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SWEEPING UP GANGS: THE EFFECTS OF TOUGH-ON-CRIME POLICIES FROM A NETWORK APPROACH *

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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. 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" (Weerman et al. 2009). These criminal groups raise concerns for several reasons, such as recruiting 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 can be outlined. One strand relies on hard punishment and sturdy prosecution, while the other focuses on integration and the reduction of crime triggering disparities. The former has been more popular concerning gangs, and interventions such as sweeps or crackdowns have been the most common. For a better understanding of the role of sweeps, it is crucial to understand the network structure of the gangs.

This paper studies the effects of police sweeps against gangs. Specifically, this paper aims to answer the following research questions: Are sweeps successful at reducing crimes committed by individuals arrested in them? Do they also diminish the crimes committed by known criminal peers? Can a network analysis provide insights to improve policy design? To answer these questions, I study the Metropolitan Area of Barcelona (MAB), where a drastic policy change towards gangs took place. The transformation involved creating a 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, which allow me to follow individuals over time and identify criminal network structures. I supplement this with information on the deployment of the sweeps. To analyze the causal effect of the sweeps, I follow a staggered difference-in-differences strategy by comparing criminal records for individuals arrested in sweeps and their known peers to those of other individuals involved in group crimes. I also study outcomes in the swept area in terms of crime and other relevant socioeconomic variables. Moreover, I use the retrieved network structure to estimate peer effects and identify key players in each gang. I use such information to conduct a counterfactual policy exercise that compares the crime changes resulting from the sweeps to 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 of 95% 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 levels, health, and education. Lastly, the counterfactual analysis shows that if sweeps had 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. First, 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, in 2012 2,500 individuals were identified by authorities as belonging to a latin gang (Herrero-Blanco 2012). While this phenomenon's level is lower than in other settings, the rapid increase is a worrisome characteristic. Second, security has become the primary non-economic concern of citizens (Barometer of the city of Barcelona). Third, a drastic policy change occurred in this setting. Until 2012, the public sector based its strategy to tackle gangs 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 public strategy transformation involved creating a gang-specialized police unit (UGOV) and 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 police records provided by the local police for the 2008–2014 period, at the individual-quarter level. This dataset has very detailed information on the crimes registered in the MAB and the arrested individuals, when available. While the former includes information on the exact date and exact place of the crime, the latter includes information on the gender, date, and country of birth of the arrested individual. I exploit the level of detail of the data in two ways. Firstly, a unique identifier allows me to follow individuals over time and map out their criminal careers. Secondly, by matching records on the exact date, hour, geocoded location, and type of crime, I retrieve criminal network structures. In this way, criminal peers are identify in the sample. Finally, I match these records with confidential information on the sweeps provided by the gang-specialized police unit. This last piece of information allows me to label individuals arrested 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 individuals arrested in sweeps and their known criminal peers before and after the sweeps to criminal records for other individuals arrested in group crimes. By doing so, I estimate the treatment effects of the gang sweeps. I follow a similar strategy to study crimes and other socioeconomic factors relevant to welfare in the areas where the sweeps took place. In this case, I define a treat-

ment indicator at the area-month level, which takes a value equal to one for the districts in which a sweep took place. This analysis allows me to assess its effects on crimes regardless of whether someone is arrested, as well as examine other welfare determinants.

Additionally, I take advantage of the retrieved network structure to estimate peer effects. I do so by following Lee et al. (2020), who develop a methodology that addresses the concerns when estimating peer effect derived from potential identification and endogeneity issues. I use these peer effect estimates to identify key players in each gang, each composed by individuals arrested in a sweep and their known criminal peers. The key player in a criminal group is the individual that leads to the most significant 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), which also considers contextual effects. Finally, I conduct a counterfactual policy exercise in which I compare the variation in crime caused by the sweeps with the theoretical prediction from removing key players. Since the sweeps were of a larger scale, I construct a predictive Cumulative Crime Reduction (CCR) measure as a function of the number of key players removed, which serves as my policy benchmark.

The results indicate significant reductions in the criminal activity of those arrested in the sweeps and their peers. Specifically, for individuals arrested in a sweep, there is an average reduction in criminal activity of 95%. This effect is immediate and persistent, consistent with these individuals' incapacitation, as in all likelihood they are in jail in the observed post-sweep period. For peers, there is also a significant reduction in criminal activity of up to 25%. For peers, the effect fades out within a year of the police intervention and the contraction involves crimes against the person but not against the property. This result on types of crime 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 indicates that the reduction in peers' crime is more related to a deterrence effect rather than a caution effect, as impulsive and less hideable crimes are the ones driving the reduction in their criminality. This outcome would imply that peers are committing fewer crimes rather than being arrested less. Finally, results from the counterfactual policy exercise indicate that all sweeps arrest the key player. However, if the sweeps had arrested more key individuals in the gang, the predicted crime reduction could have been 50% higher. Thus, this study shows that identifying and tackling a group of key players in each gang can lead to substantial improvements in police interventions.

This study contributes to the research on criminal networks in several ways. Firstly, it provides a picture of gangs' network structure, helping to better understand how these criminal groups act (Lessing 2016; Blattman et al. 2021). This is a task that has seldom been

done due to data availability. 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 these criminal groups' specific nature 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 peer effects estimates to identify key players in each gang in a similar line to Lindquist and Zenou (2014). In this way, it is one of the few studies 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. Thirdly, it contributes to the public agenda by comparing crime-fighting strategies. On this, Chalfin et al. (2021) focus on a policy shift towards "precision policing" by analyzing gang takedowns and violence in the areas where they happened. Moreover, Lindquist and Zenou (2019) provide an overview of policy lessons. However, 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. Thus, it sets one of the first precedents uniting theory and practice in this regard. Such an issue is of immense relevance as 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 study, Philippe (2017) studies the effect of incarceration on non-arrested co-offenders, and Lindquist and Zenou (2014) perform an analysis of criminal groups in Sweden using rich administrative data. They also identify 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) have been carried out by Kling et al. (2005), Bayer et al. (2009), Damm and Dustmann (2014), Grund and Morselli (2017), Corno (2017), Bhuller et al. (2018), Mastrobuoni and Rialland (2020), and Billings and Schnepel (2020). 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 research branch regarding 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 paths have been taken. Starting in the 1970s, safety policies in the United States have followed a "tough-on-crime" approach. Although there is heterogeneity in how 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) finds that tough sanctions deter criminal activity and Di Tella and Schargrodsky (2004) find a large deterrent effect of visible police presence on crime. Moreover, Machin and Marie (2011) conclude that large-scale interventions from police can reduce street crime, and Bindler and Hjalmarsson (2021) show that the introduction of professional police forces significantly reduces violent crimes. However, contributions to the literature have also 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 focuses on reducing crime-triggering disparities. This last set of strategies is important 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 (Gonzalez and Komisarow 2020, Domínguez and Montolio 2021), outcomes may be perceived over longer timeframes (Lawless et al. 2010), and interdisciplinary approaches (and coordination) are greatly needed (Machin et al. 2011). So, questions remain on implementing such contrasting paths and whether they can tackle different purposes and different criminal profiles due to each one's specifics.

2.1 The case of the Metropolitan Area of Barcelona

Latin gangs were detected by the public sector for the first time in the Metropolitan Area of Barcelona (MAB) in 2002. Even if there were other types of gangs before that date, most attention in this context has been addressed at these. 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 boy[1]. In chronological terms, the first

[1]For an overview see https://www.elperiodico.com/ronny-tapias

block to consolidate included the gangs known as *Latin Kings* and *Ñetas*, linked to migratory flows originating in Ecuador. The second block included *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 2,500[2]. In 2012, around 15 gangs were detected with most members being 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 well[3]. 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, monetary incentives, lack of social capital, family disorganization, problems at school, and socialization in the street (e.g., Feixa 2012, Blattman et al. 2021). However, what makes gangs deserve attention is their connection with criminal activities and the violence embedded in their behavioral patterns. Regarding criminal activities, most illegal activity related to gangs' business in the MAB is based on drug smuggling (Herrero-Blanco 2012). Nonetheless, several other crimes are also at the heart of gang actions. Interpersonal and violent crimes are worth highlighting. These interpersonal violent crimes include crimes that traditionally relate to gangs functioning, such as injuries, threats, and eventually homicides.

The expansion of this social phenomenon was conditioned to the specific context in which it occurred. Firstly, Spain underwent a widespread demographic change in the 2000s. The arrival of substantial migratory flows increased the share of migrants in Catalonia from 4.0% in 2000 to 17.7% in the year 2012, for which South America contributed the most foreign citizens (around 350,000 individuals in 2012 and 300,000 in 2019)[4]. Secondly, there was an important change related to security enforcement. Between 1994 and 2008, the local police's deployment was carried out, replacing the national police. This change meant that the MAB security forces were mostly dependent on the local government rather than on the national 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. While in 2004 16.3% of the people surveyed remembered being victims of any crime, in 2010 this percentage had

[2]https://www.eldiario.es/politica/bandas-juveniles.html

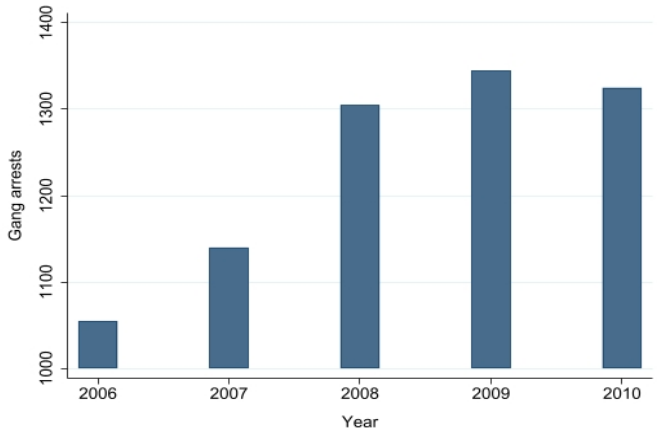
[3]It must be noted that group dynamics do not resemble those followed by groups in the United States nor are the levels of crime and violence comparable either with the United States or Latin America. According to Herrero-Blanco (2012), they mostly follow behavioral patterns present in Ecuador. This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

[4]Source: Catalan Institute of Statistics.

increased to 19.4%[5]. 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. This pattern is shown in Figure A.1.

In this context, the rise of gangs and criminal acts carried out by them took place. Figure 1 illustrates the pattern of gang arrests in Catalonia in the first decade of the 21st century. The diagnosis from the police side was one of being "worried but not alarmed"[6].

Figure 1: Arrests of gang members in Catalonia



Source: Herrero-Blanco (2012) based on general police directorate.

From a policy perspective, two periods can be distinguished in how the local public sector (local government and 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 associations[7]. This initiative 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 (Herrero-Blanco 2012; Córdoba Moreno 2015).

2. From 2012, a stricter approach was taken. In November 2011, with the approval of Decree 415/2011, the local police created a gang-specialized police unit. The "central

[5]As points of reference, the International Crime Victim Survey shows that in 2005 such value was of 13.7% in Madrid, 17.8% in Paris, 21.7% in Sao Paulo and 23.3% in New York (https://wp.unil.ch/icvs/Table-A8.pdf)

[6]https://www.abc.es/cataluna-tiene-jovenes-bandas.html

[7]The cultural association "*Latin Kings and Queens of Catalonia*" registered in July 2006, and the socio-cultural association "*Ñetas*" did so in March 2007.

unit of organized and violent youth groups" (UGOV[8]) 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 gang issues in their jurisdictions were grouped 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 were taken. These offensives were based on gang sweeps, which consisted of large-scale police interventions held close in time and territory in a coordinated fashion, with the aim of dismantling a gang through the arrest of several and important members. This change in the police was accompanied by sturdier judiciary enforcement. Act 6/2009 specifies identifying conditions for group convictions, which would lead to stricter judiciary outcomes for criminals than previously[9]. In detail, Act 6/2009 sets out the criteria that police units must consider when assigning a criminal act to the activity of gangs. The acting police units must make two evaluations. One determines if the individual matches any of the indicators of belonging to gangs. Another determines whether the criminal act is related to that militancy, for which a set of indicators is specified[10].

Hence, in 2012, there was a drastic change in how the gang problematic was tackled in the MAB. The new approach involved police specialization, large sweeps, and stricter judiciary enforcement. No other concurrent changes in policy took place regarding gangs nor other criminal activities[11]. This context provides an suitable scenario to assess a sturdier punishment policy towards gangs. It must be noted that the outcomes analyzed 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

For this study, I focus on the Metropolitan Area of Barcelona as it constitutes one of the most critical settings for latin gangs outside the American continent. This context relates to

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

[9]The 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 late 2011 that it became applicable.

[10]The first evaluation is based on identification by the own individual or family members, other gang members (from the same or another gang), police informers, or previous police investigations. The second one is declared if other gang members are involved, if gang indicators are reflected on the action, or by previous police investigations.

[11]No changes were found in patrolling hours nor in the number of police units.

the previously explained migration phenomenon in the early 2000s in Spain and large cities' attractiveness for the incoming population. The MAB is composed by 36 municipalities and comprises 4 million inhabitants. It is the fifth largest and the densest metropolitan area in Europe. Within the MAB, Barcelona municipality is the largest in population and territory (see Figure A.2 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 in smaller cities. Glaeser and Sacerdote (1999) mention as causes higher pecuniary benefits, a lower probability of arrest, and a lower probability of recognition.

This research first draws on a restricted administrative geocoded dataset of all registered crimes in the Metropolitan Area of Barcelona from 2008 to 2014. This dataset, provided by the local police, comprises information on all arrested individuals during that period. It includes information on the exact time and geocoded location of the crime as well as on the type of crime, and basic individual characteristics of the arrested individuals (gender, date and country of birth). Everyone is assigned a unique yet anonymous identifier, making it possible to see how many times each individual is arrested over time. Additionally, by matching time, geographical coordinates, and type of crime of individual registries, I can identify which individuals are arrested alongside others. This matching allows me to identify criminal peers and describe criminal networks.

Secondly, information on all sweeps carried out by the UGOV unit was provided by the unit itself. The unit was created in 2012, and sweeps are still taking place. However, due to the availability of administrative police records until 2014, I only consider sweeps carried out up to that date. The exact date, geographical area of action, and the number of arrested individuals for each sweep are registered. During the first three years of the unit (2012–2014), several sweeps took place, leading to 151 individuals being arrested in them[12]. Regarding the individual sweeps, each of them is the result of a complex police investigations on each gang. They take place when there is sufficient evidence for prosecution and when opportunity rises. Because of this, they not necessarily follow immediately after a specific set of gang crimes[13]. Because of this, in overall terms individual sweeps can be considered exogenous to crime patterns of all gang members arrested in them. This is formally tested in later sections.

Using these data sources, I build a panel dataset for the MAB at the individual-quarter level for the 2008–2014 period. This dataset includes 7,349,804 observations, coming from

[12] All major gangs present in the MAB were swept at some point in this sample period. However, due to the sensitivity of the data, it is not possible to disclose separate information for each sweep.

[13] Also, as an important factor of sweeps is the surprise element, even the police cannot perfectly predict all gang members that will be arrested in a specific sweep.

262,493 arrested individuals over 28 quarters. The panel includes individual information on individual arrests by the local police. It also informs how many times an individual has been arrested, how many of these are in a group, and how many criminal peers they have[14,15,16]. Demographic information about the individual as well as on the crimes committed is also included. Descriptive statistics are presented in Table 1.

Table 1: Descriptive statistics, individuals arrested in the MAB 2008-2014

Quarter 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
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	1	83
Times arrested in group	7,349,804	0.033	0.292	0	51
Known criminal peers	7,349,804	0.082	1.623	0	307

Source: Own construction from local police data.

As shown in Table 1, on average, 20,139 arrests take place in one quarter in the MAB, which refer to the arrest of 15,518 individuals. Of these arrests, 8,561 (42.5%) correspond to group arrests. Regarding the arrested individuals, 74.2% of them are men and 57.7% are of Spanish nationality, while 16.3% of them were born in the American continent. Moreover, individuals have been arrested from 1 to 83 times in the sample of analysis, and up to 307 criminal peers have been identified for some of them. These descriptive features correspond to the analysis of all arrested individuals in the MAB for the 2008-2014 period.

Further analysis refers to individuals arrested in sweeps and their known criminal peers. Known criminal peers are defined as individuals that were not arrested in a sweep but that were previously arrested alongside at least an individual arrested in a sweep. Out of the 151

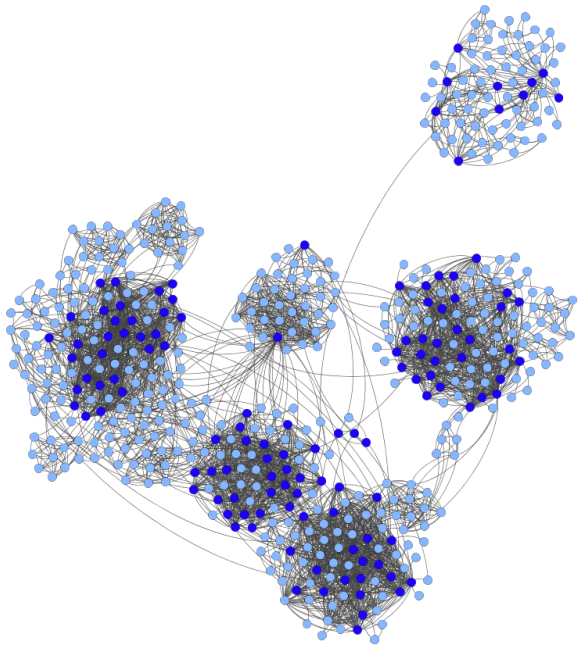
[14]If there are no arrests registered, a zero is assigned to that individual in that quarter.

[15]The information available gathers all records from the police and suffers the issue of "dark figures", that is that it does not provide information about individuals who were not arrested. This issue is common when dealing with crime data and usually does not have a solution.

[16]Another potential concern is that of selection and attrition in the sample that could stem from various sources, the most important one being migration decisions. On this matter, the migration statistics indicates that in 2014 the migration balance with other countries and Spanish regions was of -2.3% with respect to the population. Due to the small magnitude, I conclude that sample selection due to migratory processes is not an important problem in this setting.

individuals arrested in the sweeps, 127 are identified in the data[17]. For those 127 identified individuals, 413 first-order known criminal peers peers were identified. As a result, a total of 540 individuals are considered treated by UGOV's sweeps, either directly or indirectly. The network structure of these 540 individuals is shown in Figure 2. 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 took place. Concretely, 3,463 criminal links are identified among these 540 individuals.

Figure 2: Recovered criminal gang structures, before sweeps



Note: This graph presents the network structure of individuals arrested in the sweeps and first degree known criminal peers. Each dot is an individual: darker dots are individuals arrested in the sweeps, whereas lighter dots are peers. Each line indicates a criminal link between individuals. Source: Own construction from local police data and sweeps information.

A description of the network data used in this analysis is presented in Table 2, indicating the observed characteristics of the individuals arrested in sweeps as well as those of their known criminal peers. As expected, individuals arrested in UGOV sweeps are, to a large extent, young males born in Latin America. On average, individuals arrested in sweeps and their known peers have been arrested 4 times in the MAB between 2008 and 2014, but this value rises to 30 for some individuals. Moreover, individuals arrested in sweeps

[17]The difference in numbers reflects that some of these individuals were not arrested in the MAB but in other areas in Catalonia, and the last sweep took place in the last quarter of 2014. It, therefore, did not have a post-intervention period for comparison.

and their known peers have on average 13 criminal peers. Additionally, the demographic characteristics of the individuals in their criminal networks are quite similar to theirs. Figure A.3 in the Appendix shows homogeneity measures inside gangs for the most extensive sweeps in the sample. Lastly, the arrest profile of this individuals indicates that on average 11% of arrests occur in group, that 53.6% of the arrests refer to crimes against the property, 29.6% to crimes against the person and 16.8% to other types of crimes. Inside these categories, the most important typologies refer to bodily harm, disobedience to law officers, and drugs.

Table 2: Descriptive statistics, individuals arrested in sweeps and known criminal peers

	Mean	Std.Dev.	Min	Max
Own characteristics				
Female	0.124	0.330	0	1
Spanish	0.298	0.458	0	1
Latin American	0.622	0.485	0	1
Age	22.41	7.02	13	63
# Arrests	4.526	4.737	1	30
# Peers	12.83	12.67	1	77
Network characteristics				
Female	0.091	0.162	0	1
Spanish	0.289	0.267	0	1
Latin	0.636	0.298	0	1
Age	22.01	4.63	14	41
Arrest characteristics				
Against property	0.536	0.499	0	1
Against person	0.296	0.456	0	1
Other crimes	0.168	0.374	0	1
In group	0.111	0.106	0.036	0.964

Note: This table reports descriptive statistics for the 540 individuals on the identified gang structures, and their arrests. Source: local police data and sweeps information.

Moreover, Table 3 shows the results of balancing tests regarding crime characteristics for treated (individuals arrested in sweeps and known criminal peers) and all other individuals arrested in a group. This data indicates that while there are differences in the number of crimes committed by individuals arrested in sweeps and known criminal peers compared to all other individuals arrested in a group, it is not possible to rule out that the variation in the number of crimes is the same for both groups before the sweeps took place. Table 3 therefore provides the first piece of evidence in favor of the parallel trend assumption holding in this context.

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

	Treated	Control	Diff.	Std. Err.	p-value
Panel A: Crime levels					
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: Crimes 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 sweeps took place, between treated and control individuals. Source: Own construction from Barcelona city hall, local police data and sweeps information.

4 Methodology

My analysis focuses on two different yet complementary approaches. Firstly, I estimate the effects of the sweeps 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 sweeps took place. Secondly, I compare the gang level crime variation with the predicted crime reduction derived from a strategy that would remove key players in each gang. This counterfactual policy exercise sets a discussion on the implementation of the sweeps.

4.1 Sweeps analysis

In 2012 a tougher enforcement model for gangs was implemented in the MAB, under which several sweeps took place. Using the panel structure of the data described in the previous section, the primary analysis in this subsection estimates the following staggered difference-in-differences specification

$$Crime_{it} = \beta_1 + \beta_2.(Sweep.Post)_{it} + \beta_3.(Peer.Post)_{it} + \eta_i + \phi_t + \varepsilon_{it} \tag{1}$$

where the observational unit is an individual-quarter pair, and the dependent variable $Crime_{it}$ is an indicator variable showing whether the individual was arrested, or the number of times he was arrested, or the number of times he was arrested alongside others. $Sweep_i$

indicates if an individual i was arrested in a sweep, and $Peer_i$ if an individual i was an known criminal peer of an individual that was arrested in a sweep, as defined in the previous section. $Post_t$ is an indicator variable that takes a value equal to one after a sweep. η_i and ϕ_t are individual and year-quarter fixed effects, respectively. Given η_i and ϕ_t, the remaining variation reflects individual changes over time relative to its own mean that differ from the time trends in the MAB. Such variation is what identify the changes in criminal activity due to the police interventions in individuals arrested in a sweep and known criminal peers. The main coefficients of interest are thus β_2 and β_3.

For my main analysis, control individuals are those arrested in groups that are not part of any gangs arrested in the sweeps. In this way, I exclude from the primary analysis individuals that only commit crimes alone. The fundamental identifying assumption in this setting is that being arrested in a sweep is unrelated to individuals' criminal patterns when the sweeps took place in comparison to all individuals arrested in a group, as Table 3 evidenced.

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

$$Crime_{id} = \beta_1 + \sum_{d \neq -1} \phi_d \cdot (Treated.Time)_{id} + \eta_i + \varepsilon_{id} \tag{2}$$

where the observational unit is an "individual-time to intervention" pair, measured in quarters. I estimate $(Treated.Time)_{id}$ interactions, leaving $Time = -1$ as the reference period. Each ϕ_d coefficient quantifies the difference in criminal activity between the $Treated_i$ individuals (either $Sweep_i$ or $Peer_i$) and the control group relative to the period -1. The coefficients $\{\phi_{-D}, ..., \phi_{-2}\}$ identify anticipation effects, and coefficients $\{\phi_0, ..., \phi_D\}$ identify dynamic treatment effects. η_i are individual fixed effects. This exercise allows me to further check for the parallel trend assumption holding and understand the equation's post-treatment dynamics of Eq.(1).

I also take a continuous treatment approach in addition to the one shown in Eq.(1). For such an exercise $Treated_i$ takes values $\in$ [0,1] according to different criteria. The first criteria attributes a $Treated_i = 1$ to individuals arrested in a sweep ($Sweep_i = 1$) and $Treated_i \in (0, 1]$ to known peers ($Peer_i = 1$) based on the number of links to individuals arrested in sweeps, after a min-max normalization[18]. Lastly, $Treated_i = 0$ for all others. The second continuous treatment criteria I take is assigning a [0,1] treatment indicator to individuals according to different network centrality measures. In this setting, I consider

[18]For example, for an individual that $Peer_i = 1$ and that is linked to 11 individuals that $Sweep_i = 1$, the treatment value is $\frac{11-1}{22-1} = 0.476$, as 22 is the maximum number of links observed to individuals arrested in sweeps that $Sweep_i = 1$ and 1 is the minimum number.

outcomes regarding two measures: closeness and alpha centrality. 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 the min-max normalization of these measures to restrict them to the [0,1] interval. Individuals for which either $Arrested_i = 1$ or $Peer_i = 1$ will take treatment values $\in$ [0,1] and for all others it will be zero. Hence this exercise consists of estimating the following equation

$$Crime_{it} = \beta_1 + \beta_2.Treated_i + \beta_3.(Treated.Post)_{it} + \phi_t + \varepsilon_{it} \tag{3}$$

where based to the first criteria

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

or based to the second criteria

$$Treated_i = \begin{cases} \in (0,1] & \text{for both} \\ 0 & \text{for all others} \end{cases}$$

Finally, I run similar exercises to Eq.(1) at the gang level and in the sweeps areas. The first set of exercises identifies the reduction in criminality at the gang level after the sweep and shows the effect on crime at the gang/group level. The second exercise indicates whether socioeconomic outcomes change after sweeps occur in a specific area. For this, treatment is defined for areas where sweeps took place and the analysis is done for criminal outcome as for other welfare indicators. This last exercise outlines whether the effects of the sweeps exceed those related to individual arrests and criminal outcomes.

4.2 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 status relates to the fact that they connect nodes that are otherwise isolated or increase the network's number of links. The seminal paper by Ballester et al. (2006) defines the key player in a criminal group as "the individual who, when removed, leads to the most significant reduction in the group aggregate crime". Their main result indicates that a strategy that removes the key player leads to a higher reduction of overall criminal activity than removing any other

individual. Besides their significant contribution to the literature on networks and crime, results in Ballester et al. (2006) have significant implications for policy design. Specifically, a key player targeting approach might lead to substantial reductions in criminal networks' activity at a fraction of the cost of large-scale interventions.

Taking the previous points into consideration, I carry out a novel counterfactual policy exercise. I compare the change in criminal outcomes at the gang level due to the sweeps in the Metropolitan Area of Barcelona with the predicted variation in criminality when removing key players in each gang. To do so, I (1) estimate peer effects in criminality for the gangs under analysis, (2) build a key player ranking in 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. This last comparison makes room for an assessment of the policy design.

4.2.1 Peer effect estimates - structural framework

The first step to determine the predicted reduction in criminality at the gang level is computing peer effects. This parameter is needed to compute the centrality of each individual within the gang, to rank them, and to identify key players. As in Ballester et al. (2006), individuals choose how many crimes to commit to maximize their utility, which depends on all individuals' crime profiles and the network architecture. In this setting, the utility function of individual i is given by

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

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 criminal ability with contextual effects[19] (Manski 1993), 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 individual maximizes her utility, and the best-reply function can be written in matrix form as

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

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

where Y is a vector of the individual arrests, G is a diagonal adjacency matrix where each element g_{ij} indicates whether individuals i and j were arrested together, GY is a vector of the individual arrests for peers, X is a vector of the individuals' observable characteristics and $\bar{X}$ is a vector of peers' average observable characteristics. Peer effects are given by ϕ, β_1 captures observable individual heterogeneity and β_2 reflects the contextual effects.

The identification of peer effects is not straightforward and can suffer from several problems (Bramoullé et al. 2009). The first of these is the reflection problem (Manski 1993). Such an issue arises from the simultaneity in peers' choices and outcomes, making it impossible to distinguish peer effects separately from contextual effects. The second potential issue is the fact that the observed gang can be endogenous. If that is the case, it is impossible to identify whether the correlation of behavior among peers results from the network or just from homophily. Advani and Malde (2018) indicate that another challenge complicating identification of social effect parameters in network data is that of measurement error in the network.

Bramoullé et al. (2020) classify the possible strategies to follow in order to account for correlated effects and network endogeneity in the identification of network effects. In this paper, I follow the literature that proposes a structural framework to address correlated effects. In such a framework, network endogeneity is elucidated by modeling network formation and its connection to the peer effect regression. Additionally, Advani and Malde (2018) indicate that using a predicted network instead of the observed network can also alleviate mismeasurement issues in the estimation of the social effect. On this matter, Chandrasekhar and Lewis (2011) show that model based corrections can greatly reduce potential biases in social effect parameters arising from missing data.

To address and solve the identification issues of peer effects in this setting, I follow the Instrumental Variables approach in three stages proposed by Lee et al. (2020). Firstly, a predicted adjacency matrix $\hat{G}$ is constructed. A logistic regression model on link formation is estimated considering matches on available observable characteristics, and predicted probabilities of link formation are obtained to construct $\hat{G}$. Secondly, peers' criminal outcomes (GY in Eq.(5)) are predicted by the Instrumental Variables matrix $\hat{Z} = [1, X, \hat{\bar{X}}, \hat{G}1, \hat{G}X, \hat{G}\hat{\bar{X}}]$. Thirdly, Eq.(5) is regressed using the predicted values of GY to obtain peer effect estimates, $\hat{\phi}$.

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 do so, two assumptions are made. First, the gang is fixed; this implies assuming it does not vary after an individual is removed, mean-

ing no rewiring or new link formation. Second, each individual's criminal ability (previously described as α_i) does not depend on the gang.

As mentioned earlier, the key player is the individual who, once removed from the gang, leads to the largest crime reduction. Formally, this implies $max\{Y^*(r,\phi) - Y^*(r^{-i},\phi)\}$ for gang r. For peer effects ϕ, individual heterogeneity of criminal ability α, gang r, and individual i, Ballester and Zenou (2014) propose a contextual intercentrality measure, which is built as follows

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

where $\alpha_{\langle i\rangle} = (x_i, \alpha^{[-i]})'$ describes the situation where individual i has not yet been removed, so she has her attribute x_i, and the vector α is computed from the network when individual i is removed from the network, namely $\alpha^{[-i]}$. $B_\alpha(r,\phi)$ and $B_{\alpha_{\langle i\rangle}}(r,\phi)$ measure total Bonacich network centrality under contextual effects α and $\alpha_{\langle i\rangle}$ respectively, being $B_\alpha(r,\phi) = \sum_{i=1}^{n} b_{\alpha,i}(r,\phi) = 1^T M\alpha$. $M = (I-\phi G)^{-1} = \sum_{k=0}^{\infty}\phi^k G^k$ 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, and m_{ji} and m_{ii} are its corresponding elements.

This contextual intercentrality measure considers two effects. The first effect is a network effect derived from the standard centrality measure by Ballester et al. (2006). This effect, corresponding to the first term in Eq.(6), captures the direct effect on crime from removing individual i and the indirect effect on others' criminal activity from the removal of that individual from the network while keeping the vector $\alpha_{\langle i\rangle}$ unchanged. The second effect, and the novelty of this measure, is a contextual effect. This effect is captured by the last two terms in Eq.(6), and stems from the change in the contextual effect from α to $\alpha_{\langle i\rangle}$. It is the effect derived from an individual disappearing while keeping the network r unchanged.

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

4.2.3 Predicted reduction in criminality and policy comparison

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

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

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

In this setting, it is more useful to perform a broader comparison than only taking a single key player (Ballester et al. 2010; Borgatti 2006). To compare the theoretical predictions with the observed outcomes in an informative way, I perform a sequential removal exercise. As a result, I compute the predicted crime reduction conditional on the number of individuals removed, ranked by centrality. Specifically, the predicted cumulative crime reduction in gang r after removing up to individual n when sorted by centrality (labeled CCR_{nr}) is defined as

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

where $i = 1, 2, ..., n$ are individuals i in gang r sorted by the contextual intercentrality measure $\delta_i(r, \phi, \alpha)$. $i = 1$ is the top-ranked individual, and $i = n$ the lowest-ranked one.

This measure requires to first compute the predicted crime reduction when the key player is removed, CR_{1r}, as in Eq.(7). The additional reduction when removing the second-top-ranked individual is determined by computing their centrality over the remaining centrality after the first individual is removed. This 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 to give room to a discussion on the design of the sweeps.

5 Results

5.1 Sweeps analysis

5.1.1 Baseline estimates

Baseline estimates of Eq.(1) are presented in Table 4. Estimates are shown for individuals arrested in the sweeps as well as known criminal peers. The probability of committing a crime, the total number of crimes for which they are arrested, and the number of group crimes they are arrested are shown as outcomes. Control individuals are those arrested in groups but that are not linked to the sweeps.

Table 4: Effects of sweeps on crime - baseline estimates

	P(crime)	Total crimes	Group crimes
Sweep·Post	-1.782***	-0.350***	-0.302***
	(0.211)	(0.028)	(0.023)
Peer·Post	-0.469***	-0.048***	-0.051***
	(0.117)	(0.019)	(0.015)
Obs.	3,544,535	3,544,535	3,544,535
Indiv.	126,968	126,968	126,968
Indiv. FE	Y	Y	Y
Year-Quarter 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: individuals arrested in a sweep and known criminal 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 individuals are those arrested in a sweep or known criminal 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 Sweep and Peer. Robust standard errors are shown in parentheses. p<0.01, ** p<0.05, * p<0.1.

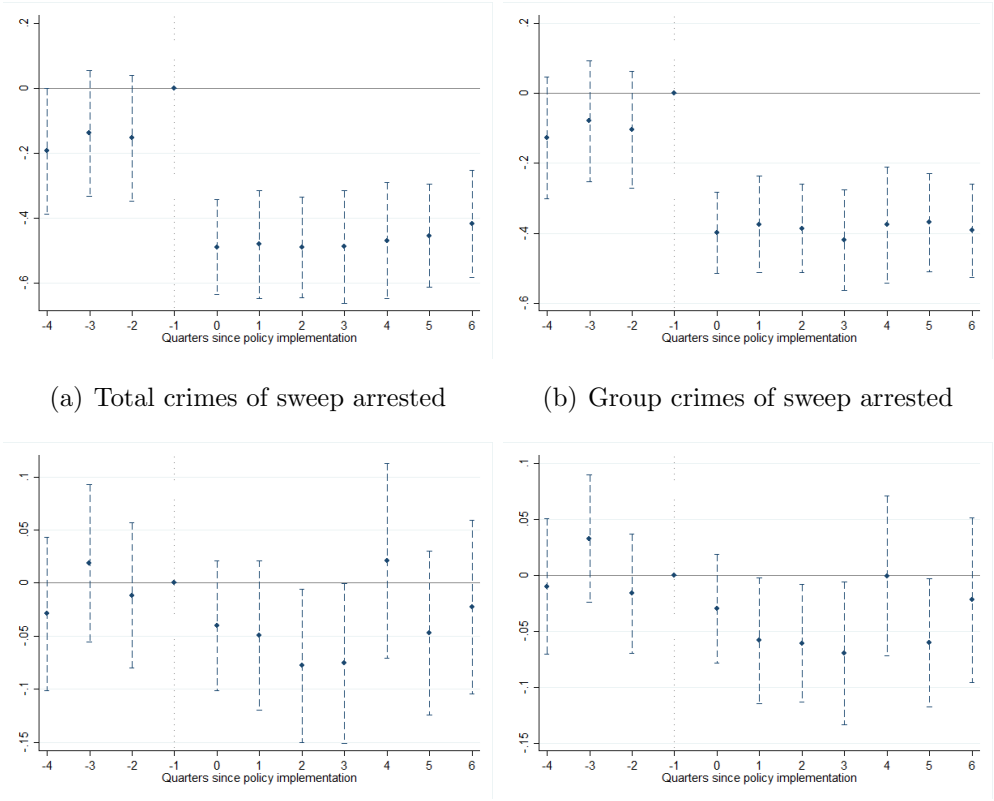
In all cases, the results show a significant decrease in criminality after the sweeps. For arrested individuals, the probability of committing a crime is reduced by half and the number of crimes is reduced by 95% with respect to the mean. For peers, the reduction in total criminality is of a smaller magnitude (26%) but also significant. Considering only crimes committed by groups, the drops in crime are even higher. In terms of individual characteristics, results (presented in Table A.1) indicate that the reduction in total criminality for arrested individuals is more considerable for those who are underage, male, and non-latin. However, no differences in outcomes are found for group crimes. Regarding peers, there appear to be differences in outcomes only by gender for total crimes and group crimes.

Event study exercises allow seeing effects over time. For arrested individuals, the crime reduction is sharp and immediate. Moreover, this reduction persists after one year and a half. For peers, a different pattern arises. The effect of the sweeps is short-lived as, after one year, the reduction in criminality is no longer statistically significant. This pattern may relate to the average time taken to resolve a process legally. According to statistics from the Spanish Judiciary System, the average timescale for "brief procedures" in Catalonia is of 9.8 months or 7.1 for procedures involving underage arrested individuals[20]. For peers, the crime

[20]The statistics are provided at the regional level. Because of this, the Catalan average is used to

reduction is no longer significant around this timescale.

Figure 3: Effects of sweeps on crime - event study exercises, 95% Confidence intervals.



(a) Total crimes of sweep arrested (b) Group crimes of sweep arrested

(c) Total crimes of known peers (d) Group crimes of known peers

Notes: This graph reports the results of an event study exercise following Eq.(2) for total crimes (left panel) and group crimes (right panel). Results are presented for individuals arrested in sweeps (upper panel) and known criminal peers (lower panel). The observational unit is an individual-quarter pair. Treated individuals are defined as in section 4.1, while treatment timing differed across individuals, according to sweep timing. Confidence intervals are based on robust standard errors.*** p<0.01, ** p<0.05, * p<0.1.

For the continuous treatment estimates, two approaches are followed as described in section 4.1. Results of these exercises are presented in Table 5. In all cases, the higher the centrality measure, the higher the crime reduction after a sweep. The results indicate that an increase of one link to the arrested individual reduces total crimes by 10%, and that an average increase on links to the arrested individuals reduces total crimes by 16% with respect to the mean. In the network centrality measures approach, the results go in the same direction of crime reduction. A one standard deviation increase in alpha-centrality reduces

approximate what takes place in the MAB. Source: http://www.poderjudicial.es/Informes-por-territorios-sobre-la-actividad-de-los-organos-judiciales/

crimes by 3.2%, whereas for closeness, there is a 2% reduction[21]. Event study exercises using the different continuous treatment measures are presented in Figure A.4 of the Appendix, and they indicate a similar pattern for all crimes and group crimes as in Figure 3. For all three, the reduction in criminality is immediate but fades over time. After six quarters, the effects are still present.

Table 5: Effects of sweeps on crime - continuous treatment estimates

	P(crime)	Total crimes	Group crimes
Panel A: number of links	-2.126***	-0.360***	-0.315***
	(0.232)	(0.029)	(0.023)
Panel B: alpha-centrality	-1.501***	-0.224***	-0.204***
	(0.151)	(0.025)	(0.020)
Panel C: closeness	-1.172***	-0.156***	-0.143***
	(0.120)	(0.019)	(0.015)
Obs.	3,544,535	3,544,535	3,544,535
Indiv.	126,968	126,968	126,968
Indiv. FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y

Notes: This table reports the results of the difference-in-differences (DiD) estimation following Eq.(3) 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 individuals are defined as those who were either arrested in a sweep or a known criminal peer, with heterogeneous treatment intensity according to each measure. Treatment timing differed across individuals, according to the timing of the sweep. The coefficient shown is that of interest in a DiD setting, being $Treated \cdot Post$. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Finally, I analyze the implications of the results at the individual level in terms of gang outcomes. Concretely, the previous set of individual results implies that one year after a sweep takes place, the overall criminal activity of the affected gangs is reduced, on average, by 61% when compared to the year before the sweep. This effect is of relative large magnitude in such a brief time frame. In terms of network structure, results indicate that after the sweeps some crime structures related to the gangs persist, but that these are rather small. Concretely, the network graph is much smaller and sparse than before the sweeps in observed

[21]Differences between these results correspond to the fact that each centrality measure reflects different issues. Closeness shows how many steps are needed to access every other node (0.11 standard deviation), reflecting how many links an individual has and how far it is from others. Alpha centrality contemplates an individual's connectedness and that of its peers, providing a notion of the node's power in the network (0.08 standard deviation).

individuals and criminal links. Before the sweeps, 540 individuals (127 arrested in sweeps and 413 known criminal peers) and 3,463 links are identified. Afterwards, 101 individuals are arrested (14 arrested in sweeps and 87 peers), and 101 links are found between them. Figure A.3 in the Appendix depicts this comparison of before and after network graphs. This certain persistence is consistent with the smaller and short-term reduction in crime for peers.

5.1.2 Mechanism analysis

Regarding the potential mechanism that may underlie the results described above, for individuals arrested in the sweeps the evidence suggests a mechanical effect driven by incapacitation. The data under analysis only shows outcomes for a relatively short period after the sweeps began (1.5 years). Thus, even if it cannot be directly verified, it is very likely that the arrested individuals are still in prison. This outcome relates to several factors. First, Act 6/2009 that accompanied the sweeps increased the probability of the arrested going into preventive prison while awaiting trial. Second, the judiciary process takes an average of 9.8 months in Catalonia indicating that arrested individuals remain in prison at least for such period. Third, those arrested in the sweeps are seized for crimes labeled as severe offenses, which translates into at least five years in prison according to the Spanish Penal Code.

For peers, the reduction in the number of times they are arrested can be attributed to several factors that are not mutually exclusive, as discussed below.

5.1.2.1 Criminal capital vs. criminal environment

The first factor that affects the peers' actions is that there is a lower incentive to commit a crime after a sweep. This reduction may be due to either a loss in "criminal human capital" that hinders new criminal activity or in a "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 fraud. In contrast, the latter derives from impulsive behaviors. This impulsiveness is more likely to take place in vandalism or violent crimes such as injuries or fights. Table 6 summarizes the evidence on this regard.

Table 6: Effects of sweeps on crime - crime typologies heterogeneity estimates

	Against Property	Against Person	Other Crimes
Sweep·Post	-0.113***	-0.062***	-0.175***
	(0.019)	(0.014)	(0.019)
Peer·Post	-0.017	-0.034***	0.002
	(0.016)	(0.007)	(0.005)
Obs.	3,544,535	3,544,535	3,544,535
Indiv.	126,968	126,968	126,968
Indiv. FE	Y	Y	Y
Year-Quarter 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: individuals arrested in a sweep and known criminal 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 individuals are those arrested in a sweep or known criminal 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 Sweep 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 for those arrested, crimes that are mainly reduced are those labeled as other crimes. This is a category which includes drug crimes and "criminal organization". For peers, crimes against the person, which include gender violence, sexual assault, injuries, threats, are the only ones showing a significant reduction. In the case of peers, no difference is found for crimes against property such as robberies or car thefts. (Table A.2 in the Appendix shows a more exhaustive division of crime categories). The patterns in Tables Table 6 A.2 and indicate that the mechanism of lost criminal human capital does not affect the incidence of these crimes. On the contrary, there is 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. On this, it is not possible to distinguish whether this reduction is taking place between or within gangs.

5.1.2.2 Updated costs of sanctions

The second factor that may reduce 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, individuals with shorter criminal careers should be more affected as they gain new information. In contrast, for more prolific criminals, no new information is received. Results on the probability of committing a new crime are presented in Table A.3, where the effect is split according to the individuals' position in the distribution of committed crimes. For this exercise, I follow a triple differences strategy (treatment-time-high crime) and find no significant difference between individuals arrested with high and low frequencies. This holds considering different thresholds for what is defined as an individual arrested with high frequency (above median, 75, 90, 95, and 99 percentiles). This result is in line to that in Philippe (2017).

5.1.2.3 Targeting vs. profiling

A third issue to be tackled regarding the previous set of results is whether a police profiling strategy drives them. This profiling would imply that individuals similar in demographic characteristics to those involved in gangs would also register a change in the arrest incidence. To check this, I compare arrests made before and after the policy change in individuals with the set of characteristics that match that of arrested individuals in the sweeps, with arrests of individuals with a different set of characteristics also perceived as "high crime" subpopulations. This exercise, presented in Table A.4 in the Appendix, shows no statistically significant differences between groups. Hence, the results point towards a targeting strategy rather than a profiling one.

5.1.2.4 Less crime vs. less arrested

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

5.1.2.5 Differential effect of sweeps vs. any arrest

Finally, there is the possibility that sweeps act in the same way as any other police arrest. To overcome such an issue, I identify criminal groups with similar characteristics to those arrested by the sweeps but arrested before the policy change in 2012. For the period 2008–2011, five similar group arrests are found that accounted for 64 individuals and 56 peers. For this exercise, I include these individuals in the pool of treated individuals to then perform the same baseline analysis but adding a term that accounts for whether the individual is linked to an arrest after the policy change. If this latter term is to demonstrate statistical significance, it would indicate that the toughening of the crime-fighting strategy in the MAB in 2012 has a differential effect on criminal outcomes.

The results of this analysis are shown in Table 7. They indicate a significant reduction in the criminal activity of arrested individuals and their known peers regardless of whether they were linked to an UGOV sweep or another arrest with similar characteristics before the policy change. This outcome holds both for the total number of crimes and those committed in groups. Moreover, the triple interaction term indicates that there is a significant negative differential for those arrested in the UGOV sweeps: the reduction in the criminal activity of individuals arrested in the UGOV sweeps is significantly higher than that of individuals arrested in similar previous police interventions. Hence, after the change in the crime-fighting policy, there is a larger decrease in criminality, indicating that the toughening strategy is more successful than the previous one at reducing crime for this type of arrests. However, the opposite takes place for peers: peers of individuals arrested by sweeps show a lower crime reduction than previous police interventions' peers. This effect may relate to the fact that the peers of those arrested in the sweeps are more prolific criminals than the peers of those arrested in previous arrests.

Table 7: Differential effect of UGOV sweeps on crime

	P(crime)	Total crimes	Group crimes
Sweep·Post	-1.636***	-0.217***	-0.224***
	(0.247)	(0.041)	(0.035)
Peer·Post	-0.878***	-0.169***	-0.155***
	(0.262)	(0.065)	(0.055)
Sweep·Post·UGOV	-0.453	-0.145***	-0.087**
	(0.343)	(0.050)	(0.041)
Peer·Post·UGOV	0.422	0.126*	0.107*
	(0.287)	(0.068)	(0.057)
Obs.	3,542,468	3,542,468	3,542,468
Indiv.	126,968	126,968	126,968
Indiv. FE	Y	Y	Y
Year-Quarter 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: individuals arrested in a sweep and known criminal 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. 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 $Treated \cdot Post \cdot UGOV$ for Sweep and Peer. Robust standard errors are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

5.1.3 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 (Borusyak and Jaravel 2017). Goodman-Bacon (2018) shows 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 observations. To overcome potential issues derived from negative weights, De Chaisemartin and d'Haultfoeuille (2020) propose another estimator that solves them. Results for the Event Study exercise following De Chaisemartin and d'Haultfoeuille (2020), presented in Figure A.5 in the Appendix, do not differ significantly from the linear regression estimator presented in Figure 3. This outcome reflects the fact that negative weights are not an issue in this analysis, as the pure control group (individuals arrested in group crimes but not by sweeps) is sufficiently large.

Finally, I conduct several exercises allowing for different specifications of the baseline estimates. Concretely, I modify the control group to consider criminals arrested for any crime, crimes against the person, other crimes, and drug crimes. Additionally, I estimate Eq.(1) following a Poisson regression. As the dependent variable in this analysis, namely

the number of total crimes, has a count data structure, this modeling type could be better suited. The results shown in Table 8 generally hold for both individuals arrested in sweeps and known criminal peers across specifications.

Table 8: Effects of sweeps on crime - alternative specifications estimates

	Baseline	Control: All criminals	Control: Against Person	Control: Other	Control: Drugs	Poisson IRR
Total Crimes						
Sweep·Post	-0.350***	-0.350***	-0.435***	-0.355***	-0.398***	0.153***
	(0.028)	(0.028)	(0.054)	(0.033)	(0.070)	(0.035)
Peer·Post	-0.048***	-0.048***	-0.067***	-0.036	-0.026	0.765***
	(0.019)	(0.019)	(0.021)	(0.030)	(0.054)	(0.084)
Group Crimes						
Sweep·Post	-0.302***	-0.302***	-0.346***	-0.311***	-0.270***	0.128***
	(0.023)	(0.023)	(0.043)	(0.026)	(0.021)	(0.035)
Peer·Post	-0.051***	-0.051***	-0.066***	-0.031	-0.041	0.643***
	(0.015)	(0.015)	(0.017)	(0.026)	(0.040)	(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
Indiv. FE	Y	Y	Y	Y	Y	Y
Year-Quarter 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: individuals arrested in a sweep and known criminal 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. 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 Sweep and Peer. Robust standard errors showed in parentheses. p<0.01, ** p<0.05, * p<0.1.

5.1.4 Area Level Outcomes

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

I now move to examine the impact of sweeps at a broader level. To do so, I look at the evolution of different outcomes in the areas where the sweeps took place. For Barcelona municipality, I consider districts as areas of influence (10 districts), whereas for the other municipalities in the MAB, I consider each municipality as a whole (35 municipalities). To analyze the impact of sweeps, I follow a difference-in-differences estimation with an AR(1) disturbance term due to the high autocorrelation demographic variables usually have. The results on registered crimes and other socioeconomic outcomes are presented in Table 9.

Regarding crime outcomes, no significant change is found for overall crime in areas after

a sweep takes place, and the same is valid for all property crimes. Statistically significant decreases are found for crimes against the person, damages 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 is a reduction in threats, disobedience, and drug crimes, the reduction is not statistically significant.

Regarding other potential outcomes at the area level, benefits seem to exceed those of certain crime reductions as they also involve other socioeconomic variables. Table 9 indicates that there are indeed other important changes in the area. Regarding educational outcomes, there is no effect on high-school enrollment in the areas with sweeps. However, there is a positive and significant effect on the number of students enrolled in the appropriate year for their age (non-lagged students). Moreover, there is a significant and negative decrease in the number of admissions to emergency rooms in the areas where there were sweeps. Although it is not possible to link either of these results with individuals or specific profiles, they indicate an improvement in these variables. Finally, no effect is found on rental markets, either for prices or number of contracts.

Table 9: Effect of sweeps on crime - area level outcomes

Crimes Against Property				
	Property	Car Theft	Robbery	Damages to Property
Treat·Post	-0.372	-0.380	0.186	-0.198***
	(2.907)	(0.364)	(0.322)	(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*	-0.200**	-0.032**	-0.058
	(0.156)	(0.079)	(0.015)	(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	-0.114	-0.068	-0.008**
	(0.175)	(0.081)	(0.064)	(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	-51.423	2.405**	-15.711*
	(12.215)	(57.423)	(1.030)	(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 areas 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 benchmark

This section compares the previously found effects of the UGOV sweeps on crime to 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 its estimation, I consider the 3SLS estimator of section 4.2 for Instrumental Variable regressions to address potential threats to identification. The first step is to obtain predicted link formation probabilities and construct $\hat{G}$. For this, every possible link in each gang (that takes empirical values of 0 or 1) is modeled on the difference on observable characteristic of

the dyad (age, gender, nationality), after which a predicted probability is computed. The link formation model estimates (shown in Table A.5 in the Appendix) evidences the presence of homophily in the sample, as matches in characteristics increase the probability of committing a crime together for the individuals under analysis. However, McFadden's pseudo-R2 of the logistic regressions is close to 0.04, indicating that the dyadic characteristics are not very informative in predicting link formation. As a result, the IV matrix $\hat{Z}$ constructed using the predicted adjacency matrix $\hat{G}$ and used in the following steps of the peer effect estimation could be a weak instrument.

The estimation results for peer effects as outlined in Eq.(5) are reported in Table 10. 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, 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 estimation rejects the null hypothesis. Given these issues, it is necessary to instrument the current 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 is 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.

Considering the GMM estimation results for peer effects, the estimated peer effects in this setting are of 0.007. This result satisfies the condition for the existence of a unique equilibrium ($|\hat{\phi}|\rho(G) < 1$), and it 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 is considerably smaller than in the current study. Moreover, while the first study conducts its analysis on suspected Swedish criminals, the second one does so in a sample of adolescents in the United States. These two different issues (network size and context) may explain the differences in peer effect estimates. Results of the present study imply that having one criminal partner increases the number of crimes committed by an individual by 0.7% in comparison to when alone ($\frac{1}{1-\hat{\phi}}$). Moreover, considering that the average number of peers is 13, the average network social multiplier in this study is of 10% ($\frac{1}{1-13\hat{\phi}}$).

A valuable exercise in this setup is to compare the above structural estimates of peer effects to the reduced form estimates backed out from the gang sweeps in the previous section. On one side, the structural effects indicate an average social multiplier of 10%. This result implies that, on average, having criminal partners increases the number of crimes committed by an individual by such magnitude. On another side, the reduced form spillover effects estimates indicate that an average increase in the number of links to arrested individuals reduces total crimes by 16%. Even if these two exercises do not measure exactly the same,

both seem to be in line with one another.

Table 10: Peer effect estimates - gangs in the Metropolitan Area of Barcelona

	OLS	2SLS	3SLS	GMM
ϕ	0.015***	0.006	0.006	0.007**
	(0.004)	(0.004)	(0.004)	(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 arrested individuals networks following Eq.(5). 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 arrested individual. 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 an invariant network assumption, the key player is the individual with the highest contextual intercentrality measure in the network. Using the GMM estimates reported, the contextual intercentrality $\delta_i(r, \phi, \alpha)$ is calculated for each individual following Eq. (6), and the key player is identified for each gang.

In terms of the sweeps, they arrested on average 23.5% of the identified gang members (127 out of 540). In terms of their relevance to the network, the sum of the centrality of the individuals arrested in the gang sweep is of 32.9%. Additionally, a logistic regression indicates a positive and significant correlation between the individual centrality measure and an indicator variable for being arrested in a sweep instead of being a known criminal peer, after controlling for gang fixed effects. Regarding the key players, in all gangs analyzed the individual identified as the key player was arrested in a sweep. In all cases, the key player is male, half of them were born in Latin America, and 70% were born after 1990. The key players identified in the gangs do not differ significantly from their peers in any demographic characteristics, nor in the number of peers they have, nor in the number of arrests. Hence, key players are not distinguishable from other individuals only from observable characteristics. Moreover, as in Ballester and Zenou (2014) and Lee et al. (2020), the key players are not those individuals with the highest values of other network centrality measures such as alpha-centrality, betweenness, closeness centrality, or even the standard intercentrality measure of Ballester et al. (2006). In this way, standard network centrality measures do not correctly identify either the key players, as they do not account for contextual effects.

Finally, I compute the predicted reduction in crime that would have been achieved by removing the key player, namely CR_{ir}. In this case, the model predicts that removing the key player in each gang would lead to a weighted average crime reduction of 17.7%. This outcome decreases with the gang's size as in previous studies. As stated in Ballester et al. (2006), that value is the largest possible reduction in crime when targeting one individual in each gang. This fact is verified in this setting. 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 considering the measure by Bonacich (1987) by 2.9%, and the most connected individual by 0.7%. These values were computed as the difference between the two scenarios. This set of results is mostly consistent with those of Lindquist and Zenou (2014) and Philippe (2017).

5.3 Discussion

When comparing the effect the UGOV sweeps' with the predictions based on removing the key player, several points are worth highlighting. Firstly, all sweeps arrest the key player in the gang. Secondly, being arrested is positively correlated with the contextual intercentrality measure of Ballester and Zenou (2014), indicating that such interventions on average catch the most relevant individuals. Nonetheless, the match is not perfect: among those arrested, only 60% are at the top of the contextual centrality ranking of each gang[22]. Thirdly, the sweeps achieve a crime reduction of 61% in the year following the intervention, result that outperforms the key player strategy by 43.3%. However, the comparison between the two strategies is not straightforward as the prediction of the removal of the key player is based on catching just one individual, and sweeps affect more individuals.

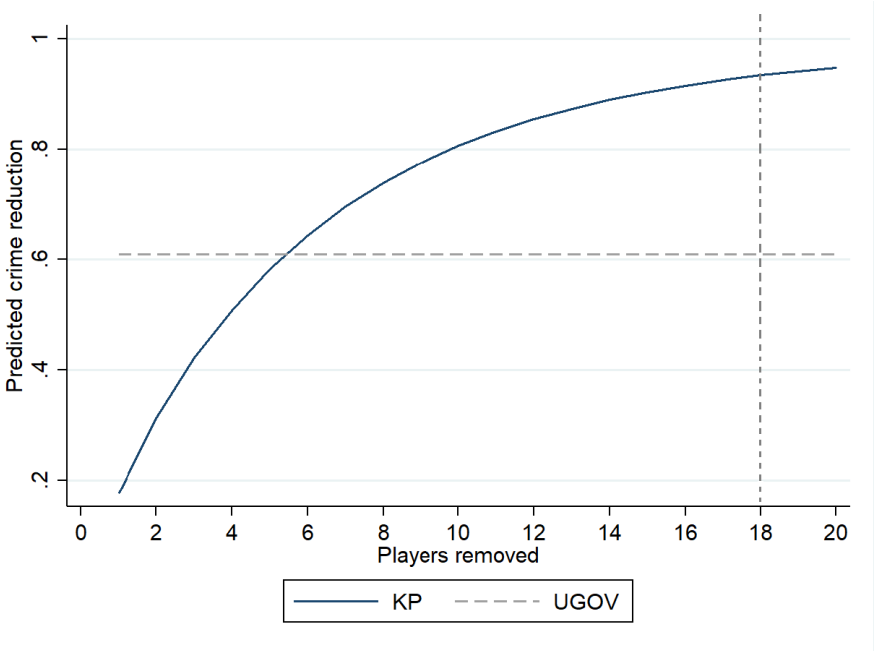
To overcome potential difficulties in comparison, I perform a sequential exercise in which I remove individuals decreasingly sorted by their contextual intercentrality measure and compute the predicted reduction in crime CCR_{nr}, as outlined in Eq.(8). Figure 5 shows the results of such an exercise as well as the average values obtained by UGOV sweeps. The exercise indicates that, holding the number of individuals arrested constant, the predicted crime reduction would have been of 92.8% instead of 61% if the sweeps would have arrested the top-ranked individuals by contextual intercentrality instead of the actual arrests. This outcome implies a 50% increase in reduced criminality compared to the one achieved. Evidence also indicates that a similar reduction in crime to that of the sweeps would have been achieved by removing the top six individuals in each gang sorted by their contextual intercentrality measure. This number of arrests corresponds on average to a third of the

[22]The match between arrested and top contextual centrality individuals is 90% of the top half of the gang, indicating there is no mismatch among the top-rated individuals.

actually arrested. Such a result is in line with results found on "precision policing", a crime fighting strategy that focuses available resources on a small number of individuals who are thought to be the primary drivers of violence. On this matter, Chalfin et al. (2021) show that gang sweeps reduced gun violence around public housing by one third in the year after.

Hence, by adequately identifying, targeting, and catching the key players in each network, the sweeps could have achieved the same crime reduction with a smaller deployment or a more considerable reduction in crime if arrests were held constant but better targeted.

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 individuals removed, ordered by contextual centrality. Such outcomes are compared with the actual reduction achieved by UGOV sweeps.

In terms of policy, two broad comparisons can be reflected upon. The first involves the targeting strategies. 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, key players are not identifiable by either observable or standard network characteristics. The second comparison is that between targeting strategies and other approaches, such as general tough-on-crime policies. In this case, the sweeps achieve a significantly higher crime reduction than that predicted by removing the key player. Still, sweeps involve a more extensive police deployment and do not always catch the most relevant individuals in terms of intercentrality. Indeed, as Figure 5 shows, by arresting more central individuals in each gang, the sweeps could have achieved a 50% larger reduction in the gangs' criminal activity.

It can be concluded thus, 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 substantially improve 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 and its analysis, since the key player is not easily identifiable. Secondly, under the invariant network assumption, the key player predictions are only valid in the short term as it is indeed unlikely for the remaining individuals to form new links in a short period 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 key player analysis. Thirdly, the key player might be an unfeasible target in reality. Given that the studied criminal networks follow a defined internal structure, it is plausible that the key player is better protected than other network individuals. It hence would be more difficult for police resources to reach, and 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 police resources compared with other sturdier approaches. Despite all these drawbacks, the exercise of removing the key player is a good benchmark with which to compare current policies because of its relevance. Concluding whether it would be worth moving towards a key player strategy may depend on the specificities of each empirical case.

The previous points do not imply however that tough-on-crime interventions are always the approaches to follow. Previous literature indicates how costly these approaches may be in many dimensions. Firstly, in the direct cost for the police in terms of human resources, training, and deployment. Secondly, in the indirect costs to society, including 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 arrested at such a young age and their meager reinsertion prospects. Additionally, there is a 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 Conclusions

This paper examines the implementation of gang sweeps addressed at dismantling them and their effects on crime. The analysis considers the effects on both individuals arrested in a sweep and their known criminal peers, as well as outcomes at the gang level and in the areas in which the sweeps take place. The analysis follows a difference-in-differences strategy in the

Metropolitan Area of Barcelona, context where gangs were a big concern among authorities and citizens, and a drastic change in policy towards them took place. To do so, criminal network structures are retrieved from administrative records of the local police from 2008 to 2014.

Results indicate significant reductions in the criminal activity of those arrested in the sweeps and their known criminal peers. For the former, there is 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 are smaller, more short-term, and focused on crimes against the person. These results would point towards a mechanism of loss of the criminal environment. In addition, sweeps translate into significant decreases in crimes against the person and disobedience against law officers at the area level. The results also demonstrate a decline in the number of emergency room admissions and lagged high school students in swept areas.

Peer effects estimates indicate that, on average, crime increases by 10% when an individual is part of a gang compared to when committing crimes alone. Based on peer effects estimates, I rank individuals in each gang by centrality, and I map the predicted reduction in criminality as a function of the number of top individuals removed. The results indicate that the same reduction in gang criminality achieved by the sweeps could have been achieved by targeting, on average, a third of the individuals arrested but more central ones.

Overall, the existence of peer effects suggests that any crime reduction may lead to future reductions in crime through reductions in peers' crime. This is a benefit of crime-fighting policies that needs to be considered when analysing them. Moreover, identifying key players in a gang can help achieve higher reductions in criminality by targeting these individuals. Therefore, policy design should incorporate them into an approach that prevents and tackles crime.

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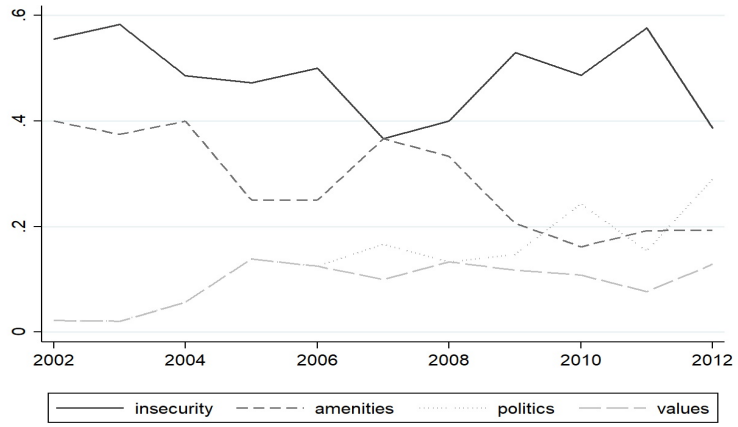
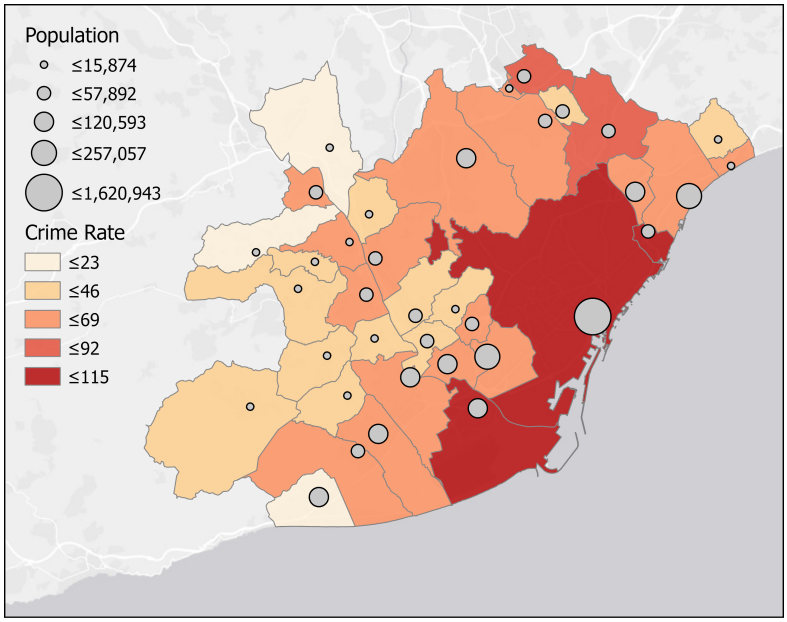
7 Appendix

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



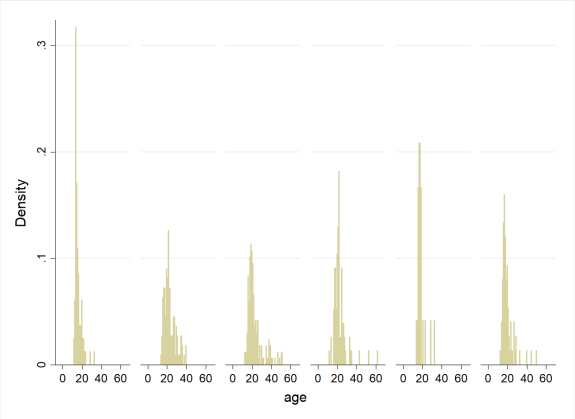
Source: Own construction from barometer of the Barcelona city hall

Figure A.2: Metropolitan Area of Barcelona and corresponding municipalities

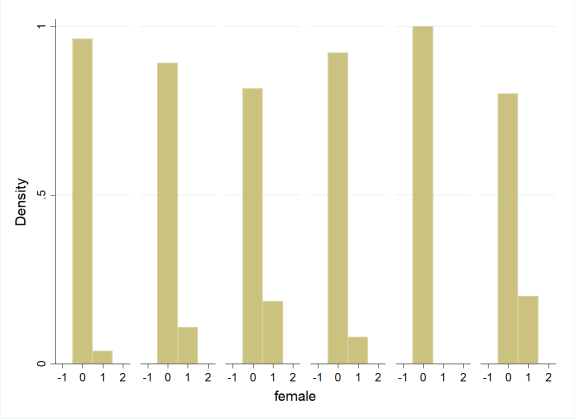


Source: Own construction from local police and Catalan institute of statistics data.

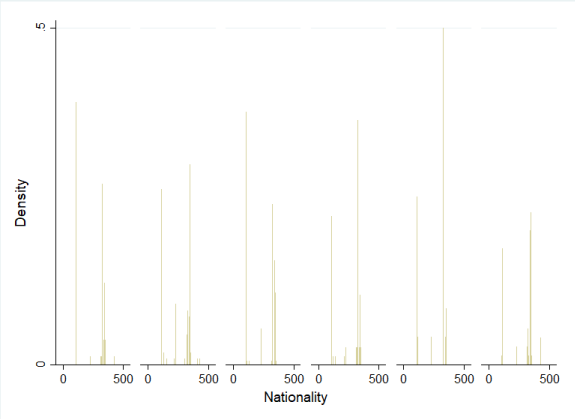
Figure A.3: Histogram of frequency of individual characteristics within gangs. Top sweeps.



(a) Age



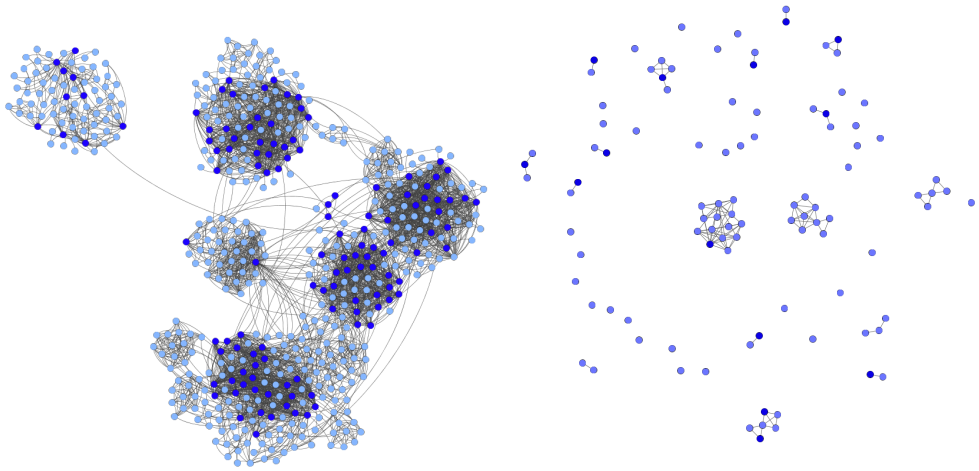
(b) Gender



(c) Nationality

Source: Own construction from local police data.

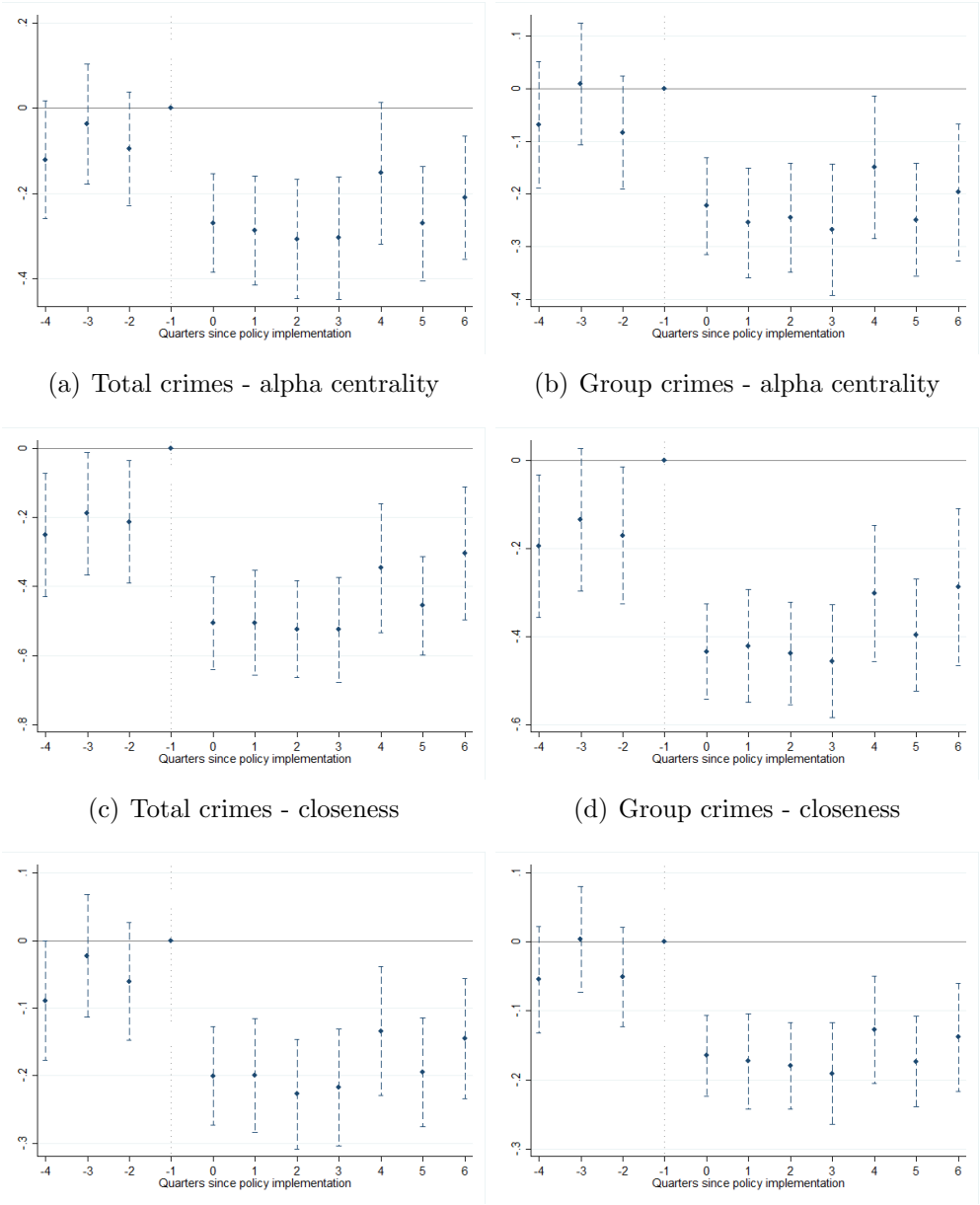
Figure A.3: Recovered criminal gang structure, before and after UGOV sweeps.



(a) Before (b) After

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 A.4: Effects of sweeps on crime - event study exercise with a continuous treatment indicator, 95% confidence intervals.



(a) Total crimes - alpha centrality

(b) Group crimes - alpha centrality

(c) Total crimes - closeness

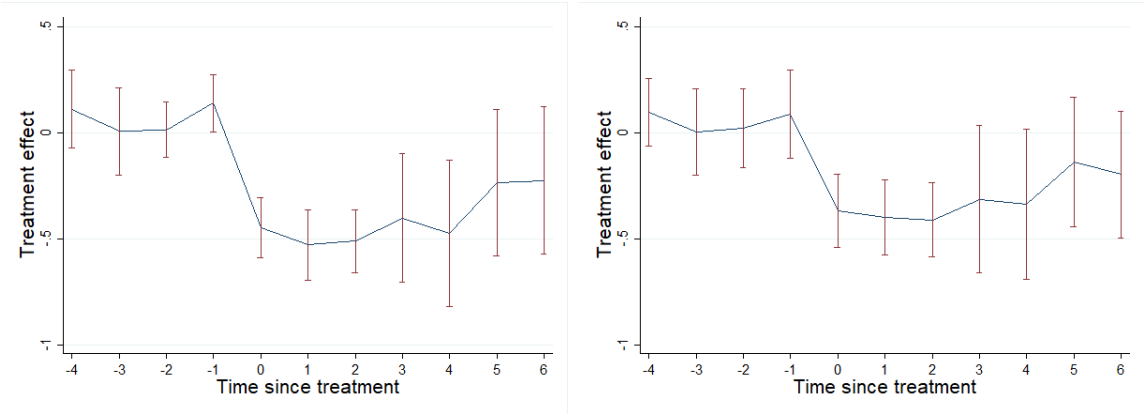
(d) Group crimes - closeness

(e) Total crimes - number of links

(f) Group crimes - number of links

Notes: This graph reports the results of an event study exercise following Eq.(2) for total crimes (left panel) and group crimes (right panel). Results are presented for pooled individuals arrested in a sweep and known criminal peers, with heterogeneous treatment intensity according to the alpha-centrality, closeness and number of links criteria. The observational unit is an individual-quarter pair. Treated individuals are defined as in section 4.1, while treatment timing differed across individuals, according to intervention timing. Confidence intervals are based on robust standard errors.*** p<0.01, ** p<0.05, * p<0.1.

Figure A.5: Effect of sweeps on crime - event study exercise à la De Chaisemartin and d'Haultfoeuille (2020), 95% confidence intervals



(a) Total crimes - sweep arrested

(b) Group crimes - sweep arrested

Notes: This graph reports the results of an event study exercise following Eq.(2) and De Chaisemartin and d'Haultfoeuille (2020) for total crimes (left panel) and group crimes (right panel). Results are presented for individuals arrested in a sweep. The observational unit is an individual-quarter pair. Treated individuals are defined as in section 4.1, while treatment timing differed across individuals, according to intervention timing. Confidence intervals are based on robust standard errors.*** p<0.01, ** p<0.05, * p<0.1.

Table A.1: Effects of sweeps on crime - individual demographics heterogeneity estimates

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

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: individuals arrested in a sweep and known criminal 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 individuals are those arrested in a sweep or their known criminal 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 Sweep and Peer. Robust standard errors are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table A.2: Effect of sweeps on crime - heterogeneity for peers by detailed crime categories

	Car Theft	Robbery	Damages to Property	Injuries	Sexual	Threats	Fraud	Disobedience	Drugs
Peer·Post	-0.003	-0.009	-0.004	-0.017***	-0.010***	-0.006	-0.009	-0.002	0.002
	(0.002)	(0.007)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.004)	(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
Indiv. FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Quarter 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 known criminal peers. The observational unit is a individual-quarter pair and only individuals ever commiting a group crime were included. Treated individuals are defined as in section 3.4.1, while treatment timing differs across individuals, 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 A.3: Effects of sweeps on crime - criminal experience heterogeneity estimates

	Above median	Above 75pc	Above 90pc	Above 95pc	Above 99pc
Peer·Post	-0.192	-0.280	-0.559***	-0.417***	-0.471***
	(0.250)	(0.197)	(0.155)	(0.125)	(0.117)
Peer·Post·High	-0.354	-0.292	0.212	-0.399	0.320
	(0.283)	(0.245)	(0.237)	(0.352)	(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
Indiv. FE	Y	Y	Y	Y	Y
Year-Quarter 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 known criminal peers. Treatment, timing and criminal intensity are the differences considered. Each column presents different estimates according to which threshold is taken to define individuals arrested with high frequency.The observational unit is an individual–quarter pair and only individuals ever arrested in a group crime were included. Treated individuals are known criminal 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.

Table A.4: Effect of sweeps on crime - falsification exercise on profiling

	All crimes	Group Crimes
Profile·Post	0.004	-0.002
	(0.004)	(0.003)
Observations	710,975	710,975
Number of individuals	25,619	25,619
Indiv. FE	Y	Y
Year-Quarter 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 arrested in a sweep (potentially profiled) with other individuals perceived as "high crime" prone, before and after the policy change. The observational unit is a individual-quarter pair and only individuals ever committing a group crime were included. Treated individuals are defined as those potentially profiled, while the post period is that after the policy change. 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 A.5: 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.

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"
2017/4, Curto-Grau, M.; Solé-Ollé, A.; Sorribas-Navarro, P.: "Does electoral competition curb party favoritism?"
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"
2017/10, Neisser, C.: "The elasticity of taxable income: A meta-regression analysis"
2017/11, Baker, E.; Bosetti, V.; Salo, A.: "Finding common ground when experts disagree: robust portfolio decision analysis"
2017/12, Murillo, I.P; Raymond, J.L; Calero, J.: "Efficiency in the transformation of schooling into competences: A cross-country analysis using PIAAC data"
2017/13, **Ferrer-Esteban, G.; Mediavilla, M.:** "The more educated, the more engaged? An analysis of social capital and education"
2017/14, Sanchis-Guarner, R.: "Decomposing the impact of immigration on house prices"
2017/15, Schwab, T.; Todtenhaupt, M.: "Spillover from the haven: Cross-border externalities of patent box regimes within multinational firms"
2017/16, Chacón, M.; Jensen, J.: "The institutional determinants of Southern secession"
2017/17, Gancia, G.; Ponzetto, G.A.M.; Ventura, J.: "Globalization and political structure"
2017/18, González-Val, R.: "City size distribution and space"
2017/19, García-Quevedo, J.; Mas-Verdú, F.; Pellegrino, G.: "What firms don't know can hurt them: Overcoming a lack of information on technology"
2017/20, Costa-Campi, M.T.; García-Quevedo, J.: "Why do manufacturing industries invest in energy R&D?"
2017/21, Costa-Campi, M.T.; García-Quevedo, J.; Trujillo-Baute, E.: "Electricity regulation and economic growth"

2018

2018/1, Boadway, R.; Pestieau, P.: "The tenuous case for an annual wealth tax"
2018/2, Garcia-López, M.À.: "All roads lead to Rome ... and to sprawl? Evidence from European cities"
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"
2018/5, Naval, J.; Silva, J. I.; Vázquez-Grenno, J.: "Employment effects of on-the-job human capital acquisition"
2018/6, Agrawal, D. R.; Foremny, D.: "Relocation of the rich: migration in response to top tax rate changes from spanish reforms"
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.; Masera, 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"
2018/12, van den Bergh, J. C.J.M.; Angelsen, A.; Baranzini, A.; Botzen, W.J. W.; Carattini, S.; Drews, S.; Dunlop, T.; Galbraith, E.; Gsottbauer, E.; Howarth, R. B.; Padilla, E.; Roca, J.; Schmidt, R.: "Parallel tracks towards a global treaty on carbon pricing"
2018/13, Ayllón, S.; Nollenberger, N.: "The unequal opportunity for skills acquisition during the Great Recession in Europe"
2018/14, Firmino, J.: "Class composition effects and school welfare: evidence from Portugal using panel data"
2018/15, Durán-Cabré, J. M.; Esteller-Moré, A.; Mas-Montserrat, M.; Salvadori, L.: "La brecha fiscal: estudio y aplicación a los impuestos sobre la riqueza"

2018/16, Montolio, D.; Tur-Prats, A.: "Long-lasting social capital and its impact on economic development: the legacy of the commons"
2018/17, Garcia-López, M. À.; Moreno-Monroy, A. I.: "Income segregation in monocentric and polycentric cities: does urban form really matter?"
2018/18, Di Cosmo, V.; Trujillo-Baute, E.: "From forward to spot prices: producers, retailers and loss averse consumers in electricity markets"
2018/19, Brachowicz Quintanilla, N.; Vall Castelló, J.: "Is changing the minimum legal drinking age an effective policy tool?"
2018/20, Nerea Gómez-Fernández, Mauro Mediavilla: "Do information and communication technologies (ICT) improve educational outcomes? Evidence for Spain in PISA 2015"
2018/21, Montolio, D.; Taberner, P. A.: "Gender differences under test pressure and their impact on academic performance: a quasi-experimental design"
2018/22, Rice, C.; Vall Castelló, J.: "Hit where it hurts – healthcare access and intimate partner violence"
2018/23, Ramos, R.; Sanromá, E.; Simón, H.: "Wage differentials by bargaining regime in Spain (2002-2014). An analysis using matched employer-employee data"

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"
2019/2, Brutti, Z.; Montolio, D.: "Preventing criminal minds: early education access and adult offending behavior"
2019/3, Montalvo, J. G.; Piolatto, A.; Raya, J.: "Transaction-tax evasion in the housing market"
2019/4, Durán-Cabré, J.M.; Esteller-Moré, A.; Mas-Montserrat, M.: "Behavioural responses to the re)introduction of wealth taxes. Evidence from Spain"
2019/5, Garcia-López, M.A.; Jofre-Monseny, J.; Martínez Mazza, R.; Segú, M.: "Do short-term rental platforms affect housing markets? Evidence from Airbnb in Barcelona"
2019/6, Domínguez, M.; Montolio, D.: "Bolstering community ties as a means of reducing crime"
2019/7, García-Quevedo, J.; Massa-Camps, X.: "Why firms invest (or not) in energy efficiency? A review of the econometric evidence"
2019/8, Gómez-Fernández, N.; Mediavilla, M.: "What are the factors that influence the use of ICT in the classroom by teachers? Evidence from a census survey in Madrid"
2019/9, Arribas-Bel, D.; Garcia-López, M.A.; Viladecans-Marsal, E.: "The long-run redistributive power of the net wealth tax"
2019/10, Arribas-Bel, D.; Garcia-López, M.A.; Viladecans-Marsal, E.: "Building(s and) cities: delineating urban areas with a machine learning algorithm"
2019/11, Bordignon, M.; Gamalerio, M.; Slerca, E.; Turati, G.: "Stop invasion! The electoral tipping point in anti-immigrant voting"

2020

2020/01, Daniele, G.; Piolatto, A.; Sas, W.: "Does the winner take it all? Redistributive policies and political extremism"
2020/02, Sanz, C.; Solé-Ollé, A.; Sorribas-Navarro, P.: "Betrayed by the elites: how corruption amplifies the political effects of recessions"
2020/03, Farré, L.; Jofre-Monseny; J., Torrecillas, J.: "Commuting time and the gender gap in labor market participation"
2020/04, Romarri, A.: "Does the internet change attitudes towards immigrants? Evidence from Spain"
2020/05, Magontier, P.: "Does media coverage affect governments'preparation for natural disasters?"
2020/06, McDougal, T.L.; Montolio, D.; Brauer, J.: "Modeling the U.S. firearms market: the effects of civilian stocks, crime, legislation, and armed conflict"
2020/07, Veneri, P.; Comandon, A.; Garcia-López, M.A.; Daams, M.N.: "What do divided cities have in common? An international comparison of income segregation"
2020/08, Piolatto, A.: "'Information doesn't want to be free': informational shocks with anonymous online platforms"
2020/09, Marie, O.; Vall Castello, J.: "If sick-leave becomes more costly, will I go back to work? Could it be too soon?"

2020/10, Montolio, D.; Oliveira, C.: "Law incentives for juvenile recruiting by drug trafficking gangs: empirical evidence from Rio de Janeiro"
2020/11, Garcia-López, M.A.; Pasidis, I.; Viladecans-Marsal, E.: "Congestion in highways when tolls and railroads matter: evidence from European cities"
2020/12, Ferraresi, M.; Mazzanti, M.; Mazzarano, M.; Rizzo, L.; Secomandi, R.: "Political cycles and yardstick competition in the recycling of waste. evidence from Italian provinces"
2020/13, Beigelman, M.; Vall Castelló, J.: "COVID-19 and help-seeking behavior for intimate partner violence victims"
2020/14, Martínez-Mazza, R.: "Mom, Dad: I'm staying" initial labor market conditions, housing markets, and welfare"
2020/15, Agrawal, D.; Foremny, D.; Martínez-Toledano, C.: "*Paraísos fiscales*, wealth taxation, and mobility"
2020/16, Garcia-Pérez, J.I.; Serrano-Alarcón, M.; Vall Castelló, J.: "Long-term unemployment subsidies and middle-age disadvantaged workers' health"

2021

2021/01, Rusteholz, G.; Mediavilla, M.; Pires, L.: "Impact of bullying on academic performance. A case study for the community of Madrid"
2021/02, Amuedo-Dorantes, C.; Rivera-Garrido, N.; Vall Castelló, J.: "Reforming the provision of cross-border medical care evidence from Spain"

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