Interventions

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1 Introduction

Since the 1980s, efforts to detect criminal organizations involved in drug trafficking have intensified, and sanctions have toughened (Mansour et al. 2006, Sweeten et al. 2013, Lessing 2016). At the same time, research has shown that individual choices regarding crime participation are affected by existing norms and networks (Glaeser and Sacerdote 1999), by providing role models, learning opportunities, and information diffusion. Crime-targeting policies should take such influences into account. The role of norms and networks in crime is particularly relevant when dealing with gangs. These are defined as “any durable, street-oriented youth group, whose involvement in illegal activities is part of their group identity”¹. These criminal groups raise concerns for several reasons, such as the recruitment of particularly vulnerable young individuals, the high degree of involvement demanded from their members, and the low prospects of reinsertion into society. On the matter of crime-fighting policies, two broad sets of strategies exist. One strand relies on hard punishment and sturdy prosecution, while the other one rests on dialogue and integration. Concerning gangs, the former has been more popular, and interventions such as sweeps or crackdowns have been the most common action. However, little is known about how they work. For a better understanding, it is crucial to understand the network structure of the gangs.

This paper studies the effects of police sweeps against gangs. Specifically, this paper answers the following research questions: Are sweeps successful at reducing crimes committed by targeted individuals? Do they also diminish the crimes committed by peers? Can a network analysis provide insights into how to improve gang sweep design? To answer these questions, I study the Metropolitan Area of Barcelona (MAB), where a drastic policy change towards gangs took place. This transformation has involved the creation of police unit specialized in gang sweeps, and tougher judiciary prosecution. To carry out this analysis, I use administrative police records for the 2008–2014 period. Such information allows me to follow individuals over time and identify criminal network structures. I supplement this with information on the sweeps. To analyze the effects of the sweeps, I follow a staggered difference-in-differences strategy, by comparing criminal records for arrested individuals and known peers with those of other group offenders. I also study outcomes in the area of the sweep, in terms of crime and other relevant socioeconomic variables. In addition, I use the retrieved network structure to estimate peer effects and identify key players in each gang. Finally, I conduct a counterfactual policy exercise that compares crime changes caused by the sweeps with a prediction based on removing key players. Results evidence significant crime reductions for arrested individuals and known peers. For the first group, the drop in crime is

¹Eurogang Network, www.umsl.edu/~cj/eurogang/euroganghome.htm

almost 100% and persistent. For the second one, the reduction is 25% and only takes place in the short term. The biggest fall occurs in crimes against the person. Additionally, the areas of the sweeps experience improvements in crime, health, and education. Nonetheless, if sweeps arrested a broader set of key players, they could have achieved a crime reduction 50% larger.

The Metropolitan Area of Barcelona (MAB) provides an appealing setting to study tough-on-crime policies against gangs for several reasons. It is a context in which Latin gangs rapidly unfolded following the start of the new millennium. Starting from the almost complete absence of Latin gangs in 2002, 2,500 individuals were identified in 2012 by authorities as belonging to a Latin gang (Blanco 2012). While the level of this phenomenon does not compare to that of other settings, the rapid increase is a worrisome characteristic. Additionally, security has become the primary non-economic concern of citizens (Barometer of the City of Barcelona). In this setting, a drastic policy change has occurred. Until 2012, the public sector based its strategy on integration into the neighborhood and discouragement from illegal activities. However, this was not successful with gang members, whose criminal activities continued to increase. In 2012 the transformation in the public strategy involved the creation of a centralized and specialized police unit focused solely on criminal investigation and sweeps against gangs. Additionally, the judiciary system implemented sturdier prosecution of criminal groups. This policy change was not concurrent with any other crime policy, providing an exogenous shock to gang arrests and a clean identification strategy.

In this analysis, I use administrative and confidential police records provided by the Local Police (Mossos d'Esquadra) for the 2008–2014 period. This dataset has very detailed information on the crimes recorded in the MAB as well as on the offenders arrested, when available. The former includes information on the exact date and exact place of the crime. The latter includes information on the gender, date, and place of birth of the individual. I exploit the level of detail of the data in two ways. Firstly, a unique identification number allows me to follow individuals over time and map out their criminal careers. Secondly, by matching information on the exact date, hour, place and type of crime, I retrieve criminal network structures. Finally, I match these records with confidential information on the sweeps. This last information allows me to label individuals involved in sweeps and their peers.

To identify the causal effects of the policy change on crime, I implement a staggered difference-in-differences strategy. I compare criminal records for arrested individuals and their known peers (identified as explained above) before and after the sweeps to the criminal records of other group offenders. By doing so, I estimate the treatment effects of the gang sweeps. I do so for both the direct and indirect impacts of the sweeps. I follow a similar

strategy to study crimes and other relevant socioeconomic factors in a broader sense. In this case, I define a treatment indicator at the area level, which takes a value equal to one for the districts in which a sweep took place. This allows me to analyze its effects on crimes regardless of whether individuals were arrested and to examine other welfare determinants as well.

I also take advantage of the retrieved network structure to estimate peer effects. I do so by following Lee et al. (2020), who developed a methodology that addresses the concerns of peer effect estimates derived from potential identification and endogeneity issues. I also use these peer effect estimates to identify key players in each gang. The key player in a criminal group is the individual that leads to the largest crime reduction in aggregate crime when removed (Ballester et al. 2006). To identify these key players, I rank individuals in each gang according to the centrality measure proposed by Ballester and Zenou (2014). Finally, I conduct a counterfactual policy exercise in which I compare the variation in crime caused by the sweeps with the theoretical prediction of a policy that removes the key players. Since the sweeps were of a larger scale, I cannot compare them with a scenario in which I remove one individual. For this reason, I construct a predictive Cumulative Crime Reduction (CCR) measure as a function of the number of key players removed. I compare the contraction in crime after the sweeps with this CCR benchmark.

The results indicate significant reductions in the criminal activity of those arrested in the sweeps and of their peers. Specifically, for arrested offenders, there was an average reduction in criminal activity of 96%. This effect was immediate and persistent and is consistent with the incapacitation of these individuals, as they were in jail in the post-sweep period. For peers, there was also a significant reduction in criminal activity of up to 25%. For peers, the effect faded out within a year of the police intervention. No heterogeneity in peers was found in relation to age or nationality. The contraction in crime involved crimes against the person but not against property. This suggests that lower activity is due to a loss from the criminal environment (“bad influences”) rather than a loss of criminal capital (“crime machinery”). The evidence also suggests that the reduction in crime in peers is related to a deterrence effect rather than a caution effect. This would imply that peers are committing fewer crimes rather than being arrested less. Finally, I compare crime outcomes at the gang level after the sweeps with a theoretical benchmark derived from a policy that would have removed key players. For this, I estimate peer effects, identify key players, and compute the predicted reduction in criminality as a function of the number of key players removed. The results of this counterfactual policy exercise indicate that all sweeps arrested the key player. However, if the sweeps had arrested most central individuals in the gang, the predicted crime reduction would have been 50% higher.

The results of this study clearly show that identifying and tackling a group of key players in each gang can lead to substantial improvements in police interventions. Nonetheless, there are issues that need addressing. Firstly, key player identification is informationally costly as it requires detailed knowledge of the gang and thorough analysis. Secondly, key player predictions are only valid in the short term, as they hold under an invariant network assumption. Thirdly, the key player might be an unfeasible target in reality. Hence, a key player strategy might not always be the optimal strategy for police forces. Despite these drawbacks, the counterfactual exercise is a valuable benchmark with which to compare real policies.

This study contributes significantly to the research on criminal networks in several ways. Firstly, it provides a picture of the network structure of gangs, providing a better understanding of how these criminal groups act. Second, it gives new estimates of spillover and peer effects on criminal activities. In this regard, it is similar to Philippe (2017), Bhuller et al. (2018) and Lee et al. (2020), but it extends the research of peer effects on crime to a context of gang crime. Due to the specific nature of these criminal groups and the relevance of the Metropolitan Area of Barcelona as a gang enclave outside the American continent, the outcomes provide new insights regarding peer effects and their implications for policy analysis. This study goes further and makes use of such estimates to identify key players in each gang in a similar line to Lindquist and Zenou (2014). This study is one of the first to apply a key player analysis to real and worrisome criminal groups and to test the long-standing yet little contrasted theoretical predictions on this subject. Thus, it sets one of the first precedents uniting theory and practice in this regard. Thirdly, it contributes to the public agenda by comparing crime-fighting strategies. On such an issue, Lindquist and Zenou (2019) provided an overview of policy lessons. But there have been few studies involving counterfactual policy exercises from which recommendations could be extracted. Specifically, this paper speaks on how to improve the effectiveness of policy design considering well-established theoretical benchmarks. Such an issue is of immense relevance nowadays, when police funding and interventions are in the spotlight.

More broadly, this paper fits into the growing literature of network analysis of criminal groups. Although there is a vast list of theoretical contributions (see Jackson et al. (2017) for a summary), many applications refer to adolescent petty crime (Patacchini and Zenou (2008), Patacchini and Zenou (2012), Lee et al. (2020)). However, in recent years empirical criminal network analysis has developed in line with increasing data availability. The contribution of this paper mostly relates to this area. Closely related to this paper, Philippe (2017) studied the effect of incarceration on non-caught co-offenders, and Lindquist and Zenou (2014) performed an analysis of criminal groups in Sweden using rich administrative data.

They also identified key players in such a criminal context. Studies on peer effects in several criminal contexts (neighborhoods, residential areas, juvenile corrections centers, or among the homeless) were carried out by Kling et al. (2005), Bayer et al. (2009), Damm and Dustmann (2014), Corno (2017) and Bhuller et al. (2018). Other papers related to this one are those of Grund and Morselli (2017) and Billings and Schnepel (2017). While the former recreated the internal structure of a criminal gang in London and analyzed the role of ethnicity, the latter analyzed the role of pre-incarceration social networks on recidivism. Although this set of recent literature identifies causal estimates and is of high relevance to the field, there is much room to contribute to this branch of research in terms of policy design and evaluation.

The remainder of the paper is structured as follows. Section 2 deals with the tough-on-crime approach towards crime prevention, and its application in the Metropolitan Area of Barcelona. Section 3 presents the data under analysis. Section 4 introduces the methodology. Section 5 presents the results of this research. Section 6 contains the concluding remarks.

2 How to tackle gangs? Policy answers

When designing crime-fighting strategies, different approaches are possible. Without being too general, they can be split into two groups. The first and more traditional is labeled as the hard approach. Starting in the 1970s, safety policies in the United States have followed this “tough-on-crime” approach. Although within this framework there is heterogeneity in the way such an approach is followed in each context, they share characteristics that include police search and seizure, strict criminal codes, and severe sentences. The economics literature has long emphasized the potential deterrence capacity of the justice system (Becker 1968; Ehrlich 1973). Empirical studies have confirmed the same: Levitt (1997) found that tough sanctions deter criminal activity, while Di Tella and Schargrodsy (2004) found a large deterrent effect of visible police presence on crime. However, more recent contributions to the literature have shown that in many circumstances “tough-on-crime” measures can be expensive (Lynch 1997), ineffective (Kovandzic et al. 2004) and discriminatory (Arora 2018). As an alternative, innovative strategies to prevent crime have been carried out, in which new societal agents play a key role. This second approach, loosely labeled as soft, focuses on reducing crime-triggering disparities. Soft approaches are of importance in deprived areas, where social interventions are most needed (Crowley 2013), and a strong police presence may have a disruptive effect. Although these soft interventions are usually far less expensive (Domínguez and Montolio 2019), outcomes may be perceived over longer timeframes (Lawless et al. 2010), and interdisciplinary approaches (and coordination) are greatly needed. So,

questions remain on the implementation of these approaches, and whether they can serve different purposes and tackle different criminal profiles due to each one's specificities.

2.1 The case of the Metropolitan Area of Barcelona

Gangs were detected for the first time in the Metropolitan Area of Barcelona (MAB) in 2002. Over the following decade, there was a steady increase in the presence of such criminal groups. Their public notoriety increased significantly in 2004, after the murder of a teenage boy². In 2012, around 15 gangs were detected. In chronological terms, the first block to consolidate included the gangs known as the *Latin Kings* and *Ñetas*, linked to migratory flows originating in Ecuador. The second block included the *Black Panthers* and *Trinitarios*, and was linked to migratory flows from the Dominican Republic. The third block, composed by *Mara Salvatrucha* and *Barrio 18* from El Salvador and Honduras was the last to consolidate. Estimates indicate that while in 2003 there were around 70 members, after 2009 the number of members stabilized at around 2,500³. Most members are young men between 12 and 25 years old. Although most of them trace their origins to Latin America, Spaniards and individuals of other nationalities are frequently involved as well⁴. The factors mentioned in the sociological literature influencing involvement in gangs include, among others: social disorganization, presence of gangs in the neighborhood, barriers or lack of social and economic opportunities, lack of social capital, family disorganization, problems at school, and socialization in the street (e.g. Feixa 2012). However, the characteristics that most make gangs deserve attention are their connection with criminal activities and the violence embedded in their behavioral patterns.

The expansion of this social phenomenon was conditioned to the specific context in which it occurred. Firstly, Spain underwent widespread demographic change in the 2000s. The arrival of substantial migratory flows increased the percentage of the immigrant population from less than 3.6% in the year 2000 to 14.3% in the year 2012⁵. South America contributed the most foreign citizens (around 350,000 individuals in 2012 and 300,000 in 2019). Secondly, there was an important change related to security enforcement. Between 1994 and 2008 the deployment of the Local Police (*Mossos d'Esquadra*) was carried out, replacing the

²For an overview see <https://www.elperiodico.com/es/barcelona/20061127/confirmada-la-condena-por-la-muerte-de-ronny-tapias-5404839>

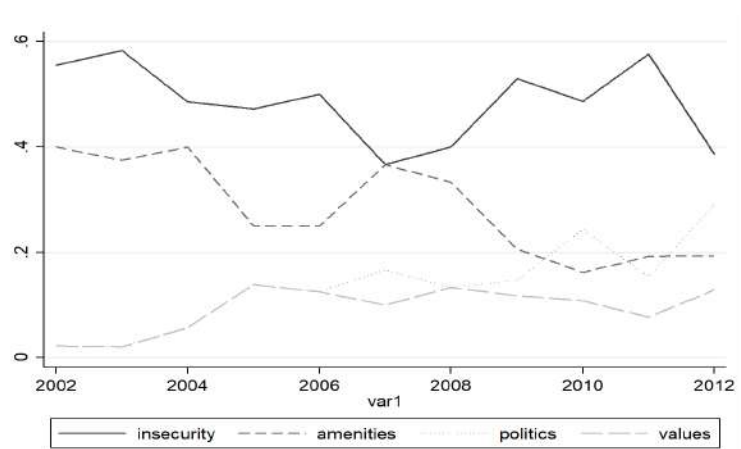
³<https://www.eldiario.es/politica/bandas-juveniles-estancan-cataluna-pandilleros15572184.html>

⁴It must be noted that group dynamics do not resemble those followed by groups in the United States nor are the levels of crime and violence comparable either with the United States or Latin America. According to Blanco (2012), they mostly follow behavioral patterns present in Ecuador. This refers to the organization inside the group (hierarchical structure) but also regarding behavior outside the group and rivalries.

⁵In Catalonia such figures rise to 4.0% and 17.7% respectively. Source: National Institute of Statistics <https://www.idescat.cat/pub/?id=pmh>

National Police. This change meant that security forces in the MAB were mostly dependent on the Local Government rather than on the Central Government and therefore had more autonomy to set police strategies. Finally, victimization data (Public Safety Survey of Catalonia, ESPC) shows that between 2004 and 2010, the prevalence of criminal incidents in the population increased. Thus in 2004 16.3% of the people surveyed remembered being victims of crimes, in 2010 this percentage had increased to 19.4%. Finally, according to the Barometer of the City of Barcelona, among non-economic concerns, citizens saw insecurity as the most concerning, with increasing weight given to this from 2007 onwards (Figure 1).

Figure 1: Main concerns for Barcelona residents, excluding the economy

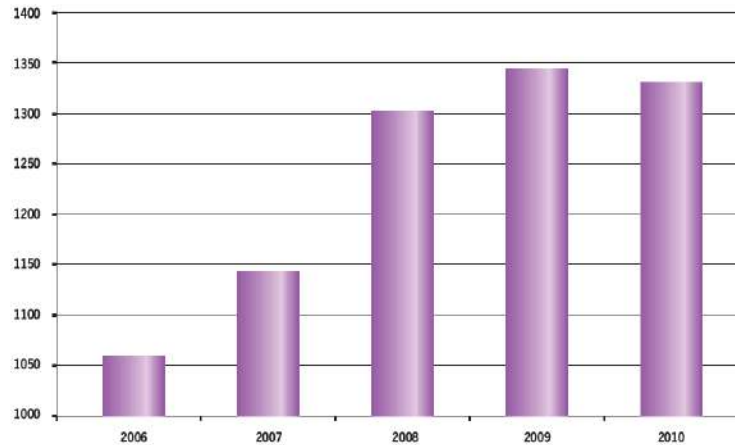


Source: Own construction from Barometer of the City of Barcelona

It was in this context that the rise of gangs and criminal acts carried out by them took place. Figure 2 illustrates the pattern in the first decade of the 21st century. The diagnosis from the police side was one of being “worried but not alarmed”⁶.

⁶<https://www.abc.es/espana/catalunya/abci-cataluna-tiene-jovenes-bandas-201107070000noticia.html>

Figure 2: Arrests of gang members in Catalonia



Source: Blanco (2012) based on General Police Directorate.

From a policy perspective, two very clear periods can be distinguished in the way the Local Public Sector (Generalitat de Catalonia and Barcelona City Hall) decided to tackle the existence and operation of gangs.

1. From 2004 until 2012 a lenient approach was followed. In 2004, Barcelona City Hall commissioned a report on the gang situation (Feixa 2012). At this time, gangs were given the possibility of moving towards integration and becoming legally recognized associations⁷. This was intended to give them visibility, and for members joining the associations to explicitly renounce the use of violence. Although this process had some positive effects, most gang members did not welcome it, which caused the extent of the newly created associations to quickly decrease (Blanco 2012; Córdoba Moreno 2015).
2. From 2012 a tougher approach was taken. In November 2011, with the approval of Decree 415/2011, the Local Police created a specialized unit. The “central unit of organized and violent youth groups” (UGOV⁸) was put in charge of the “investigation of crimes that affect people’s life or health and those criminal activities carried out by gangs”. This unit was created by shifting police resources from other jurisdictions rather than from new hiring. Specifically, 30 community police officers already involved in issues related to gangs in their jurisdictions were grouped at the central level and reassigned exclusively to tackle them. As a result, a “zero tolerance” approach against gangs was implemented: in addition to applying preventive measures, offensive ones

⁷The cultural association “Latin Kings and Queens of Catalonia” registered in July 2006 and the socio-cultural association “Ñetas” did so in March 2007.

⁸Spanish acronym for Unidad central de Grupos juveniles Organizados y Violentos.

were taken. These offensives were based on gang sweeps or crackdowns, which consisted of large-scale police interventions that arrested several and important gang members in a coordinated fashion. This change in the Police was accompanied by stronger judiciary enforcement. Act 6/2009 specified identifying conditions for group convictions, which would lead to tougher judiciary outcomes for criminals than previously⁹. In detail, Act 6/2009 sets out the criteria that police units must take into account when assigning a criminal act to the activity of gangs. The acting police units must make two evaluations: one to determine if the individual matches any of the indicators of belonging to gangs listed in the police database of gangs and another one to determine whether the criminal act committed is related or not to that militancy, for which a set of indicators is specified.

Hence, as explained above, in 2012 there was a drastic change in the way the situation regarding gangs was approached and tackled in the MAB. The new approach involved police specialization, large sweeps and tougher judiciary enforcement. No other concurrent changes in policy took place regarding gangs nor other criminal activities¹⁰. This context provides a good scenario with which to assess the effectiveness of a sturdier punishment policy towards gangs. It must be noted that the outcomes are due to the compound effect of concomitant policy modifications (police and judiciary), as from the public sector viewpoint they were coordinated and seen as one.

3 Data

This research first draws on a restricted-use administrative geocoded dataset of all registered crimes in the Metropolitan Area of Barcelona (MAB) from 2008 to 2014. This dataset was provided by the Local Police (Mossos d'Esquadra) and comprises information on all formalized offenders during that period. It includes information on the exact time (yy-mm-dd; hh-mm) and place of the crime (x-y geographical coordinates) as well as on the type of crime, and some individual characteristics of the offenders (age, gender and country of birth). Everyone is assigned a unique identifier (allowing them to remain anonymous), making it possible to see how many times he/she was arrested over time. Additionally, by exactly matching time, geographical coordinates and type of crime of individual registries, I can identify which offenders were caught alongside others. This allows me to identify and

⁹The Act, although passed in June 2009, states that 18 months would be given to local governments to identify relevant criminal groups, characteristics and actions that would lead to group convictions. As a result, it was only in 2011 that it became applicable.

¹⁰No significant changes were found in patrolling hours nor in number of police units.

thoroughly describe real criminal networks.

For this study I focus on the Metropolitan Area of Barcelona as it constitutes one of the most important settings for Latin gangs outside the American continent. This relates to the previously explained migration phenomenon that took place in the early 2000s in Spain, and the attractiveness of large cities for the incoming population. The MAB is composed of 36 municipalities and comprises 4 million inhabitants. It is the fifth largest and the densest Metropolitan Area in Europe. Within the MAB, the municipality of Barcelona is the largest in terms of population and territory (see Figure A1 in the Appendix). Additionally, it is one of the municipalities with the highest crime rates. In this regard, it is a well-established fact that crime rates are much higher in big cities than smaller cities. Glaeser and Sacerdote (1999) mentioned as causes higher pecuniary benefits, a lower probability of arrest and a lower probability of recognition.

Secondly, I have information about all sweeps carried out by the UGOV unit. The unit was created in 2012, and sweeps are still taking place. However, due to the availability of criminal administrative police records only until 2014, I only consider sweeps carried out up to that date. The exact date, geographical area of action and number of arrested individuals are included in the records. During these first three years (2012–2014), several sweeps took place, leading to 151 individuals being arrested¹¹.

Using these two data sources, I build a panel dataset for the MAB at the individual-quarter level for the 2008–2014 period. This includes 7,349,804 observations, coming from 262,493 individuals over 28 quarters. The panel includes individual information on whether the individual was arrested by the police¹²¹³, and if so, information on how many times they were arrested, how many of these were in a group and how many partners there were. Demographic information about the individual as well as on the crimes committed is also included. Descriptive statistics are presented in Table 1.

¹¹Due to the sensitivity of the data, it is not possible to disclose specific information on the sweeps.

¹²If not, a zero is imputed for the criminal actions committed by that individual in that quarter. This allows to build a balanced panel.

¹³The information available gathers all records from the police, and suffers the issue of “dark figures”, that is that it does not provide information about offenders who were not arrested. This is a common issue when dealing with crime data, and it is difficult to resolve. However, the data used still provides a solid base upon which to build this analysis.

Table 1: Descriptive statistics, main variables

Individual Variables	Observations	Mean	Std. Dev.	Min	Max
Female	262,493	0.258	0.438	0	1
Spanish	262,493	0.577	0.494	0	1
Other European	262,493	0.127	0.333	0	1
African	262,493	0.087	0.282	0	1
American	262,493	0.163	0.370	0	1
Asian	262,493	0.046	0.209	0	1
Year of Birth	262,493	1976	12.979	1901	2000
Arrested	7,349,804	0.059	0.236	0	1
Times arrested	7,349,804	0.077	0.423	0	83
Times arrested in group	7,349,804	0.033	0.292	0	51
Known peers	7,349,804	0.082	1.623	0	307
Global Variables	Observations	Mean	Std. Dev.	Min	Max
Arrests	28	20,139	1,114	17,516	22,311
Arrested individuals	28	15,518	728	13,335	16,567
Group crimes	28	8,561	688	7,498	10,126

Source: Own construction from Catalan Police data

4 Methodology

My analysis focused on two different, yet complementary approaches. Firstly, I estimate the effects of the sweep on criminality at the individual level. I do this for individuals arrested in sweeps and their known criminal peers. I also evaluate changes in criminality at the gang level. Additionally, I analyze the impact on other outcomes in the area where the sweep took place. Secondly, I compare the results at the gang level with the predicted crime reduction derived from a strategy that would remove key players in each gang. This counterfactual policy exercise helped to set a discussion on the implementation of the sweeps.

4.1 UGOV sweeps' analysis

In 2012 a tougher enforcement model for gangs was implemented in the Metropolitan Area of Barcelona, under which several sweeps took place. Using the panel structure described in the previous section, the main analysis in this subsection consists of estimating variants of the following staggered difference-in-differences specification:

$$\begin{aligned}
 Crime_{it} = & \beta_0 + \beta_1.Arrested_i + \beta_2.Peer_i + \beta_3.Post_{it} \\
 & + \beta_4.(Arrested.Post)_{it} + \beta_5.(Peer.Post)_{it} + \eta_i + \phi_t + \varepsilon_{it}
 \end{aligned} \tag{1}$$

where the dependent variable $Crime_{it}$ is an indicator variable showing whether the individual was arrested, the number of times he was arrested, and the number of times he was

arrested alongside others. $Arrested_i$ is an indicator variable that takes a value equal to one for individuals arrested by a sweep and $Peer_i$ is an indicator variable that takes a value equal to one for individuals not arrested in sweeps but linked to gang members that were arrested. $Post_{it}$ is an indicator variable that takes a value equal to one after each sweep and is sweep-specific. η_i and ϕ_t are individual and year-quarter fixed effects respectively. The observational unit is an "individual-quarter" pair and the main coefficients of interest are β_4 and β_5 . The key identifying assumption in this setting is that being arrested in a sweep is unrelated to the criminality of individuals when the sweeps took place. Moreover, in the absence of the sweeps, the criminality of those arrested in the sweep would have changed in the same way as for all others. I exclude from the main analysis individuals that only commit crimes alone. Thus, control units are individuals that are arrested in groups but are not part of any of the gangs arrested in the sweeps.

I also conduct event study exercises focusing either on the arrested individuals or known peers. I perform fixed-effects regressions of the following type:

$$Crime_{id} = \alpha + \eta_i + \gamma \cdot Treated_i + \sum_{d \neq -1} \phi_d \cdot (Treated_i \cdot Time_d)_{id} + \varepsilon_{id} \quad (2)$$

where the observational unit is an "individual-time to intervention" pair (measured in quarters), $Treated$ indicates whether the individual was either $Arrested$ or $Peer$ as defined above, and η_i are individual fixed effects. I estimate $Treated \cdot Time$ interactions, leaving $Time = -1$ as the reference period. Each of the ϕ_d coefficients quantifies the difference in criminal activity between the $Treated$ individuals and the control group relative to the period -1. The coefficients $\{\phi_{-D}, \dots, \phi_{-2}\}$ identify anticipation effects, and coefficients $\{\phi_0, \dots, \phi_D\}$ identify dynamic treatment effects. This exercise allows me to check for the parallel trend assumption but also to understand the post treatment dynamics of equation (1).

I also take a continuous treatment approach in addition to the one shown in equation 1. In this case $Treat_i$ takes values $\in [0,1]$ according to different criteria. The first criteria I use attributes a value equal to one to arrested individuals and values $\in (0,1]$ to known peers based on the number of links to arrested offenders after a min-max normalization¹⁴, and zero to all others. Hence:

$$Crime_{it} = \beta_0 + \beta_1 \cdot Treat_i + \beta_2 \cdot Post_{it} + \beta_3 \cdot (Treat \cdot Post)_{it} + \eta_i + \phi_t + \varepsilon_{it} \quad (3)$$

¹⁴For example, for a peer that is linked to 11 arrested individuals, the treatment value is $\frac{11-1}{22-1} = 0.476$, as 22 is the maximum number of links observed to arrested offenders and 1 is the minimum number.

where

$$Treat_i = \begin{cases} 1 & \text{for individuals arrested in a sweep} \\ \in (0, 1] & \text{for known peers} \\ 0 & \text{for all others} \end{cases}$$

Another criteria I take is to assign a [0,1] treatment indicator to individuals according to different network centrality measures. In this setting, I consider outcomes regarding two other centrality measures: closeness and alpha centrality¹⁵. While closeness relates to the inverse average distance between one individual and all others (and as stated in Mastrobuoni and Patacchini (2012) it is a good measure for how isolated individuals are), alpha-centrality is a measure of the influence of the individual in the group (Bonacich 1987). I also consider min-max normalization of these measures to restrict them to the [0,1] interval.

Finally, I run similar exercises at the gang level and at the area level where the sweeps took place. The first set of exercises identifies the reduction in criminality at the gang level after the sweep, and thus shows the effect on crime at a broader level. The second exercise indicates whether there are other outcomes that change after sweeps took place, indicating whether their benefits exceed those related to criminal outcomes.

4.2 How far were the interventions from the “most effective” approach? A comparison with a key-player targeting strategy

In a framework of crime and networks, “key players” can be identified. Although such individuals can be defined in different ways, in all cases they play a crucial role. This relates to the fact that they can connect nodes that are otherwise isolated, or they can increase the number of links in the network. The seminal paper by Ballester et al. (2006) defined the key player in a criminal group as the individual who when removed leads to the largest reduction in the group aggregate crime. Their main result indicates that a strategy that removes the key player leads to the highest reduction of overall criminal activity compared to removing any other individual. Besides their significant contribution to the literature on networks and crime, Ballester et al. (2006)’s results have significant implications for policy design. Specifically, a key-player targeting approach might lead to substantial reductions in the activity of criminal networks at a fraction of the cost of large-scale interventions.

Taking the previous points into consideration, I carry out a counterfactual policy exercise in which I compare the change in criminal outcomes at the gang level as a consequence of the sweeps in the Metropolitan Area of Barcelona with the predicted variation in criminality

¹⁵See Appendix for a full Social Network Analysis and its dimensions

when removing key players in each gang as in the model by Ballester and Zenou (2014). To do so I (1) estimate peer effects in criminality for the gangs under analysis, (2) build a key player ranking inside each gang according to the centrality measure proposed by Ballester and Zenou (2014), (3) compute the predicted reduction in criminality at the gang level as a function of the number of key players removed and (4) compare those predictions with the outcomes observed following the sweeps.

4.2.1 Peer effect estimates

The first step to determine the predicted reduction in criminality at the group level involves computing peer effects in criminality. This parameter is needed to measure the centrality of each individual within the gang and to rank them. In this setting, agents choose how many crimes to commit in order to maximize their own utility, which depends on the crime profile of all agents in the gang and on its architecture. In this game the utility function of individual i is given by

$$u_i(y, G) = \alpha_i y_i + \phi \sum_{j=1}^n g_{ij} y_i \cdot y_j - c y_i - 1/2 y_i^2 \quad (4)$$

The utility function has a cost-payoff structure as in Becker (1968), where the payoff is given by the first two terms and the cost by the latter two. y_i is the criminal outcome of individual i , α_i reflects individual heterogeneity of crime productivity¹⁶, and g_{ij} is an indicator variable that takes a value of one if individuals i and j are linked and zero otherwise.

In equilibrium, each agent maximizes his/her utility and the best-reply function can be written in matrix form as

$$Y = \phi G Y + \beta_0 + X \beta_1 + \bar{X} \beta_2 + u \quad (5)$$

where Y is a vector of the individual outcomes (crimes), G is a diagonal adjacency matrix¹⁷, $G Y$ is a vector of the individual outcomes for peers, X is a vector of agents' characteristics and \bar{X} is a vector of peers' average characteristics. Peer effects are given by ϕ , β_1 captures observable individual heterogeneity and β_2 reflects the contextual effects.

¹⁶ $\alpha_i = \beta_0 + X_i \beta_1 + \bar{X}_i \beta_2 + u_i$, where X is a vector of observable exogenous characteristics and \bar{X} is the average exogenous characteristics of agent i 's connections

¹⁷Specifically, each element g_{ij} indicates whether individuals i and j were arrested together.

4.2.1.1 Threats to identification and solution

The identification of peer effects is not straightforward and suffers several problems. The first of these is the well-known reflection problem (Manski 1993). Such an issue arises from the simultaneity in the choices and outcomes of peers, which in turn makes it impossible to distinguish separately peer effects from contextual effects. The second potential issue is the fact that the observed gang is presumed to be endogenous. When this is the case it is not possible to identify whether the correlation of behavior among peers is a result of the network or just of homophily (similar observable characteristics).

As stated in Lee et al. (2020), both issues can be solved by an Instrumental Variables approach in three stages. Firstly, the observed adjacency matrix G needs to be replaced by a predicted adjacency matrix \hat{G} . The latter is based on exogenous covariates of the individuals. A logistic regression model on link formation is estimated considering matches on available observable characteristics, and a predicted probability of link formation is obtained for each element of \hat{G} . Secondly, peers' criminal outcomes (GY in equation 5) are regressed against the IV matrix $\hat{Z} = [1, X, \hat{X}, \hat{G}1, \hat{G}X, \hat{G}\hat{X}]$. Thirdly, equation 5 is run with the predicted value of GY .

4.2.2 Centrality measure and key player ranking

Once peer effects are adequately identified and estimated, it is possible to compute the centrality of each individual in each gang. In order to compute such a measure two assumptions are made. First, that the gang is fixed. This implies assuming it does not vary after an individual is removed, meaning no rewiring or new link formation. Second, that the criminal productivity of each individual (previously described as α_i) does not depend on the gang.

As mentioned earlier, the key player is the individual that once removed from the gang leads to the largest reduction in crime. Formally, this implies $\max\{Y^*(r, \phi) - Y^*(r^{-i}, \phi)\}$.

For all gangs r and for all individuals i , Ballester and Zenou (2014) proposed a ‘‘contextual intercentrality measure’’ that considers (1) a network effect, derived from the centrality measured proposed by Ballester et al. (2006). This effect captures the direct effect on delinquency after the removal of an individual and the change in the gangs structure when an individual is removed. And (2) a contextual effect, derived from the removal of an individual but keeping the gang unchanged. This measure is built as follows:

$$\delta_i(r, \phi, \alpha) = b_{\alpha_{\langle i \rangle}}(r, \phi) \cdot \frac{\sum_{j=1}^n m_{ji}(r, \phi)}{m_{ii}(r, \phi)} + b_{\alpha}(r, \phi) - b_{\alpha_{\langle i \rangle}}(r, \phi) \quad (6)$$

where $\alpha_{\langle i \rangle} = (X_i, \alpha^{[-i]})'$ describes the situation in which the contextual vector α is computed

from the network r when individual i is removed, that is $r^{[-i]}$, and $\alpha^{[-i]}$ is the vector α after removing individual i . $b_{\alpha,i}(r, \phi)$ is the centrality of individual i in network r . m_{ji} and m_{ii} are the corresponding elements of matrix $M = (I - \phi G)^{-1} = \sum_{k=0}^{\infty} \phi^k G^k$. M tracks the number of walks in network r starting from i and ending in j , where walks of length k are weighted by ϕ^k .

After computing this centrality measure, it is possible to rank individuals in each gang in decreasing order. This allows key players to be identified.

4.2.3 Predicted reduction in criminality and policy comparison

Lindquist and Zenou (2014) showed that the predicted crime reduction in each gang r after removing an individual i (CR_{ir}) is equal to 100 times the centrality of this individual divided by the total centrality of the gang

$$CR_{ir} = \frac{100 \cdot \delta_i(r, \phi, \alpha)}{B_\alpha(r, \phi)} \quad (7)$$

As equation (7) indicates, as $\delta_i(r, \phi, \alpha)$ is highest for the key player in each gang, so is the crime reduction at the gang level. However, it must also be noted that equation 7 computes the predicted crime reduction when a single individual is removed from the gang. For this reason, by itself it is not a good benchmark with which to compare the outcomes of the sweeps as they were of a larger scale.

In order to compare the prediction of the model with the observed outcome in an informative way, I perform a sequential removal exercise in which the result is the predicted crime reduction as a function of the number of individuals removed, ranked by centrality. Specifically, the predicted cumulative crime reduction in each gang r after removing up to individual n when sorted by centrality (CCR_{nr}) is defined as

$$CCR_{nr} = CR_{1r} + CR_{2r}(1 - CR_{1r}) + \dots + CR_{nr}(1 - CR_{1r} - \dots - CR_{(n-1)r}) \quad (8)$$

Firstly, this requires computing the predicted crime reduction when the key player is removed as in equation (7). Secondly, the additional reduction when removing the second-top-ranked individual is determined by computing their centrality over the remaining criminal activity after the first individual is removed. The second exercise is performed as many times as there are individuals in the gang. As a result, a map of the predicted crime reduction at the gang level as a function of the number of “key players” removed is obtained. Such predictions are compared with those observed after the sweeps. The resulting deviation speaks in terms of the effectiveness of the interventions.

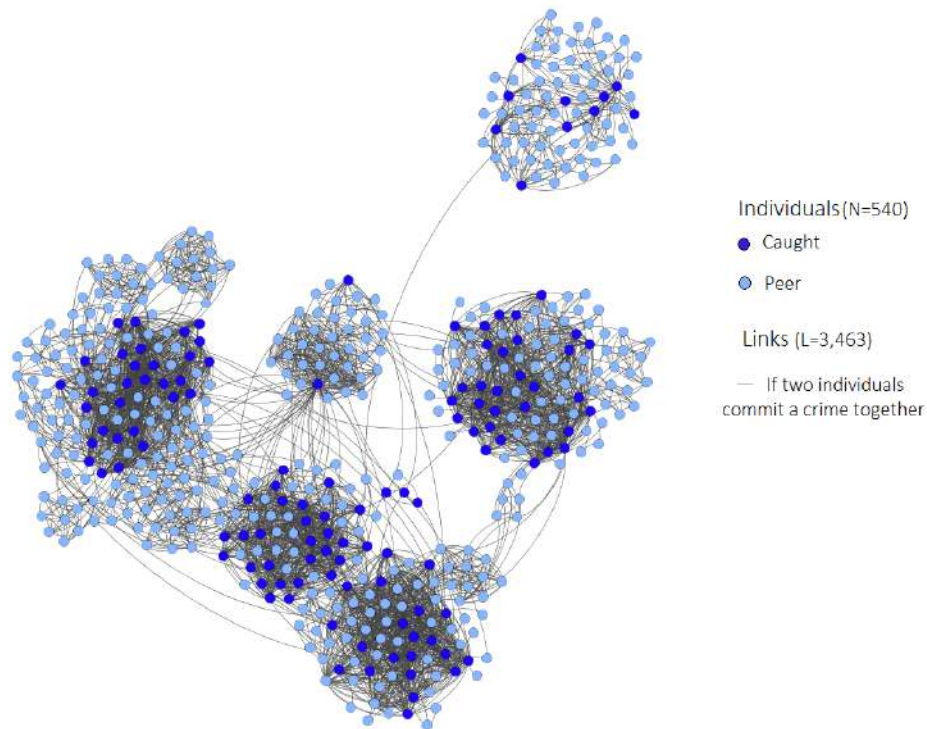
5 Results

5.1 Analysis of UGOV's sweeps

Out of the 151 individuals arrested in the sweeps, 127 individuals were identified in the data. The difference in numbers reflects the fact that some of these individuals were not caught in the MAB (but in other areas of Catalonia), and the last operation took place in the last quarter of 2014, and therefore did not have a post-intervention period for comparison. For those 127 individuals identified, 413 first-order peers were identified, matching them in date, time, geographical coordinate and type of crime in records on arrests. As a result, a total of 540 individuals are considered treated by UGOV's sweeps, either directly or indirectly.

The network structure of the individuals involved is shown in Figure 3. This graph presents the network structure of individuals arrested in the sweeps and first-degree known peers. Each dot is an individual; darker dots are individuals arrested in the sweeps whereas lighter dots are peers. Each line between individuals indicates that those two individuals had committed at least one crime together before the sweeps.

Figure 3: Recovered criminal gang structure, before sweeps



Note: This graph presents the network structure of individuals arrested in the sweeps and first degree known peers. Each dot is an individual and each line indicates a link between individuals. Source: Own construction from Local Police data.

A description of the data used in this analysis is presented in Table 2, indicating the observed characteristics of the individuals under analysis and the peer averages. As expected, individuals involved in UGOV sweeps were to a large extent young males born in Latin America¹⁸. Table 3 shows the results of balancing tests regarding crime characteristics for treated (arrested individuals and peers) and control individuals. This data indicates that while there may be differences in the number of crimes committed by treated individuals in comparison to control individuals, it is not possible to rule out the possibility that the variation the number of crimes is the same for both groups. This data therefore provides the first piece of evidence in favor of the parallel trend assumption holding in this context.

Table 2: Data description – characteristics of individuals arrested in sweeps and their known peers

	Mean	Std. Dev.	Min	Max
Own characteristics				
Female	0.124	0.330	0	1
Spanish	0.298	0.458	0	1
Latin	0.622	0.485	0	1
Age	22.406	7.016	13	63
# Crimes	4.526	4.737	1	30
Peers	12.826	12.673	1	77
UGOV-arrested	0.235	0.425	0	1
Peer characteristics				
Female	0.091	0.162	0	1
Spanish	0.289	0.267	0	1
Latin	0.636	0.298	0	1
Age	22.012	4.632	14	41

Note: This table reports descriptive statistics for the 540 individuals linked to UGOV sweeps. Source: Administrative data of the Catalan Police.

¹⁸See Figure A2 in the Appendix for homogeneity measures inside gangs for the largest sweeps in the sample.

Table 3: Balancing tests on crime for treated and control individuals

	Treated	Control	Diff	Std. Err.	p-value
Panel A: Level					
All crimes	0.107	0.086	0.021	0.008	0.007
Group crimes	0.068	0.056	0.012	0.006	0.042
Against property	0.063	0.042	0.021	0.005	0.000
Against person	0.027	0.030	-0.003	0.004	0.538
Other	0.017	0.014	0.003	0.003	0.369
Panel B: Variation					
All crimes	-0.050	-0.047	-0.003	0.005	0.569
Group crimes	-0.041	-0.037	-0.004	0.004	0.325
Against property	-0.026	-0.026	0.000	0.004	0.942
Against person	-0.021	-0.021	0.000	0.003	0.888
Other	-0.011	-0.011	0.000	0.002	0.941

Note: This table presents balancing tests for criminal characteristics (number of crimes and crime variation) before the UGOV sweeps took place, between treated and control individuals. Source: Own construction from Barcelona City Hall and Catalan Police data.

5.1.1 Baseline estimates

Baseline estimates of Eq.(1) are presented in Table 4. Estimates are done for individuals arrested in the sweeps as well as known peers. The probability of committing a crime, the total number of crimes for which they were caught and the number of group crimes for which they were caught are shown. Control individuals are those arrested in groups but are not part of any of the gangs arrested in the sweeps.

In all cases, the results show a significant decrease in criminality after the sweeps. In the case of arrested individuals, the probability of committing a crime was reduced by almost half, while the number of crimes was reduced by 95%. For peers, reductions in criminality were of a smaller magnitude (26%) but also significant. Considering only crimes committed by groups the decreases in crime were even higher.

Table 4: Baseline estimates - effects of sweeps on crime

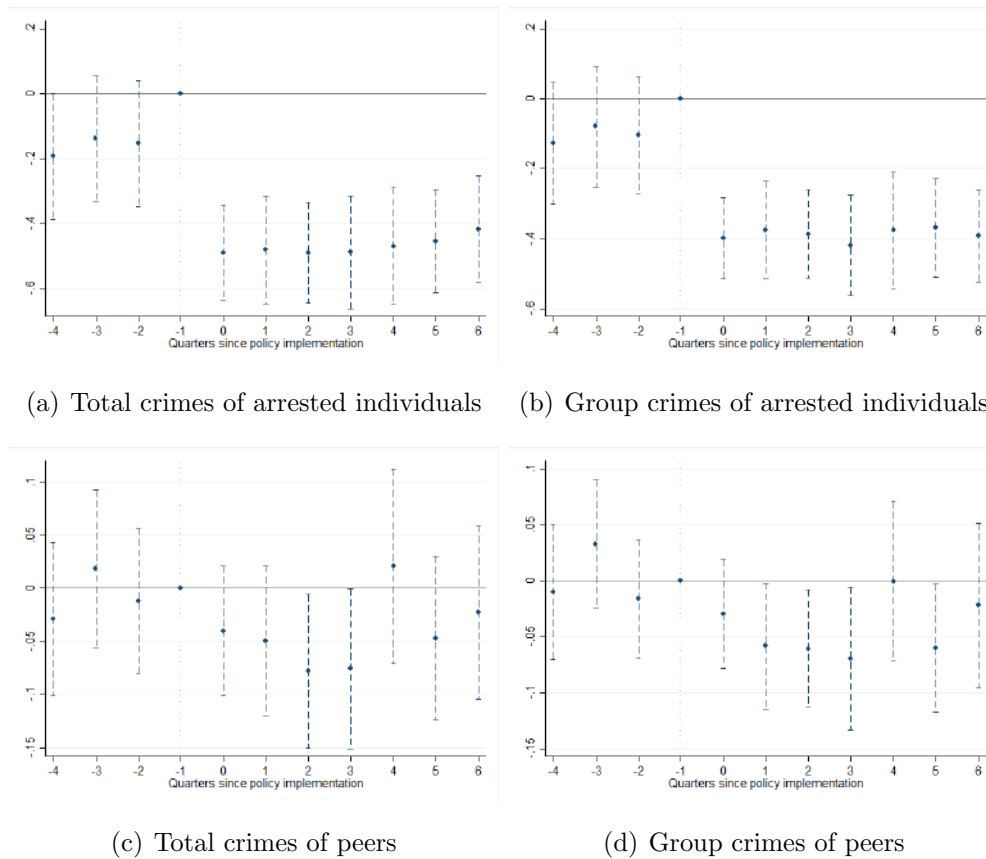
	P(crime)	Total crimes	Group crimes
Arrested·Post	-1.782*** (0.211)	-0.350*** (0.028)	-0.302*** (0.023)
Peer·Post	-0.469*** (0.117)	-0.048*** (0.019)	-0.051*** (0.015)
Obs.	3,544,535	3,544,535	3,544,535
Indiv.	126,968	126,968	126,968
i FE	Y	Y	Y
t FE	Y	Y	Y
% change arrested	-44%	-95%	-99%
% change peers	-12%	-26%	-43%

Notes: This table reports the results of the difference-in-differences (DiD) estimation following Eq. (1) for the 2008-2014 period. Each row presents estimates for different groups: arrested individuals and peers. The first column indicates the results for the probability of committing a crime, column two indicates the total number of crimes and column three indicates the number of group crimes. The observational unit is an individual-quarter pair and only individuals ever arrested in a group crime were included. Treated units are arrested individuals or peers. Treatment timing differed across individuals, according to the timing of the sweep. The coefficient shown is that of interest in a DiD setting, being *Treated·Post* for Arrested and Peer. Robust standard errors are shown in parentheses. $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Event study exercises allow effects to be seen over time. For arrested individuals the reduction in crime was drastic and immediate. Moreover, this reduction persisted after 1.5 years. For peers, a different pattern arose. The effect seemed to be short-lived as after one year the reduction in criminality was no longer significant. This pattern may relate to the average time taken to resolve a process legally. According to statistics from the Spanish Judiciary System, in Catalonia the average timescale for “brief procedures” is 9.8 months or 7.1 for procedures involving minors¹⁹. For peers the reduction in crime was no longer significant around this timescale.

¹⁹The statistics are provided at the regional level, thus the Catalan average is used to approximate what takes place in the MAB. Source: <http://www.poderjudicial.es/cgpj/es/Temas/Estadistica-Judicial/Estadistica-por-temas/Actividad-de-los-organos-judiciales/Juzgados-y-Tribunales/Informes-por-territorios-sobre-la-actividad-de-los-organos-judiciales/>

Figure 4: Event study exercise on the effects of sweeps on crime. 95% Confidence intervals.



Notes: This graph reports the results of an event study exercise following Eq. (3) for total crimes (left panel) and group crimes (right panel). Results are presented for arrested individuals (upper panel) and peers (lower panel). The observational unit is an individual-quarter pair. Treated units are defined as in section 4.1, while treatment timing differed across units, according to intervention timing. Confidence intervals are based on robust standard errors.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

I also analyze the previous outcomes in terms of individual characteristics. The results are presented in Table 5 both for individuals arrested in the sweeps and their peers. These results indicate that for arrested individuals the reduction in total criminality was larger for offenders who were underage, male and non-Latin. However, no differences in outcomes were found for group crimes. Regarding peers, for total crimes as well as for group crimes, there appeared to be differences in outcomes only by gender: female offenders showed a larger decrease in crime following sweeps.

Table 5: Heterogeneity estimates - effects of sweeps on crime

	Total Crimes	Group Crimes
Arrested·Post	-0.445*** (0.062)	-0.353*** (0.048)
Arrested·Post·Underage	-0.197** (0.077)	-0.114 (0.088)
Arrested·Post·Female	0.122*** (0.041)	0.057 (0.042)
Arrested·Post·Latin	0.136** (0.065)	0.075 (0.051)
Peer·Post	-0.042 (0.042)	-0.056* (0.032)
Peer·Post·Underage	-0.064 (0.047)	-0.046 (0.038)
Peer·Post·Female	-0.093** (0.044)	-0.068* (0.037)
Peer·Post·Latin	0.011 (0.043)	0.024 (0.034)
Obs.	3,544,535	3,544,535
Indiv.	126,968	126,968

Notes: This table reports the results of the difference-in-differences (DiD) estimation following Eq. (1) for the 2008-2014 period. Each row presents estimates for different groups: arrested individuals and peers by heterogeneous individual characteristics. The first column indicates the results for the total number of crimes and the second column indicates the results for the number of group crimes. The observational unit is an individual-quarter pair and only individuals ever arrested in a group crime were included. Treated units are defined arrested individuals or peers. Treatment timing differed across units, according to the timing of the sweep. The coefficient shown is that of interest in a DiD setting, being $Treated \cdot Post$ for Arrested and Peer. Robust standard errors are shown in parentheses.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The network structure remaining after the sweeps indicates that some crime structures persisted after the sweeps, which is consistent with the fact that the level of crime reduction for peers was smaller and short term. However, the network graph was much smaller and sparse than before in terms of number of observed individuals but also importantly in terms of criminal links. Before the sweeps 540 individuals (127 arrested and 413 peers) and 3,463 links were identified. Afterwards, 101 individuals were arrested (14 arrested in sweeps and 87 peers), and 101 links were found between them²⁰.

Finally, I analyze results at the gang level. These indicate that one year after the sweeps, criminal activity at the gang level had reduced by 61% compared to the year before.

²⁰See Figure A3 in the Appendix for a comparison of before and after network graphs.

5.1.2 Continuous treatment estimates

For the continuous treatment estimates two approaches are followed. In the first, the number of links to arrested individuals is considered in a min-max standardized way as described in section 4.1. The second approach takes two network centrality measures amongst arrested individuals and peers: alpha-centrality and closeness. The first is a measure of the influence of a node in a network, and the second measures the average length of the shortest path between the node and all other nodes in the graph.

In all cases, the higher the centrality measure, the higher the crime reduction. The results indicate that an increase of one link to the arrested individual reduced total crimes by 13%. In the network centrality measures approach, the results went in the same direction of crime reduction but the magnitudes differed: a one standard deviation increase in alpha-centrality reduced crimes by 3.2%, whereas for closeness there was a 2% reduction²¹.

²¹Differences between these results correspond to the fact that each centrality measure reflects different issues. While closeness shows how many steps are needed to access every other node (0.11 standard deviation) reflecting not only how many links an individual has but also how far it is from others, alpha centrality contemplates an individual's own connectedness and also that of its peers, providing a notion of the power of the node in the network (0.08 standard deviation).

Table 6: Continuous treatment estimates - effects of sweeps on crime

	P(crime)	Total crimes	Group crimes
Panel A: number of links	-2.126*** (0.232)	-0.360*** (0.029)	-0.315*** (0.023)
% change	-5.3%	-13.0%	-11.4%
Panel B: alpha-centrality	-1.501*** (0.151)	-0.224*** (0.025)	-0.204*** (0.020)
% change	-3.7%	-3.2%	-2.9%
Panel C: closeness	-1.172*** (0.120)	-0.156*** (0.019)	-0.143*** (0.015)
% change	-2.9%	-2.0%	-1.9%
Obs.	3,544,535	3,544,535	3,544,535
Indiv.	126,968	126,968	126,968
i FE	Y	Y	Y
t FE	Y	Y	Y

Notes: This table reports the results of the difference-in-differences (DiD) estimation following Eq. (1) for the 2008-2014 period. Each panel presents estimates for different continuous treatment indicators: number of links, alpha-centrality and closeness measures. The first column indicates the results for the probability of committing a crime, column two indicates the total number of crimes and column three indicates the number of group crimes. The observational unit is an individual-quarter pair and only individuals ever arrested in a group crime were included. Treated units are defined as individuals who were either arrested or a peer, with heterogeneous treatment intensity according to each measure. Treatment timing differed across units, according to the timing of the sweep. The coefficient shown is that of interest in a DiD setting, being $Treated \cdot Post$. Robust standard errors are shown in parentheses. Robust standard errors shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Event study exercises using the number of links, alpha-centrality and closeness measures indicated a similar pattern for all crimes and group crimes as in Figure 4²². For all three the reduction in criminality was immediate but decreased over time. However, after six quarters the effects were still present.

²²See Figure A4 Appendix for the same exercise considering continuous treatment measures.

5.1.3 Mechanism analysis

Regarding the potential mechanism that may underlie the results described above, I focus on the peers, because for individuals arrested in the sweep the evidence suggests that there is a mechanical effect driven by incapacitation. The data under analysis only shows outcomes for a relatively short time span, when it is very likely that the arrested individuals were in prison. This relates to the fact that Act 6/2009 that accompanied the sweeps increased the probability of them going into preventive prison while waiting trial and that the penal process takes an average of 9.8 months in Catalonia. Moreover, those arrested in the sweeps are seized for crimes labeled as serious offences, which in the Spanish Penal Code means at least 5 years in prison. For peers, the reduction in the number of times they were arrested can be attributed to several factors that are not mutually exclusive, as discussed below.

5.1.3.1 Criminal capital vs. criminal environment

The first factor that affects the peers' actions is the fact that after an arrest in the sweeps, there is less incentive to commit a crime. This may be due to either a loss in "criminal human capital" that hinders new criminal activity, or to a loss in "criminal environment" that deters otherwise attractive criminal activities. As stated by Philippe (2017), the former relates to criminal activities that require specialization, knowledge and planning. This specialization is a priori more likely for crimes against property, such as burglary, theft or forgery. In contrast, the latter derive from impulsive behaviors. This is more likely to take place in vandalism, or violent crimes such as injuries or fights.

Table 7: Crime heterogeneity - UGOV sweeps

	Against Property	Against Person	Other crimes
Arrested·Post	-0.113*** (0.019)	-0.062*** (0.014)	-0.175*** (0.019)
Peer·Post	-0.017 (0.016)	-0.034*** (0.007)	0.002 (0.005)
Obs.	3,544,535	3,544,535	3,544,535
Indiv.	126,968	126,968	126,968
i FE	Y	Y	Y
t FE	Y	Y	Y
% change arrested	-83%	-73%	-123%
% change peers	-15%	-76%	8%

Notes: This table reports the results of the difference-in-differences (DiD) estimation following Eq. (1) for the 2008-2014 period. Each row presents estimates for different groups: arrested individuals and peers. The first column indicate results for the number of property crimes, column two indicates results for the number of crimes against the person and column three indicate results for all others. The observational unit is an individual-quarter pair and only individuals ever arrested in a group crime were included. Treated units are arrested individuals or peers. Treatment timing differed across individuals, according to the timing of the sweep. The coefficient shown is that of interest in a DiD setting, being *Treated* for Arrested and Peer. Robust standard errors are shown in parentheses.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

When analyzing outcomes by type of crime, those that were mostly reduced are labeled as “others” for those arrested (since this category includes drug crimes as well as those labeled as “criminal organization”). For peers, personal crimes (crimes against the person include gender violence, sexual assault, injuries, threats) were the only crimes showing a significant reduction, with no difference found for property crimes such as robberies, motor thefts or burglaries²³. This indicates that the mechanism of lost criminal capital had no effect on the incidence of these crimes. On the contrary, there was a reduction in the number of crimes labeled as injuries, threats or sexual assault. Such outcomes, of a more impulsive nature, support the hypothesis of a reduction in the criminal environment. However, it was not possible to distinguish whether this reduction was taking place between or within gangs.

5.1.3.2 Updated costs of sanctions

The second factor that may lead to a reduction in crime for peers relates to a more salient risk of getting arrested. According to Philippe (2017), if there is indeed an increase in the perceived costs of sanctions, offenders with shorter criminal careers should be more affected as they gain new information, whereas for more prolific criminals no new information is received.

²³See Table A1 in the Appendix for a more exhaustive division of crime categories.

Results on the probability of committing a new crime are presented in Table 8, where the effect is distinguished according to the individuals’ position in the distribution of committed crimes. For this exercise I follow a triple differences strategy (treatment/time/crime level) and found no significant difference is found between high and low offenders, considering different thresholds for what is defined as a high offender (above median, 75, 90, 95 and 99 percentiles).

Table 8: Crime heterogeneity for peers by criminal experience - UGOV sweeps

	Above median	Above 75pc	Above 90pc	Above 95pc	Above 99pc
Peer·Post	-0.192 (0.250)	-0.280 (0.197)	-0.559*** (0.155)	-0.417*** (0.125)	-0.471*** (0.117)
Peer·Post·High	-0.354 (0.283)	-0.292 (0.245)	0.212 (0.237)	-0.399 (0.352)	0.320 (1.518)
Obs.	3,551,548	3,551,548	3,551,548	3,551,548	3,551,548
Indiv.	126,841	126,841	126,841	126,841	126,841
i FE	Y	Y	Y	Y	Y
t FE	Y	Y	Y	Y	Y

Notes: This table reports the results of a triple difference estimation for the 2008-2014 period applied to the probability of committing a crime for peers. Treatment, timing and criminal intensity are the differences considered. Each column presents different estimates according to which threshold is taken to define high crime offenders. The observational unit is an individual–quarter pair and only individuals ever arrested in a group crime were included. Treated units are peers. Treatment timing differed across individuals, according to the timing of the sweep. The coefficient shown is that of interest in a triple DiD setting, being $Treated \cdot Post \cdot High$ for Peer. Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.1.3.3 Targeting vs. profiling

A third issue to be tackled regarding the previous set of results is whether they are driven by a profiling strategy carried out by the police. This would imply that individuals similar in demographic characteristics to those involved in gangs would also show a change in the incidence of arrest. To check this, I compare arrests made before and after UGOV’s creation in individuals with the set of characteristics (age, gender, nationality) that matches that of arrested individuals in the sweeps, with arrests of individuals with a different set of characteristics (age, gender, nationality) but that are also perceived as belonging to “high crime” subpopulations. The results of this regression showed no statistically significant differences between groups²⁴. Hence, the results point towards a targeting strategy rather than a profiling one.

²⁴See Table A2 in the Appendix.

5.1.3.4 Less crime vs. less caught

Another potential concern is that peers still commit crimes but are more careful when doing so. Previous results by typology indicate that those crimes that are reduced are mostly those associated with impulsive rather than planned behavior. This would indicate that the hypothesis supporting an avoidance of detection might not be in place. Secondly, the nature of the administrative data also goes against this hypothesis as records are based on the date the crime and not the detention took place. Hence, they cover both “red handed” criminals and those that avoided detection for a period but were then caught. Moreover, Lindquist and Zenou (2014) stated that the longer the period under analysis, the more difficult it is for all active peers to systematically avoid detection. They found very similar results when using either a 3- or a 6-year window for the post-crime period.

5.1.3.5 Differential effect of sweeps vs. any arrest

Finally, there is the possibility that UGOV sweeps act in the same way as any other police intervention towards gangs. If this were the case, the estimated effects would be the same as those of just arresting these individuals. To overcome such an issue, I identify criminal groups with similar characteristics to those arrested by the sweeps, but that were arrested before 2012 (and the creation of the unit). For the period 2008–2011, five similar group arrests were found that accounted for 64 individuals (versus the 127 identified by UGOV arrests) and 56 peers (versus the 413 identified linked to those arrested by UGOV). For these groups I perform the same analysis as in the baseline estimates, while adding a term that accounts for whether the individual was linked to a sweep or not. If this latter term were to demonstrate statistical significance, it would indicate that the toughening of the crime fighting strategy of the Metropolitan Area of Barcelona derived from the sweeps and Act 6/2009 had a differential effect on the criminal outcome of those arrested and their known peers.

The results of this analysis are shown in Table 9 and indicate a significant reduction in the criminal activity of arrested individuals and their known peers regardless of whether they were linked to a sweep or to another arrest with similar characteristics and prior to the creation of the unit. This is true both for the total number of crimes and those committed in groups. Moreover, the triple interaction term indicates that for those individuals arrested in the sweeps there was a significant negative differential: the reduction in the criminal activity of individuals arrested in the sweeps was significantly higher than that of individuals arrested in similar interventions previously. Hence, after the change in the crime fighting policy, there was a greater decrease in the criminality of those arrested, indicating that the toughening

of the strategy was more successful than the previous strategy at reducing crime. However, the opposite was the case for known peers: peers of individuals arrested by sweeps seemed to show a lower crime reduction than the peers of previous interventions. This may relate to the fact that the peers of those arrested in the sweeps were more prolific criminals than the peers of those arrested in pre-UGOV interventions.

Table 9: Baseline estimates - Differential effect of UGOV sweeps

	P(crime)	Total crimes	Group crimes
Arrested·Post	-1.636*** (0.247)	-0.217*** (0.041)	-0.224*** (0.035)
Peer·Post	-0.878*** (0.262)	-0.169*** (0.065)	-0.155*** (0.055)
Arrested·Post· sweep	-0.453 (0.343)	-0.145*** (0.050)	-0.087** (0.041)
Peer·Post· sweep	0.422 (0.287)	0.126* (0.068)	0.107* (0.057)
Obs.	3,542,468	3,542,468	3,542,468
Indiv.	126,968	126,968	126,968
i FE	Y	Y	Y
t FE	Y	Y	Y

Notes: This table reports the results of a triple difference estimation for the 2008-2014 period. Treatment, timing and sweeps are the differences considered. Each row presents estimates for different groups: arrested individuals and peers. The first column indicates the results for the probability of committing a crime, column two indicates the total number of crimes and column three indicates the number of group crimes. The observational unit is an individual-quarter pair and only individuals ever arrested in a group crime were included. Treated units are peers. Treatment timing differed across individuals, according to the timing of the sweep. The coefficient shown is that of interest in a triple DiD setting, being $Treated \cdot Post \cdot High$ for Arrested and Peer. Robust standard errors are shown in parentheses.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.1.4 Results for alternative empirical strategies

Very recently there have been several methodological contributions regarding treatment effect estimations in staggered difference-in-differences (DiD) settings such as the one studied here. Goodman-Bacon (2018) (and Bailey and Goodman-Bacon 2015) showed that a DiD estimator is a weighted average of all possible two-group/two-period DiD estimators. Moreover, in such a setting weights may even be negative for some units. To overcome potential issues derived from negative weights, de Chaisemartin and d’Haultfoeuille (2019) proposed another estimator that solves this issue. Results derived from an estimation following de Chaisemartin and d’Haultfoeuille (2019) did not differ significantly from the linear

regression estimator presented previously²⁵. This reflects the fact that negative weights are not an issue in this analysis²⁶, as the pure control group (individuals caught in group crimes but not by sweeps) was sufficiently large.

Finally, I conduct several exercises allowing for different specifications of the baseline estimates. Specifically, I modify the control group to consider criminals arrested for any crime, crimes against the person, for other crimes, and for drug crimes. Additionally, I estimate Eq.(1) with a Poisson regression. As the dependent variable in this analysis, namely the number of total crimes, has the structure of count data, this type of modelling might be better suited. The results generally held for both arrested individuals and peers across specifications.

Table 10: Alternative control groups and specifications - UGOV sweeps

	Baseline	All criminals	Criminals against person	Criminals other crimes	Criminals drugs	Poisson IRR
Total Crimes						
Arrested·Post	-0.350*** (0.028)	-0.350*** (0.028)	-0.435*** (0.054)	-0.355*** (0.033)	-0.398*** (0.070)	0.153*** (0.035)
Peer·Post	-0.048*** (0.019)	-0.048*** (0.019)	-0.067*** (0.021)	-0.036 (0.030)	-0.026 (0.054)	0.765*** (0.084)
Group Crimes						
Arrested·Post	-0.302*** (0.023)	-0.302*** (0.023)	-0.346*** (0.043)	-0.311*** (0.026)	-0.270*** (0.021)	0.128*** (0.035)
Peer·Post	-0.051*** (0.015)	-0.051*** (0.015)	-0.066*** (0.017)	-0.031 (0.026)	-0.041 (0.040)	0.643*** (0.090)
Obs.	3,544,535	7,339,235	3,359,767	2,058,479	278,999	3,542,923
Indiv.	126,968	262,493	120,233	73,701	10,013	126,775
i FE	Y	Y	Y	Y	Y	Y
t FE	Y	Y	Y	Y	Y	Y

Notes: This table reports the results of the difference-in-differences (DiD) estimation for the 2008-2014 period. Each row presents estimates for different groups: arrested individuals and peers. Each column indicates a different specification, considering different control groups for columns 2 to 5 and a Poisson model in column 6. The observational unit is an individual-quarter pair and only individuals ever arrested in a group crime were included. Treated units are peers. Treatment timing differed across individuals, according to the timing of the sweep. The coefficient shown is that of interest in a DiD setting, being $Treated \cdot Post$ for Arrested and Peer. Robust standard errors showed in parentheses. $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

²⁵See Figure A5 in the Appendix

²⁶Concretely, no negative weights were identified in this setting.

5.1.5 Area Level Outcomes

Previous evidence shows that sweeps reduce most criminality indicators of those individuals arrested and also of their known peers. Moreover, the magnitude of such reductions is sizable, negative and statistically significant.

I therefore examined the impact of sweeps at a broader level. To do so, I look at the evolution of different outcomes in the area in which the sweeps took place. For the case of Barcelona, I consider districts as areas of influence (10 districts), whereas for the other municipalities I consider each as a whole (35 municipalities). To analyze the impact of sweeps, I follow a fixed-effects model with an AR(1). The data on registered crimes and other socioeconomic outcomes are presented in Table 11.

Regarding crime outcomes, no significant change was found for overall crime in areas after a sweep took place, and the same was true for all property crime. Statistically significant decreases were found for crimes against the person, damage to property, injuries, and family crimes. These results may reflect the lower presence of criminals and criminal groups in the area, as these crime typologies are particularly sensitive to their presence. Finally, although there was a reduction in threats, disobedience and drug crimes, the reduction was not statistically significant.

Regarding other potential outcomes at the area level, benefits in the area exceeded those of a crime reduction for certain typologies and involved other socioeconomic variables. Table 11 indicates that there were indeed important changes in the area. Regarding educational outcomes, there was no effect on high-school enrollment in the areas in which there were UGOV interventions. However, there was a positive and significant effect on the number of students enrolled in the appropriate year for their age (non-lagged students). Moreover, there was a significant and negative decrease in the number of admissions to Emergency Rooms in the areas in which there were UGOV sweeps. Although it is not possible to link either of these results with individuals or certain profiles, they indicate an improvement in these variables. Finally, no effect was found on rental markets (either for prices or number of contracts).

Table 11: Area level outcomes: crime and other socioeconomic variables

Crimes against property				
	Property	Motortheft	Robbery	Damages
Treat·Post	-0.372 (2.907)	-0.380 (0.364)	0.186 (0.322)	-0.198*** (0.069)
Obs.	850	850	850	850
Areas	45	45	45	45
Area FE	Y	Y	Y	Y
Crimes against person				
	Person	Injuries	Family	Threats
Treat·Post	-0.276* (0.156)	-0.200** (0.079)	-0.032** (0.015)	-0.058 (0.043)
Obs.	850	850	850	850
Areas	45	45	45	45
Area FE	Y	Y	Y	Y
Other crimes				
	Other	Disobedience	Drugs	Arson
Treat·Post	-0.190 (0.175)	-0.114 (0.081)	-0.068 (0.064)	-0.008** (0.004)
Obs.	850	850	850	850
Areas	45	45	45	45
Area FE	Y	Y	Y	Y
Other outcomes				
	Rent prices	HS enrollment	Non-lagged students	ER admissions
Treat·Post	-7.181 12.215	-51.423 57.42314	2.405** 1.03	-15.711* (9.178)
Obs.	180	180	111	190
Areas	36	36	37	10
Area FE	Y	Y	Y	Y

Notes: This table reports the results of the difference-in-differences (DiD) estimation following Eq.(1) for the 2009-2014 period, incorporating an AR(1) disturbance term. Each column presents results for different outcomes. The observational unit is an area-year pair. Treated units are defined as those in which an UGOV sweep took place. The coefficient showed is that of interest in a DiD setting, being $Treated \cdot Post$. Robust standard errors are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

5.2 Key-player targeting benchmark

While the previous section analyzed the effect of the UGOV sweeps on the criminality of arrested individuals and known peers, the aim of this section is to compare such outcomes with those that network theory predicts would derive from targeting the key player in each gang. To do this, I first estimate a peer-effects model, as described by Eq. (5). On the matter of model estimation, and as previously explained, I consider the 3SLS estimator presented in section 4.2 for Instrumental Variable regressions. For this, I obtain \hat{G} by running a logistic regression to predict link formation probabilities. For each potential link in each network (that took empirical values of 0 or 1), the outcome is regressed on the match (difference)

in each observable characteristic available (age, gender, nationality). For link formation probabilities there is strong evidence of homophily as matches in characteristics increase the probability of committing a crime together for the individuals under analysis²⁷. However, the McFadden’s pseudo-R2 of the logistic regressions was close to 0.04, indicating that the dyadic characteristics were not very informative in predicting link formation. As a result the IV matrix \hat{Z} constructed using the predicted adjacency matrix \hat{G} is likely to be a weak instrument.

The estimation results for Eq.(5) are reported in Table 12. The first column presents OLS estimates, column 2 presents IV estimates with IV matrix Z, column 3 shows IV estimates with IV matrix \hat{Z} , and column 4 presents GMM estimates. Regarding the estimates of the first two columns, it is likely they may suffer from endogeneity issues, derived from the reflection problem and the fact that the network itself is not exogenous. Moreover, the overidentification test for the 2SLS-G estimation rejects the null hypothesis. Given these issues, it is necessary to instrument the actual G matrix with a predicted \hat{G} following the link formation model previously shown, as in column 3. In this case, the validity of the instruments was not rejected. However, a weak instruments issue is likely to be present and therefore modeling the best response function by GMM may help tackle this issue.

The GMM estimate of peer effects is 0.007²⁸, result that is smaller than in Lindquist and Zenou (2014) and Lee et al. (2020). Here it must be noted that in both references the average network size was considerably smaller than in the current study. Moreover, the first authors conducted their analysis on suspected Swedish criminals, and the second ones did so in a sample of adolescents in the US. These two different issues (network size and context) may explain the differences in peer effect estimates. The one of this study implies that having one criminal partner increases the number of crimes committed by an individual when alone by 0.7% ($\frac{1}{1-\hat{\phi}}$). Moreover, considering that the average number of peers was 13, the average network social multiplier would be of 10% ($\frac{1}{1-13\hat{\phi}}$).

²⁷See Table A3 in the Appendix for outcomes of the link formation model.

²⁸This result satisfies the condition for the existence of a unique equilibrium ($|\hat{\phi}|\rho(G) < 1$), which in turn allows the M matrix to be built.

Table 12: Peer Effect Estimates

	OLS	2SLS-G	3SLS	GMM
ϕ	0.015*** (0.004)	0.006 (0.004)	0.006 (0.004)	0.007** (0.003)
Observations	540	540	540	540
R-squared	0.110	0.100	0.101	0.093
Own characteristics	Y	Y	Y	Y
Peer characteristics	Y	Y	Y	Y
First Stage F		389.24	210.18	210.18
OIR p-value		0.00	0.16	0.16

Notes: This table reports the results of the best reply function of the criminal networks following Eq. (4). Each column presents results by different estimation methods. For the third and fourth columns, \hat{G} was constructed by using the outcomes of a logistic model of link formation. In all cases individual characteristics as well as those of peers were included as controls. The observational unit is the criminal. The coefficient of interest (that of peer effects) is provided by ϕ . Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Under the invariant network assumption (that is, that the network does not rewire after an agent is removed), the key player is the agent with the highest contextual intercentrality measure in the network (Ballester and Zenou 2014). As explained by the authors, failure to include contextual effects can lead to spurious inference on social network effects as individuals may adjust behavior because of common influences. Using the GMM estimates reported, the contextual intercentrality measure can be calculated for each agent following Eq.(6) and the key player can be identified for each network.

Regarding the key player themselves, they were caught in all the sweeps analyzed. In all cases the key player was male, half of them were born in Latin America and 70% of them were born in 1990 or later. The key players identified in the gangs did not differ significantly from their peers in any demographic characteristics (age, gender or nationality). Moreover, there were no significant differences either in the number of peers they had or in the number of crimes for which they were caught. Therefore, key players are not distinguishable from other agents if gang structure is not considered. Additionally, as in Lindquist and Zenou (2014) and Lee et al. (2020), the key players were not those individuals with the highest values of other centrality measures such as alpha-centrality, betweenness or closeness centrality. Hence, common network centrality measures did not correctly identify the key player in Ballester et al. (2006) either.

Finally, following Ballester and Zenou (2014) and Lindquist and Zenou (2014) it is possible to compute the predicted reduction in crime that would be achieved by removing the key player. The model predicted that removing the key player would lead to a weighted average crime reduction for the mean gang of 17.7%, an outcome that decreases with the size of

the gang. As stated in Ballester et al. (2006), that would be the largest possible reduction when targeting one individual in each gang. This fact is also verified in the current study: on average targeting the key player would achieve a crime reduction that would outperform targeting the most active criminal by 2.3%, targeting the most central individual (Bonacich 1987) by 2.9% and the most connected individual by 0.7%²⁹. This set of results is consistent with those of Lindquist and Zenou (2014) and Philippe (2017). Although some of the current results differ from their results, the focus of the current study was on different types of networks: youth criminal groups (Lindquist and Zenou 2014 considered all types of crime and Philippe 2017 focused on pairs or groups of 7 or less). Hence, the outcomes and policy comparisons may differ.

5.3 Discussion

When comparing the effect the UGOV sweeps' with the predictions based on the removal of the key player, several points are worth highlighting. Firstly, as already mentioned, all sweeps caught the key player in the gang. Secondly, and as already mentioned, the sweeps achieved a crime reduction of 61% in the year following the intervention. This reduction was 3.4 times higher than that predicted after removing the key player and outperformed the key player strategy by 43.3%. However, the comparison between the two strategies is not as straightforward: while the prediction of the removal of the key player was based on catching just one individual, sweeps affected more individuals³⁰. Thirdly, it is possible that treatment (being caught) was positively and significantly correlated with the intercentrality measure of Ballester and Zenou (2014), indicating that such interventions on average catch the most relevant individuals. Nonetheless, the match was not perfect: among those caught only 60% were in the top of the intercentrality ranking of each gang³¹. Finally, performing a sequential exercise by removing more than one key player³² indicates that according to the predictions of the key player theory, a similar reduction in crime to that achieved by the UGOV sweeps would have been achieved by removing the top six individuals according to the generalized intercentrality ranking (a third of the average actually caught). The

²⁹As in Lindquist and Zenou (2014) these values were computed as the difference between the two scenarios.

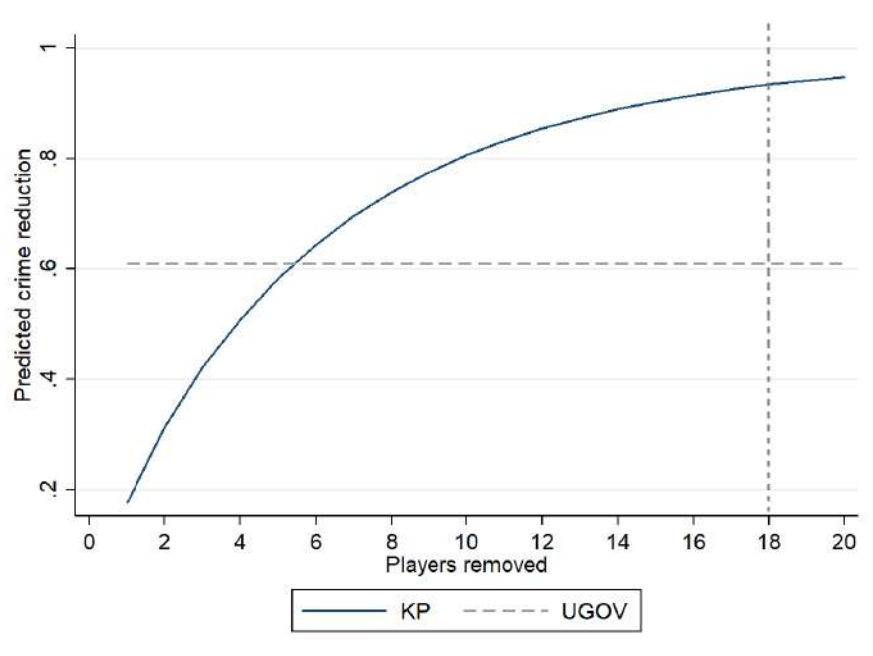
³⁰They caught on average 18 individuals per gang, or 24% of the gang.

³¹Considering the top half, the match between caught and top intercentrality individuals was 90%. Therefore, there was no mismatch among the top-rated individuals.

³²In order to do so, I first computed the classical key player exercise: I removed the highest intercentrality individual and estimated the predicted reduction in crime in the gang. After this, I computed the same exercise for the second-ranked individual and computed the predicted crime reduction in the fraction of crime that would remain after the removal of the first key player. I did this in several steps, as many as there were individuals caught in each gang

outcomes of the exercise also indicate that if instead of catching those actually caught the UGOV would have caught the top ranked individuals by intercentrality (holding the number of individuals caught constant), the predicted crime reduction would have been 92.8%. This implies a 50% increase in reduced criminality compared to the one recorded. Hence, by adequately identifying, targeting and catching the “key players” in each network, the UGOV sweeps would have achieved the same crime reduction with a smaller deployment, or a larger reduction in crime if resources were held constant.

Figure 5: Predicted reductions in criminality, by number of key players removed



Note: This graph presents the predicted crime reductions as a function of the number of agents removed, ordered by intercentrality. Such outcomes were compared with the actual reduction achieved by UGOV sweeps.

In terms of policy, two broad comparisons can be reflected on. The first involves the targeting strategies. It is clear that removing the key player outperforms any other individual targeting. However, it is also a more costly strategy in terms of information and identification, since as mentioned the key player is not identifiable by either observable or gang characteristics. The second comparison is that between targeting strategies and other approaches, such as general tough-on-crime policies. In this case, the sweeps achieved a significantly higher reduction in crime than that predicted by the key player theory. Nonetheless, this strategy arguably involved a larger police deployment, and did not always catch the most relevant individuals in terms of intercentrality. Indeed, by catching the “key players” in each gang the sweeps would have achieved a 50% larger reduction in the criminal activity of the

affected networks. From the analysis above it can be concluded that, in comparison with the sweeps, removing only one key player would be less effective. However, identifying and tackling a group of key players in each gang can lead to substantial improvements in the crime reduction after police interventions.

Nonetheless, key player identification is informationally costly. It only makes sense to consider such a policy if its benefits outweigh the cost of collecting the data (if there is no availability) and of data analysis (since as mentioned the key player is not easily identifiable by sociodemographic, criminal or network characteristics). Secondly, under the invariant network assumption, the key player predictions are only valid in the short term, as it is unlikely for the remaining agents to form new links in the short period of time after the removal of the key player. In the long run however, it is necessary to estimate a network formation model to produce meaningful counterfactuals for the long-run key player analysis. And thirdly, the key player might be an unfeasible target in reality. Given that the criminal networks under study follow a well-defined internal structure rather than being a decentralized unit, it is plausible that the key player is better protected than other agents in the network, and hence would be more difficult for police resources to reach. Additionally, networks would respond endogenously to the extraction of the key player by restructuring or re-grouping in order to continue committing crime. Hence, a key player strategy might not be the optimal strategy for police forces, if their cost is too high in terms of investment, or not low enough in terms of police resources when compared with other tougher approaches. Despite all these drawbacks, the exercise of removing the key player is a good benchmark with which to compare actual policies because of its relevance and concluding whether it would be worth moving towards a key player strategy may depend on the case.

However, this does not mean that tough-on-crime interventions or police specialization such as the sweeps are always the approach to follow. Previous literature indicates how costly these approaches may be in many dimensions. Firstly, the direct cost for the police in terms of human resources, training and deployment. Secondly, the indirect costs to society, which include individual costs related to the dangers of police profiling, the burden or stigma for individuals and areas under intervention, and also the high human capital costs that individuals may suffer as a result of being caught at such a young age and their very low reinsertion prospects. Additionally, there is the broader discussion on whether the budget assigned to such interventions could be shifted to other pressing issues still related to crime, such as early prevention, training programs for prisoners or vulnerable populations at risk of committing crimes.

6 Concluding remarks

This study examines the implementation of gang sweeps addressed at dismantling them, and their effects on criminality levels. The analysis considered the effects on both arrested individuals and their known peers. I also study outcomes at the gang level and in the areas in which the sweeps took place. To do so, I retrieved the structure of real criminal networks from administrative records of the Local Police (Mossos d'Esquadra) from 2008 to 2014 and performed the analysis using a difference-in-differences (DiD) strategy in the Metropolitan Area of Barcelona (MAB). In this context, gangs were a big concern among authorities and citizens, and a drastic change in policy towards them took place.

My results indicate significant reductions in the criminal activity of those arrested in the sweeps and of their known peers. For the former there was an immediate and sharp drop in criminal activity. This result, alongside average trial and prison times is consistent with an incapacitation effect. In the case of peers, reductions in criminal activity were smaller, more short term, and focused on crimes against the person. This points towards a mechanism of loss of the criminal environment. At the area level, sweeps translate into significant decreases in crimes against the person and disobedience against law officers. The results also demonstrated a decline in the number of Emergency Room admissions and lagged High School students.

The peer-effects estimations indicate that, on average, crime increases by 10% when an individual is part of a gang compared to when committing crimes alone. Based on this estimate, I ranked individuals in each gang by centrality, and I plotted the predicted reduction in criminality as a function of the number of individuals removed. The results indicated that as the same reduction in gang criminality achieved by the sweeps could have been achieved by targeting on average a third of the individuals arrested.

Overall, the existence of peer effects suggests that any crime reduction may lead, through reductions in peers' crimes, to future reductions in crime, a benefit that needs to be accounted for. Moreover, the identification of key players in a gang can help achieve higher reductions in criminality by targeting these individuals. From a policy point of view, hard, soft, and behavioral approaches towards fighting crime need to be thought of as complementary rather than as substitutes. Policy design should therefore incorporate them into a broad approach that tackles crime and combines and coordinates all efforts.

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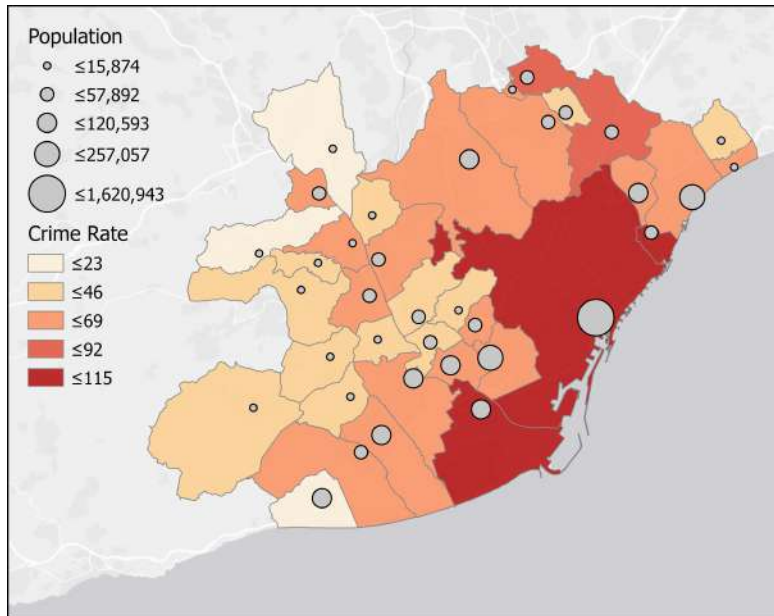
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Appendix

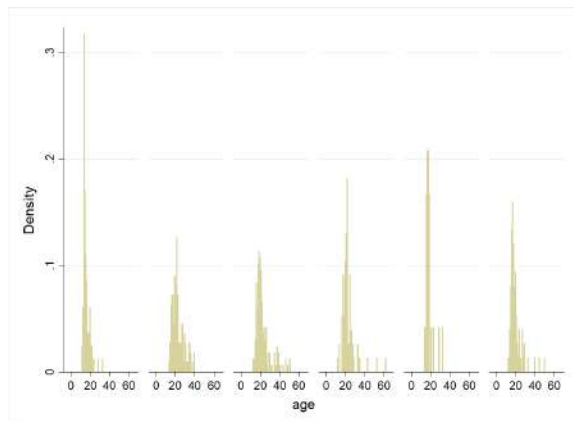
Appendix 1: Complementary information and additional results

Figure A1: Metropolitan Area of Barcelona, and corresponding municipalities

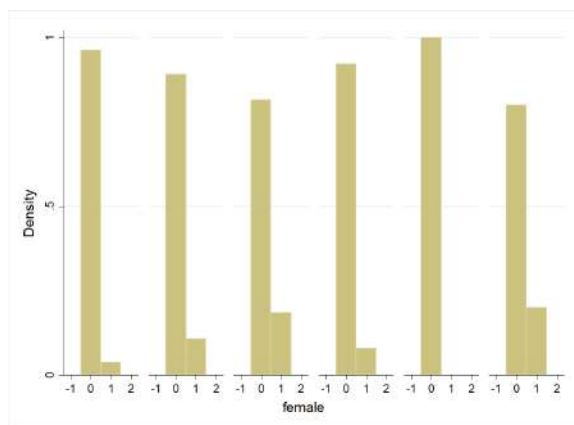


Source: Own construction from Police Data and National Institute of Statistics.

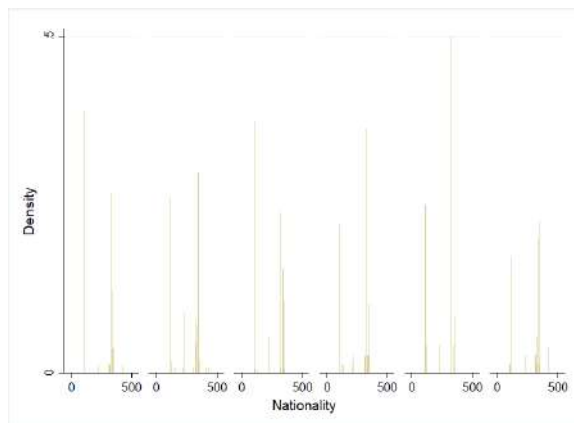
Figure A2: Histogram of frequency of individual characteristics within gangs. Top sweeps.



(a) Age

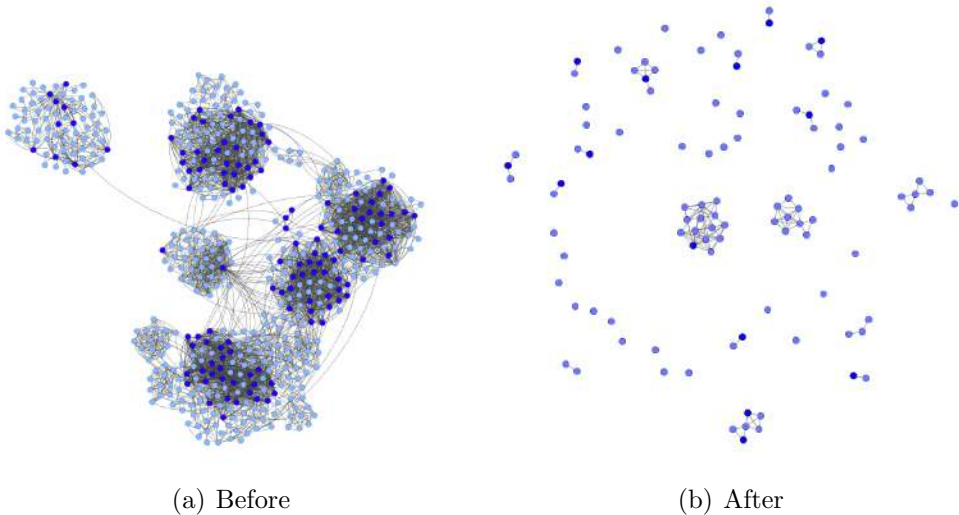


(b) Gender



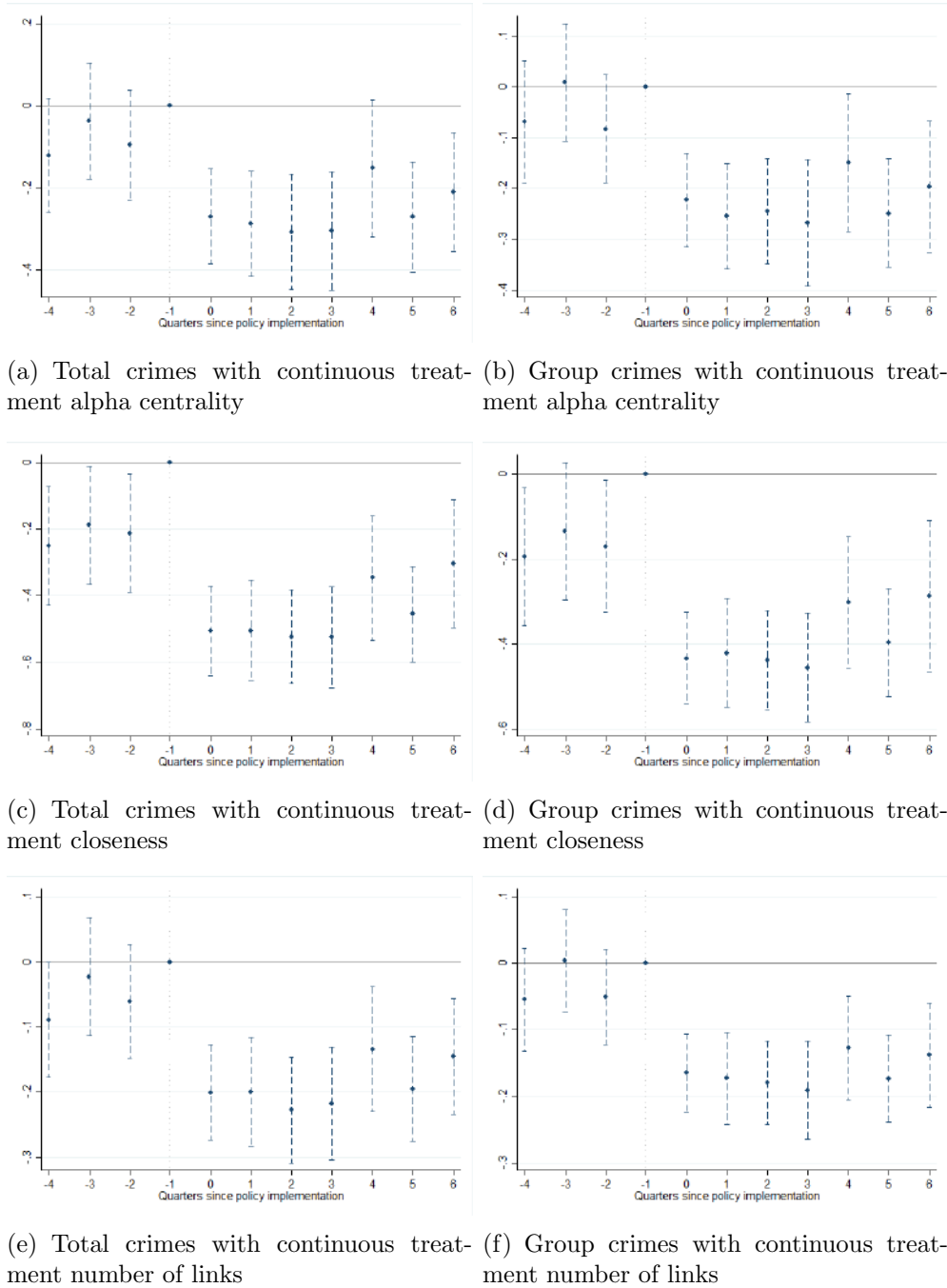
(c) Nationality

Figure A3: Recovered criminal gang structure, before and after UGOV sweeps.



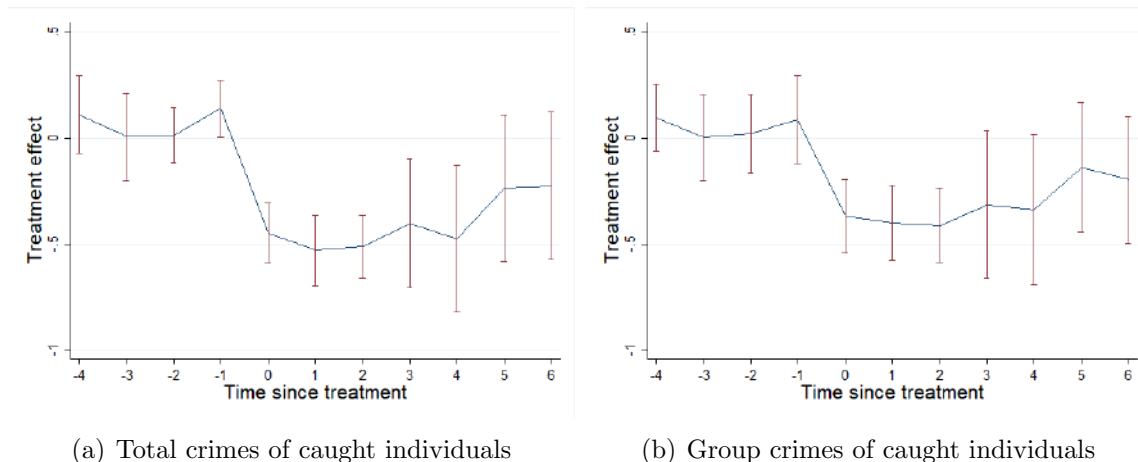
Note: This graph presents the network structure of individuals arrested in the sweeps and first degree known peers before and after the sweeps were carried out. Each dot is an individual and each line indicates a link. Source: Own construction from Local Police data.

Figure A4: Event study exercise for all crimes and group crimes with a continuous treatment indicator. 95% confidence intervals.



Notes: This graph reports the results of an event study exercise following Eq. (3) for total crimes (left panel) and group crimes (right panel). Results are presented for pooled caught individuals and non-caught co-offenders, with heterogeneous treatment intensity according to the alpha-centrality, closeness and number of links criteria. The observational unit is an individual-quarter pair. Treated units are defined as in section 4.1, while treatment timing differed across units, according to intervention timing. Confidence intervals are based on robust standard errors.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A5: Event study exercise considering the estimator proposed by de Chaisemartin and d’Haultfoeuille (2019)



Notes: This graph reports the results of an event study exercise following Eq. (3) and de Chaisemartin and d’Haultfoeuille (2019) for total crimes (left panel) and group crimes (right panel). Results are presented for caught individuals. The observational unit is an individual-quarter pair. Treated units are defined as in section 4.1, while treatment timing differed across units, according to intervention timing. Confidence intervals are based on robust standard errors.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A1: Detailed crime heterogeneity for peers - UGOV sweeps

	Motortheft	Robbery	Damages	Injuries	Sexual	Threats	Forgery	Disobedience	Drugs
Peer-Post	-0.003 (0.002)	-0.009 (0.007)	-0.004 (0.003)	-0.017*** (0.005)	-0.010*** (0.003)	-0.006 (0.004)	-0.009 (0.006)	-0.002 (0.004)	0.002 (0.001)
Obs.	3,543,458	3,543,458	3,543,458	3,543,458	3,543,458	3,543,458	3,543,458	3,543,458	3,543,458
Indiv.	126,841	126,841	126,841	126,841	126,841	126,841	126,841	126,841	126,841
i FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
t FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports the results of the difference-in-differences (DiD) estimation following Eq. (1) for the 2008-2014 period for peers. The observational unit is a individual-quarter pair and only individuals ever committing a group crime were included. Treated units are defined as in section 4.1, while treatment timing differs across units, according to intervention timing. The coefficient showed is that of interest in a DiD setting, being Peer-Post. Robust standard errors are shown in parentheses.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2: Falsification exercise - Profiling

	All crimes	Group Crimes
Profile:Post	0.004 (0.004)	-0.002 (0.003)
Observations	710,975	710,975
Number of individuals	25,619	25,619
i FE	Y	Y
t FE	Y	Y

Notes: This table reports the results of a difference-in-differences (DiD) regression comparing criminal outcomes of individuals with similar characteristics to those caught by UGOV interventions (potentially profiled) with other individuals perceived as “high crime” prone, before and after the unit creation. The observational unit is a individual-quarter pair and only individuals ever committing a group crime were included. Treated units are defined as those potentially profiled, while the post period is that after the UGOV creation. The coefficient showed is that of interest, being Profile·Post. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Link Formation Estimation

Female Match	0.278*** (0.046)
Age Match	0.267*** (0.064)
Age Difference	-0.091*** (0.013)
Age Difference ²	0.001*** (0.000)
Nationality Match	0.803*** (0.045)
Latin Match	0.343*** (0.077)
Pseudo R2	0.035
Number of obs	145,530

Notes: This table reports the results of a logistic regression for a link formation model. The dependent variable is an indicator on whether a pair of criminals are linked or not. The observational unit is a pair of criminals. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 2: Social Network Analysis

Social network analysis (SNA) is a process through which social structures are analyzed using graph theory and its visualization. This approach fully characterizes the existing networks in terms of their agents (called nodes) and links. The first step towards an SNA is to build an adjacency matrix. In the simplest case, this matrix A is a square matrix of dimension n (the number of nodes), and the element a_{ij} (known as a dyad) equals one when there is a link from node i to node j , and zero otherwise. In this case, I create an adjacency matrix in which the a_{ij} element is equal to 1 when individuals i and j are co-offenders. Such a task can be challenging due to its dimensions. Although this approach is merely descriptive of the dataset and potential networks, it is also extremely enlightening and provides a first approach to the existing criminal links. On this matter, I tested two hypotheses that are well established in the existing literature regarding similarity between criminal partners and interactions conditional on crime severity.

1) I determine what characteristics drives co-offending among individuals. The homophily principle states that similarity breeds connection. This principle structures network ties in every type of relationship, making such ties homogeneous with regards to many demographic, economic and even geographical characteristics. In the current study I only consider demographics as it was the only available information. The resulting outcomes of the SNA are studied as an outcome variable in the following way:

$$a_{ij} = \alpha + B\text{IndividualCharacteristics}_{ij} + \Gamma\text{NetworkCharacteristics}_{ij} + \varepsilon_{it} \quad (\text{A1})$$

where a_{ij} is the ij -element of the previously built adjacency matrix (dyad), taking values of either zero or one. Individual characteristics include homophily (similarity in characteristics), which in this case will be defined by age, gender, and nationality. For networks characteristics, a term for triangles is included in some specifications.

The previous equation is estimated using an Exponential Random Graph Model. Exponential family random graph models (ERGMs) are a general class of models based in exponential-family theory for specifying the probability distribution for a set of random graphs. Within this framework, it is possible to obtain maximum-likelihood estimates for the parameters of a specified model for a given data set.

2) I test the relationship between crime severity and social interactions, derived from the model presented by Glaeser and Sacerdote (1999). This model provides an index of social interactions that suggests that the amount of social interactions is highest in petty crimes, moderate in more serious crimes, and almost negligible in murder and rape. However, I will simply tabulate the number of identified offenders per offence for each crime typology. Although this approach is much simpler, it provides evidence in a similar direction.

Results

From a first approach to the administrative data provided by the Catalan Police, we observe that Using the administrative data provided by the Catalan Police, I identify 563,889 arrests registered in the Metropolitan Area of Barcelona. These correspond to 262,493 individuals, as a significant proportion of criminals were caught more than once. Moreover, 216,472 of these arrests involved individuals acting in groups. In terms of characteristics, almost a third

were labeled as thefts, while 30% took place in Barcelona city.

When I analyze group crimes (those committed by more than one individual), I observe that patterns regarding crime types and locations follow the same patterns as the general trend. Additionally, and consistent with Glaeser et al. (1996), Table A4 indicates that around half of all co-offending crimes were in petty-money-driven crimes such as thefts. Another crime type that is prevalent in the co-offending structure is that of injuries. This could relate to bar fights in which many individuals are caught at the same time and location but are not necessarily a co-offending group or criminal network. Moreover, geographical concentration in Barcelona City is higher. The table below shows that the vast majority of the co-offending structure is composed of small groups. Indeed, more than two-thirds of the co-offending sample was composed of co-offending pairs, and almost 90% of registered criminal groups were composed of less than three individuals. However, this does not imply that the same individual cannot commit crimes with more than three others at separate events. Additionally, almost 6% of group crimes were committed by five or more individuals. To provide a comprehensive yet concise analysis of these issues, new tools must be used.

Table A4: Main descriptives, caught offenders

All acts (A=563,889; O=262,493)		Group acts (A=216,472; O=126,968)	
Offenders		Offenders	
1	77.10		
2	16.15	2	70.54
3	4.04	3	17.65
4	1.36	4	5.94
5+	1.35	5+	5.87
Crime Type		Crime Type	
Theft	28.2	Theft	33.6
Injuries	10.9	Injuries	14.1
Fraud	9.6	Fraud	12.9
Threats	9.0	Robbery	9.7
Road	8.2	Disobedience	7.1
Disobedience	7.7	Threats	6.8
Robbery	6.5	Damages	3.6
Gender Violence	4.3	Drugs	3.3
Damages	3.7	Gender Violence	2.7
Other person	3.2	Car Theft	2.2
Drugs	2.7	Other person	2.1
Municipality		Municipality	
Barcelona	61.9	Barcelona	65.9
L'Hospitalet	6.2	L'Hospitalet	5.9
Badalona	5.6	Badalona	5.5
El Prat	2.7	El Prat	2.4
Cornellà	2.5	Cornellà	2.2

Source: Own construction from Catalan Police data

Taking a deeper look into the individuals involved in all criminal acts, as already mentioned, 262,493 individual criminals were identified. These offenders are the so-called nodes of the SNA, and their main characteristics are shown in Table A5. Their demographics did not follow the same pattern as that of the population in the city: only 25% of all offenders were female, and 58% were Spanish nationals. For the overall population both figures are higher. Regarding the age profile, it was also a younger population than the average. All of these features are consistent with what was expected. On the matter of criminality, 55% of all criminals were only arrested once. In turn, 45% of the sample were repeat offenders, and almost 20% of the sample had been arrested at least four times.

Table A5: Node Characteristics (262,493 individuals)

Gender	
Female	25.8
Male	74.2
Nationality	
Spanish	57.7
Foreign	42.3
Year of Birth	
Prev 1950	4.1
1950-1960	7.6
1960-1970	17.3
1970-1980	28.5
1981-1990	29.4
1991-2000	13.1
Detentions	
1	55.6
2	17.2
3	8.2
4	4.7
5+	14.3

Source: Own construction from Catalan Police data.

Regarding co-offending and repeat offender patterns, and as mentioned above, 45% of all registered offenders were registered in the Police records with at least one other criminal (co-offending). Moreover, 30% were registered more than once. From the intersection of these two criteria, 20% of the sample was composed of criminals that had committed crimes in groups and on repeated occasions (recidivism). Hence, from an empirical point of view, understanding criminal networks, co-offending and recidivism is a highly relevant issue.

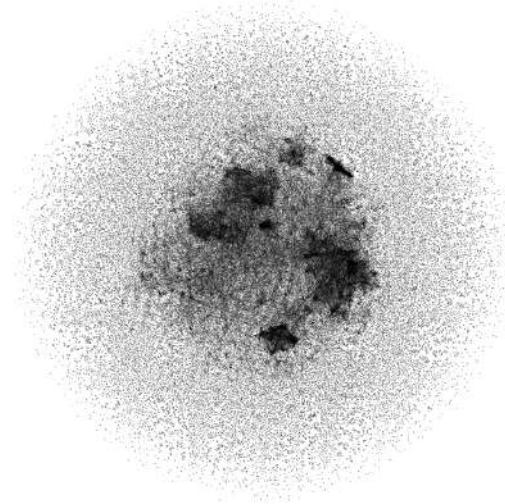
Table A6: Co-offending and recidivism

	No repeated	Repeated	Total
No co-offending	45	11	55
Co-offending	25	20	45
Total	70	30	100

Source: Own construction from Catalan Police data.

Looking closer at co-offending patterns, it was possible to identify 216,472 unique co-offending pairs or links/edges in the SNA. One way to visualize SNA results is graphically. In the figure below I plot both criminal individuals (nodes) and their connections (links) for the entire sample. It is apparent that while some nodes are not connected whatsoever with other observational units, some others are. Furthermore, some clusters or cores of darker spots appear in the graph: this means nodes that are connected to third parties that are also connected. To further understand this network some basic descriptive statistics are presented in Table A7.

Figure A6: Criminal links in the Metropolitan Area of Barcelona.



Source: Own construction from Catalan Police data.

Table A7: Network descriptive

	All	Degree>1
#Nodes	262,493	126,968
#Links	216,472	216,472
Avg. degree	1.1	3.5
Diameter	37.0	
Avg. path length	10.5	
Density	6.29e-06	

Source: Own construction from Catalan Police data.

The first feature that can be noticed by visual inspection of the network is that it is relatively sparse. This was confirmed statistically as the density value (indicating the proportion of present edges from all possible edges in the network) is very low. This is also reflected in the fact that the average degree (how many neighbors a given node has in the network) is very close to 1. This also translates into the fact that the average path length (number of steps along the shortest paths for all possible pairs of network nodes) is relatively high, as is the diameter (the longest of all the calculated shortest paths in a network). When keeping only those nodes for which the degree is higher than one (which means that they are at least connected to one other individual), the sample was reduced to 126,968 nodes, while keeping the same number of links. As a result, this network is more dense and connected. In particular, the average degree increases to 3.5. The descriptive statistics for the network restricted only to nodes with at least one link were similar to those reported by Lindquist and Zenou (2014) (they reported a degree of 2.99, an average path length of 17 and a clustering coefficient of 0.55).

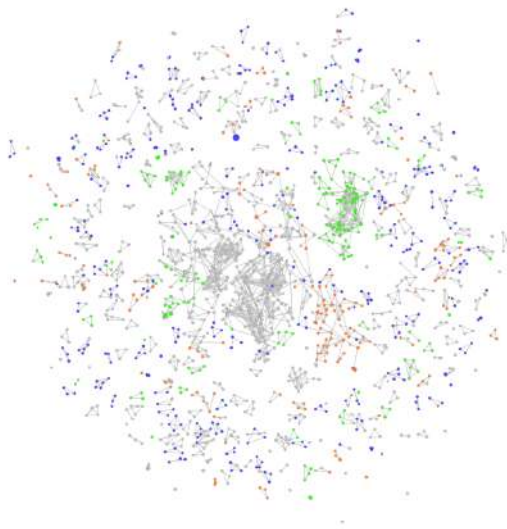
Figure A7: Nodes and links' attributes, network subsample



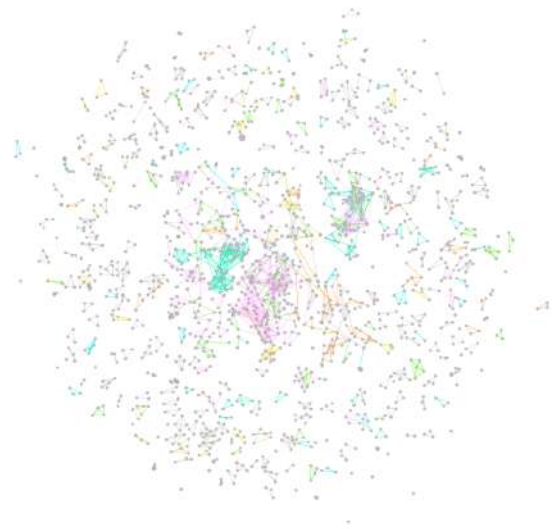
(a) Nodes and Edges



(b) Red=Female; Green=Male



(c) Blue=Native; Orange=For1; Green=For2



(d) Pink=Theft; Blue=Robbery; Green=Drugs

Source: Own construction from Catalan Police data

All these features as a whole indicate that although the network is not dense, there appears to be local clustering related to nodes' characteristics. This is illustrated in the above set of figures, where I highlight (one at a time) characteristics of nodes and edges. For visualization purposes, for this set of figures only individuals caught in 2008 in District 1 of the City of Barcelona were included. In these graphs, each dot is a node (individual) and each line is an edge (link). The dots' size indicates the number of detentions, while the thickness of the line indicates how many times that link was formed. In all cases, it is clear that the plotted characteristics regarding nodes such as gender or nationality, or regarding

edges such as crime type, appear in a clustered manner. In other words, there is homogeneity of each of these characteristics within the clusters of individuals.

Testing the homophily and severity hypotheses

The homophily principle states that similar individuals are more likely to interact. As already mentioned, few characteristics that could be used to determine this were recorded in the data: only age, gender, and nationality of the offender. Coefficients (β) can be interpreted in a similar way to results from a logistic model. The coefficient on Edges can be seen as the intercept, as it indicates the conditional log-odds for a tie that does not match in characteristics nor will create a triangle. All other parameter estimates are interpreted as log-odds. While for gender, nationality and age matches the coefficients β are the components of the B vector of equation (1), the estimate for triangles pertains to the γ parameter of equation (1). To obtain the odds for a tie I compute (e^β) and for the corresponding probability I compute the ratio ($e^\beta/(1 + e^\beta)$). Both of these are presented, alongside estimated coefficients, in Table A8.

Table A8: ERG Model Results, Homophily

	Model 1	Model 2	Model 3	Model 4
Edges	-9.00*** (0.02)	-9.49*** (0.02)	-10.67*** (0.05)	-10.92*** (0.06)
Triangle		5.99*** (0.03)		4.76*** (0.03)
Gender match			0.84*** (0.04)	0.85*** (0.07)
Nationality match			2.50*** (0.03)	2.16*** (0.04)
Age match			1.29*** (0.05)	1.17*** (0.08)
BIC	76958	71753	71079	66816

Figure A8: ERG Model diagnostics

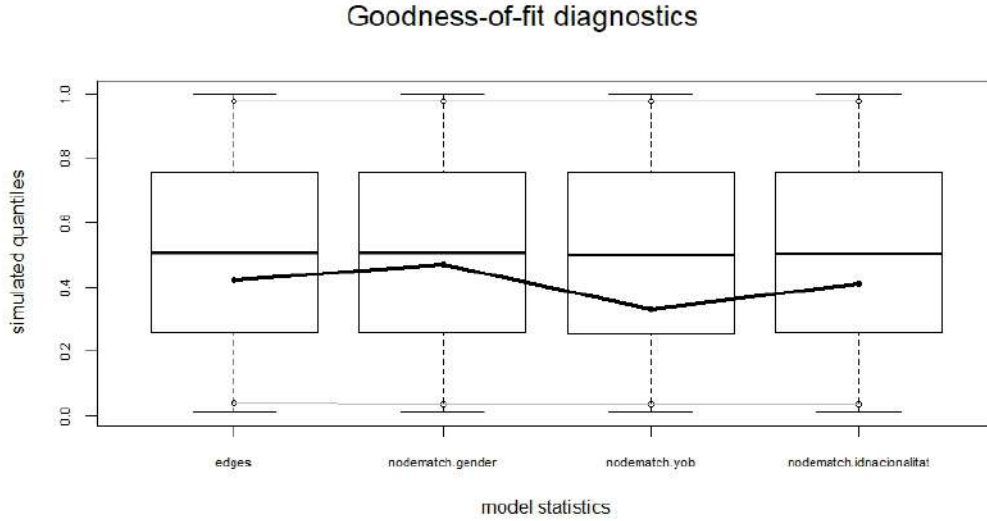


Table A9: Interpretation of coefficients in homophily model

	Beta β	Odds (e^β)	Probability ($e^\beta/(1 + e^\beta)$)
Edges	-10.92	2E-05	2E-05
Triangle	4.76	116.75	0.99
Gender match	0.85	2.34	0.70
Nationality match	2.16	8.67	0.90
Age match	1.17	3.22	0.76

Note: This table presents the results of fitting an Exponential Random Graph Model to test the homophily principle among offenders. While the first column presents the estimated coefficients, columns two and three present odds-ratios and probabilities of a tie.

The results from the ERG model provide very strong evidence of homophily in all three characteristics³³. On the matter of the interpretation of coefficients, the probability of a tie that does not close a triangle nor share any characteristic is 0%. Additionally, the odds for a tie between criminals of the same gender (holding everything else constant) is 2.3 times higher than for a tie between criminals from a different gender (or 70% more likely). Concerning age, the odds rises to 3.2 and probability to 76%, while for nationality the odds is 8.7 and probability is 90%. Nonetheless, the triangle parameter has the highest odds of 116.8. This term speaks on the matter of closed triangles, which is usually seen as a clustering measure.

³³I present results for the most complete model ran, which is also the one with the best fit to the data, as it had the lowest BIC value. Moreover, and as presented in the Appendix, goodness-of-fit was also sufficient as it passed the test diagnostics

This set of results would imply that, holding everything else constant, triad formation would be the largest predictor of network formation, followed by offenders' match on nationality.

Lastly, I tested in a very simple way the prediction of Glaeser and Sacerdote (1999) on social interactions and severity. The conclusion these authors reached is that the higher the severity of the crime, the lower the social/criminal interactions. In order to test this in a simple way, I tabulated (by type of crime) the number of criminals per single act, as a share of all acts of that type. The results of this exercise confirmed the above conclusion.

Table A10: Criminals per criminal act, shares by crime type

	1	2	3	4	5+
Family	0.96	0.03	0.00	0.00	0.00
Sexual	0.90	0.07	0.02	0.01	0.00
Gender violence	0.89	0.10	0.01	0.00	0.00
Threats	0.85	0.12	0.02	0.01	0.00
Damages	0.81	0.13	0.04	0.01	0.01
<i>Overall Crime</i>	<i>0.77</i>	<i>0.16</i>	<i>0.04</i>	<i>0.01</i>	<i>0.01</i>
Motortheft	0.74	0.20	0.04	0.01	0.00
Drugs	0.73	0.21	0.04	0.01	0.01
Injuries	0.71	0.20	0.05	0.02	0.02
Theft	0.70	0.22	0.06	0.02	0.01
Fraud	0.69	0.17	0.06	0.02	0.06
Robbery	0.62	0.25	0.08	0.03	0.02

Note: This table presents for each crime typology the distribution of acts depending on the number of co-offenders. Source: Own construction from Catalan Police data.

Overall, the descriptive statistics above indicate that 77% of all criminal acts were committed by one individual, 16% by two individuals, and 1% by at least five individuals. When I performed the same analysis for different crime categories, I found that those crimes that can be labeled as more serious due to the harm they inflict on the victim (such as sexual assault or gender violence) had a higher share committed by just one individual. In fact, in these cases, 90% of criminal acts were single-authored. Hence, social interactions are low in severe crimes. On the contrary, other categories that are usually defined as petty crime (such as robbery or theft) had larger shares of criminal acts committed by more than one individual. In such cases, individual criminal acts dropped to 70% or 60%. Thus, in less severe crimes, social interactions are indeed higher.

2017

- 2017/1, **González Pampillón, N.; Jofre-Monseny, J.; Viladecans-Marsal, E.**: “Can urban renewal policies reverse neighborhood ethnic dynamics?”
- 2017/2, **Gómez San Román, T.**: “Integration of DERs on power systems: challenges and opportunities”
- 2017/3, **Bianchini, S.; Pellegrino, G.**: “Innovation persistence and employment dynamics”
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- 2017/5, **Solé-Ollé, A.; Viladecans-Marsal, E.**: “Housing booms and busts and local fiscal policy”
- 2017/6, **Esteller, A.; Piolatto, A.; Rablen, M.D.**: “Taxing high-income earners: Tax avoidance and mobility”
- 2017/7, **Combes, P.P.; Duranton, G.; Gobillon, L.**: “The production function for housing: Evidence from France”
- 2017/8, **Nepal, R.; Cram, L.; Jamasb, T.; Sen, A.**: “Small systems, big targets: power sector reforms and renewable energy development in small electricity systems”
- 2017/9, **Carozzi, F.; Repetto, L.**: “Distributive politics inside the city? The political economy of Spain’s plan E”
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- 2017/16, **Chacón, M.; Jensen, J.**: “The institutional determinants of Southern secession”
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- 2017/18, **González-Val, R.**: “City size distribution and space”
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2018

- 2018/1, **Boadway, R.; Pestieau, P.**: “The tenuous case for an annual wealth tax”
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- 2018/3, **Daniele, G.; Galletta, S.; Geys, B.**: “Abandon ship? Party brands and politicians’ responses to a political scandal”
- 2018/4, **Cavalcanti, F.; Daniele, G.; Galletta, S.**: “Popularity shocks and political selection”
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- 2018/7, **García-Quevedo, J.; Kesidou, E.; Martínez-Ros, E.**: “Inter-industry differences in organisational eco-innovation: a panel data study”
- 2018/8, **Aastveit, K. A.; Anundsen, A. K.**: “Asymmetric effects of monetary policy in regional housing markets”
- 2018/9, **Curci, F.; Maserà, F.**: “Flight from urban blight: lead poisoning, crime and suburbanization”
- 2018/10, **Grossi, L.; Nan, F.**: “The influence of renewables on electricity price forecasting: a robust approach”
- 2018/11, **Fleckinger, P.; Glachant, M.; Tamokoué Kamga, P.-H.**: “Energy performance certificates and investments in building energy efficiency: a theoretical analysis”
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- 2018/13, **Ayllón, S.; Nollenberger, N.**: “The unequal opportunity for skills acquisition during the Great Recession in Europe”
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2019

- 2019/1, Mediavilla, M.; Mancebón, M. J.; Gómez-Sancho, J. M.; Pires Jiménez, L.:** “Bilingual education and school choice: a case study of public secondary schools in the Spanish region of Madrid”
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2021

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