UNIVERSITAT DE BARCELONA

Essays on Networks and Crime

Magdalena Domínguez Pérez

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A Los más mejores

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Contents

1 Introduction

Crime is a salient problem that affects wellbeing, even if it is not one of its most studied determinants. Back in the 19th century, Marshall stated that economics "examines that part of individual and social action which is most closely connected with the attainment [...] of wellbeing" (Marshall 1890, p.1). On its part, the economics of crime "focuses on the effect of incentives on criminal behavior [...] and the use of a benefit-cost framework to assess alternative strategies to reduce crime" (Freeman 1999, p.3533). Currently, crime is both an important economic activity and a key determinant of a society's welfare. For example, in the European Union, crime remains a threat to society. In 2018, 11.5% of the population reported crime, violence or vandalism in the area where they live[1].

The pioneer model by Becker (1968) sets the ground for the field of economics of crime. It addresses crime as an economic activity, moving aside from postulates linking criminal behavior with mental sanity. In this model, Becker frames crime as a rational act with costs and benefits, concluding that individuals might turn to crime if the latter outweigh the former. After this seminal contribution, a rich strand in the economic literature sought to prove the model's theoretical predictions. An early example is Ehrlich (1973), that shows how deterrence variables are good crime predictors. Since then, research has focused on explaining criminal behavior through individual, regional and macroeconomic determinants. In the following decades, the field has grown significantly. In 1999, 12 papers related to crime and the criminal justice system were published in general interest or top field journals in Economics. Publications rose to 27 in 2009 and 50 in 2019[2]. Through the field's advances, the causal effects of education, labor market, health, criminal justice, policing, and public policies on crime (among others) have been studied (Buonanno 2003). Some of the most notable contributions have been summarized in Di Tella et al. (2010), Cook et al. (2013) and Draca and Machin (2015).

The traditional cost-benefit analysis does not fully explain specific stylized facts about crime. One of them is its geographic concentration. As stated in Glaeser and Sacerdote (1999), crime is much higher in large cities than in other areas. This

[1] EU Statistics of Income and Living Conditions Survey (EU-SILC): https://ec.europa.eu/eurostat/Population-reporting-crime.

[2] Source: Jennifer Doleac's database of published crime-related papers.

pattern is ratified in recent data. In the European Union in 2018, 17.4% of those living in cities perceived there had been crime, violence, or vandalism in the area where they live. For those living in towns and suburbs, only 9.2% reported so[3]. The prevalence of men and the young in crime is another fact not fully explained by traditional cost-benefit analysis (Hough and Mayhew 1983; Freeman 1999). As stated by Levitt and Lochner (2001), individuals aged 15 to 19 years old accounted for over 20% of arrests for violent offenses in the United States but only were 7% of the population.

Social interactions are a missing factor in a traditional cost-benefit analysis that could account for the excess crime in urban areas and the young. Crime participation choices are significantly affected by existing norms and networks close to the individual. Indeed, social interaction models (Sampson 1988; Glaeser et al. 1996; Glaeser and Sacerdote 1999; Glaeser et al. 2002; Calvó-Armengol and Zenou 2004; Calvó-Armengol et al. 2005) outline that individual criminal behavior depends on each one's incentives and on the behavior of its peers. On one side, social interactions can raise aggregate crime levels by providing role models, learning opportunities, information diffusion, or imitation of peer behavior. In this way, a crime "social multiplier" can explain the excess crime in certain circumstances. On another side, social interactions can reduce aggregate crime levels by increasing the opportunity costs of committing a crime, returns on non-criminal activities, detection probabilities, and social sanctions (Sampson 1988; Sampson and Groves 1989; Coleman 1988; Guiso et al. 2011; Flaherty and Brown 2010; Takagi et al. 2012; García-Hombrados 2020). Henceforth, there is no consensus on the empirical correlation between social networks and crime, whether it reflects a causal link and its implications for policy-making.

To correctly account for the effects of social interactions on crime, good data is crucial. Theoretical crime models indicate that many of these determinants occur at the individual level. In contrast, much empirical analysis on the determinants of crime is based on aggregate data. Once again, social interactions are the unaccounted factor: aggregate data seldom reflect them. The most recent contributions to the field have overcome data limitations and provide accurate causal evidence. In many cases, individual data that retrieves social interactions provides estimates of the causal determinants of crime (Bayer et al. 2009; Patacchini and Zenou 2012; Damm and Dustmann 2014; Mastrobuoni 2015; Billings and Schnepel 2020; Mastrobuoni and Rialland 2020; Stuart and Taylor 2021; Ang 2021). In some others, causal effects are pinpointed with small aggregation levels (Freedman and Owens 2016; Acemoglu and Jackson 2017; Sviatschi 2018; García-Hombrados

[3]EU Statistics of Income and Living Conditions Survey (EU-SILC): https://ec.europa.eu/eurostat/Physical-safety-by-degree-of-urbanisation

2020; Blattman et al. 2021). Being able to account for social interactions, local characteristics, and specific events that affect individual involvement in crime has been crucial for the field. The availability of better data, alongside the advances in causal inference in the last decade, allows for significant advances.

In terms of policy, there is still considerable debate over the approaches to follow for crime prevention. On one side, starting in the 1970s, safety policies followed a "tough-on-crime" approach. Starting in the United States and spreading worldwide, these include police search and seizure, strict criminal codes, and severe sentences. The economics literature has emphasized the potential deterrence capacity of police actions and the justice system (Becker 1968; Ehrlich 1973; Levitt 1997; Di Tella and Schargrodsky 2004; Machin and Marie 2011; Bindler and Hjalmarsson 2021). In this line, sanctions have toughened for criminal organizations and larger efforts to dismantle them have been deployed (Mansour et al. 2006; Sweeten et al. 2013; Lessing 2016). Notwithstanding, research has shown that, in many scenarios, tough policies can be expensive, ineffective, and discriminatory (Lynch 1997; Kovandzic et al. 2004; Arora 2018). As stated in Owens (2020), in recent years, research has made significant advances towards identifying the extent to which greater police efforts lead to larger crime reductions. Still, the author also outlines the need for better empirical evidence on the costs and benefits of law enforcement to identify socially optimal policing.

As an alternative to policing, another set of strategies to prevent crime focuses on reducing crime-triggering disparities (Crowley 2013; Lawless et al. 2010). So-called "soft" approaches are of importance in deprived areas, where social interventions are most needed, and strong police presence may be disruptive (Geller et al. 2014; Brayne 2014). Crowley (2013) states that policymakers wishing to install effective and efficient developmental crime programs should invest in interventions that deliver prevention programs as well as engage innovative mechanisms for investing in crime prevention efforts. For example, Machin et al. (2011) show that improving education can be a crucial policy tool to reduce crime. Although these "soft" interventions are usually less expensive, outcomes unfold over longer timeframes, and interdisciplinary approaches are greatly needed as new societal agents play a crucial role. As Owens (2019) explains, acknowledging both the costs and benefits of aggressive policing is a first step to identifying policies that provide social benefits with minimal social costs. Questions remain on the implementation of the approaches mentioned above and if they can serve different purposes.

Meanwhile, crime prevention has become a substantial economic activity worldwide. In 2018, government expenditure for public order and safety was 1.7% of the Gross Domestic Product (GDP) in the European Union and 2.0% in the United

States[4]. Regarding its composition, data for the European Union shows that 53% of total expenditure was spent on police services, 18% on law courts, and 24% of GDP on fire protection services and prisons. For most OECD countries, these values have remained stable over the last decade, in line with recent global crime trends.

This Ph.D. dissertation provides new research on the role of networks on criminal outcomes in an urban context. While doing so, it sheds light on the functioning of traditional and non-traditional preventive policies. The final goal is to improve the understanding of criminal drivers, how different networks deter or encourage them, and how they interact with socioeconomic factors. With these considerations, Chapter 2 studies the effects on crime of a non-traditional public policy that bolsters community ties. Thus, it deals with the role of social networks. Chapter 3 analyzes the impact of a tough-on-crime policy on the criminal outcomes of the arrested individuals and their peers. Henceforth, it focuses on the role of criminal networks. Chapter 4 examines gangs' territorial influence and crime composition. In this way, it analyzes social networks in the context of solid criminal networks. Outcomes of this dissertation contribute to academic research and offer guidance for policy-making to deter crime.

Throughout the dissertation, the empirical analysis focuses on the Metropolitan Area of Barcelona (MAB). The MAB comprises 4 million inhabitants and is the fifth largest and the densest metropolitan area in Europe. It is also one of the European metropolitan areas with the highest crime rates[5]. According to Eurostat, in 2010, Barcelona placed second in thefts (10,166, behind Berlin), second in robberies (22,250, behind Paris), third in intentional homicides (56, behind Paris and Berlin) and fourth in burglaries (13,529, behind Paris, Copenhagen and Amsterdam) across European cities[6]. Moreover, data from the victimization survey of Barcelona registers some worrisome trends[7]. On one side, the global victimization index rose. Concretely, the share of individuals declaring being a victim of a crime increased from 23.3% in 2015 to 30.9% in 2019. Secondly, the global reporting index fell. Data indicates that the share of individuals reporting a crime to the police decreased from 21.5% in 2015 to 19.5% in 2019. Lastly, the city security perception dropped from 6.2 (over a possible score of 10) in 2016 to 5.2 in 2020. However, there were no changes in Local Police services perception, stable at 6.8 (over a possible score of 10). Similarly, the barometer of Barcelona City Hall[8] shows that among non-economic concerns, citizens saw insecurity as the most concerning one. From these

[4]https://ec.europa.eu/eurostat/expenditure-on-public-order-and-safety
https://data.oecd.org/gga/general-government-spending

[5]https://ec.europa.eu/eurostat/databrowser/view/met_crim_gen/

[6]Last available year.

[7]https://www.bcn.cat/estadistica/castella/dades/anuari/Anuari2020.pdf

[8]https://ajuntament.barcelona.cat/Barometre

stylized facts, it is clear that crime is a pressing issue in the Metropolitan Area of Barcelona.

For this dissertation, I was granted access to a restricted administrative dataset. This dataset accounts for all criminal registries in the MAB for the 2008-2014 period and is provided by the Local Police (*Mossos d'Esquadra*). Registries include information on the crime that occurred, with exact information on the date, time, place (geocoded), and type of crime. This dataset accounts for registries on one million reported crimes. Over 300 types of crime are recorded, covering more than 190 articles of the Spanish Penal Code. Moreover, when identified, there is information on the offender and the victim of the crime and their basic demographic characteristics (date of birth, country of birth, and gender). This unique dataset, alongside new criminal theories and cutting-edge statistical methods, allows me to perform a causal analysis on criminal outcomes in an urban context.

Chapter 2, titled *"Bolstering community ties as a means of reducing crime"*[9], analyzes how non-traditional policies can deter crime. Concretely, this chapter studies the impact of community ties on crime in an urban context. Existing literature emphasizes that more tightly knit social networks can raise aggregate crime levels (Calvó-Armengol and Zenou 2004; Glaeser et al. 1996; Calvó-Armengol et al. 2005), yet they can also increase the opportunity cost of committing a crime (Guiso et al. 2011; Coleman 1988; Flaherty and Brown 2010; Cozens 2008; Lawless 2006). On this matter, community-based interventions can play a crucial role, particularly in deprived areas. The Local Government Association of the United Kingdom (LGA) defines community action as "any activity that increases the understanding, engagement, and empowerment of communities in the design and delivery of local services" (Local Government Association 2016). This chapter argues that initiatives that bolster community ties in disadvantaged neighborhoods can reduce local crime rates, especially for crimes not driven by a monetary incentive. I test this hypothesis by analyzing a community health policy (*Barcelona Salut als Barris*, (BSaB)) deployed in a quasi-random way in the city of Barcelona. The program aimed to improve health outcomes and reduce inequality between the disadvantaged neighborhoods and the rest of the city. BSaB is implemented through community-based interventions, and it is managed in each neighborhood by the local health center alongside a community group. Due to the high degree of involvement that BSaB requires from neighbors, I expect the building of closer links within the neighborhood.

To evaluate the impact of BSaB on local crime, I adopt a staggered difference-in-differences approach. I quantify BSaB's impact on crime as the difference be-

[9] Coauthored with Daniel Montolio.

fore and after its implementation in neighborhoods where it took place versus those where it did not but were eligible. Estimates are intention-to-treat coefficients, as the take-up rate is unknown inside each neighborhood. Regarding data, I use administrative police records provided by the Local Police, enriched with sociodemographic controls. A key identification trait is that the gradual roll-out of BSaB in the territory did not follow any specific pattern concerning socioeconomic or demographic characteristics. This roll-out allows it to be regarded as a quasi-random experiment. Another critical factor in the policy roll-out is that these interventions were mainly managed in each neighborhood by the local health center. Because each local health center has a specific area and population under its responsibility that the administration sets, the outlined identification strategy strengthens as spillovers from one neighborhood to another are highly unlikely.

Results indicate a negative and significant impact of BSaB on local crime rates. Even if there is no general decrease in crime after the policy's implementation, there are significant reductions in key aspects in light of BSaB. Specifically, I find that it reduces crimes against the person and those with a very close personal link between offender and victim, which I label as intimate crimes. I also find a reduction in drug crimes one year after the policy's implementation. Finally, the safety and victim survey for Catalonia indicates that the presence of BSaB raises the probability of perceiving an improvement in safety by approximately 3%.

Regarding the underlying mechanisms, evidence suggests that the effects are linked as hypothesized to a more robust social fabric. While no effect is found on health or labor-market outcomes, a Bacon decomposition shows no heterogeneity in outcomes due to different program contents. This result supports the statement that the policy's content is less relevant than connecting people.

This chapter's contribution is multiple. Firstly, I answer a crucial question adding to the limited existing causal evidence on the effects of local social ties on crime (Akçomak and Ter Weel 2012; Damm and Dustmann 2014; García-Hombrados 2020). Secondly, I use a highly detailed database with information on victims, offenders, and crime typologies. These features allow for a fine grained analysis in terms of crime typologies and those individuals involved. Finally, this work offers specific guidance for policy-making to deter criminal activity, moving beyond traditional approaches (Buonanno et al. 2009; Machin et al. 2011; Takagi et al. 2012).

Chapter 3, titled *"Sweeping up gangs: The effect of tough-on-crime policies from a network approach"*, examines the effect of a tough-on-crime policy from a network approach. Concretely, this chapter studies the impact of police sweeps against gangs and their peers. Among criminal groups, gangs raise concerns for recruiting vulnerable young individuals, their high degree of involvement, and low prospects for reinsertion into society. Concerning gangs, sweeps have been the most common strategy worldwide. However, little is known about how they work. For a better understanding, it is crucial to understand the network structure of the gangs.

This chapter studies whether sweeps are successful at reducing crimes of arrested gang members and their peers, and if a network analysis can improve sweep design. The Metropolitan Area of Barcelona is an appealing setting to study because latin gangs rapidly unfolded between 2000 and 2010. Consequently, there was a drastic policy change towards a stricter approach. In 2012, the public strategy transformation involved creating a gang-specialized police unit (UGOV) focused solely on criminal investigation and performing sweeps against gangs. Additionally, the judiciary system implemented a 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 once again use the administrative police records provided by the Local Police for the Metropolitan Area of Barcelona. I exploit the level of detail of the data in two ways. Firstly, a unique identification number allows me to follow individuals over time and map out their criminal careers. Secondly, by matching information on the exact date, hour, place, and type of crime, I retrieve criminal network structures. I match these records with confidential information on the sweeps provided by the gang-specialized police unit (UGOV). To identify the causal effects of the policy change on crime, I implement a staggered difference-in-differences strategy. I also take advantage of the retrieved network structure to estimate peer effects and identify key players inside each gang. Finally, I conduct a counterfactual policy exercise in which I compare the variation in crime caused by the sweeps with the theoretical prediction of a policy that removes the key players.

Results indicate significant reductions in the criminal activity of those arrested in the sweeps and of their peers. There is an average reduction in criminal activity of 96% for arrested offenders, which is immediate, persistent, and consistent with the incapacitation of these individuals. For peers, there is a significant reduction in criminal activity of 26%. In such a case, the effect fades out within a year of the police sweep. The evidence also suggests that the drop in peers' crime would be related to a deterrence effect rather than a caution effect. Finally, results of this counterfactual policy exercise indicate that all sweeps arrested the key player (Ballester et al. 2006; Ballester and Zenou 2014; Lindquist and Zenou 2014; Lee et al. 2020). However, if the sweeps had arrested a key group in the gang, the predicted crime reduction would have been 50% higher. The results of this study clearly show that identifying and tackling a group of key players in each gang can lead to substantial improvements in police interventions.

This chapter contributes to the research on criminal networks in several ways.

Firstly, it provides a picture of the network structure of gangs at a small geographical level (e.g., Lessing 2016; Blattman et al. 2021), a task seldom perform due to data availability. Second, it gives new estimates of spillover and peer effects on criminal activities (Kling et al. 2005; Bayer et al. 2009; Damm and Dustmann 2014; Lindquist and Zenou 2014; Corno 2017; Philippe 2017; Billings and Schnepel 2020; Bhuller et al. 2018; Lee et al. 2020; Mastrobuoni and Rialland 2020). In this regard, it extends the research of peer effects on crime to the context of gang crime. Moreover, it is one of the first attempts to apply a key player analysis to real and worrisome criminal groups. It also contributes by testing main theoretical predictions on this subject that had yet not been proved empirically. Thirdly, it contributes to the public agenda by comparing crime-fighting strategies (Lindquist and Zenou 2019). Specifically, this chapter speaks on how to improve the effectiveness of policy design considering well-established theoretical benchmarks.

Chapter 4, titled *"Behind closed doors: Crime composition in gang territory"*[10], studies crime patterns and gang presence in an urban setting. Criminal organizations and their presence carry acute adverse effects on welfare for many societal agents. Gangs are particularly worrisome as they primarily affect youngsters at risk of social exclusion or with low prospects. Still, their impact goes beyond their members: it affects family and friends, as well as the neighbors of their area of influence. This influence is due to their functional structure, in which territory is an important part. It is also important to highlight that gang crime differs from overall crime. This pattern relates to the fact that the two phenomena stem from different drivers. However, despite having documented these different criminal patterns for gang and non-gang crime, economics literature has not devoted much effort to analyze non-gang crime in gang-controlled controlled areas.

In this chapter, I study gangs' presence and influence in an urban area in a developed country at a small geographical level. I analyze whether there is a tipping point in gang presence that affects criminal patterns, and I test for discontinuities in crime levels and composition. To answer the questions above, I exploit the already explained detailed dataset built from Local Police administrative records for the 2008–2014 period. I make use of the information related to the registered crimes, as well as data on offenders and victims. Moreover, based on Chapter 3 and the gang-specialized police unit (UGOV) information, I link offenders to their status on gang membership. To quantify gang intensity in the territory, I construct a Getis-Ord G_i^* statistic, a local statistic that measures spatial association. I explore whether once gang presence exceeds a tipping point linked to spatial support, there are discontinuities in crime patterns as in Card et al. (2008).

[10]Coauthored with Daniel Montolio.

Results indicate that the number of crimes is not significantly different across the gang boundary. Nonetheless, there are significant differences in its composition. Across the gang boundary, evidence indicates a higher share of crimes against the person in detriment of crimes against property. Additionally, there is also a higher share of male offenders to female victims. Even if there is no significant change in the number of crimes, these changes in composition towards more severe crimes carry meaningful welfare implications. A brief exploration of mechanisms would suggest that results are driven by territorial control, under-reporting, and gender role models.

The contribution of this chapter is threefold. Firstly, I identify gangs' areas of influence at a very small geographical level (Kennedy et al. 1996; Lessing 2016; Blattman et al. 2021). Secondly, I assess the impact of organized crime on welfare (Grogger 2002; Pinotti 2015; Dell et al. 2019; Dell 2015; Bruhn 2019; Melnikov et al. 2020; Melnikov et al. 2020; Owens et al. 2021). On this matter, I document the importance of gangs beyond their crimes to state their rowdiness. Finally, I explore mechanisms beyond territorial control as a cause of their effect: I study the role of gender roles in gangs and their social surroundings (Miller 1998; Miller and Decker 2001; Trickett 2016).

Finally, Chapter 5 provides concluding remarks. Firstly, it summarizes the main results of the previous chapters. It then discusses the policy implications of this dissertation's findings. Finally, it briefly outlines future lines of research.

2 Bolstering community ties as a means of reducing crime[1]

2.1 Introduction

Urban economics has studied numerous differences between and within cities, among which growth and inequality have occupied the most attention. However, as pointed out by Glaeser et al. (1996) and Glaeser and Sacerdote (1999), the proliferation of contrasts related to crime is also striking, and their findings are of particular relevance to both individual and overall welfare. The existing literature suggests that individual choices concerning participation in crime may be significantly affected by existing norms and networks (Glaeser et al. 1996; Patacchini and Zenou 2012).

Recent work emphasizes that more tightly knit social networks can raise aggregate crime levels due to the sharing of know-how among criminals (Calvó-Armengol and Zenou 2004) or imitation of peer behavior (Glaeser et al. 1996; Calvó-Armengol et al. 2005). However, they also increase the opportunity cost of committing a crime. Such a possibility is closely related to the concept of social capital, defined by Guiso et al. (2011) as a set of values and beliefs that help cooperation within a community. Indeed, Coleman (1988) already related the strength of social sanction to social network closure. Additionally, systemic models of community organization are built on the notion that well-developed local network structures reduce crime (Flaherty and Brown 2010). This reduction is related to the fact that networks may increase returns on non-criminal activities and raise detection probabilities. On this matter, community-based interventions and initiatives can place a crucial role, particularly in deprived areas.

This research deals with the impact of community ties on crime in an urban context, a line of research that is highly relevant to the economics of crime. The ultimate goal is to understand better the empirical determinants of criminal activity, how social networks deter or encourage them, and how they interact with socioeconomic factors. Concretely, in this chapter I argue that initiatives that bolster community

[1] Research coauthored with Daniel Montolio.

ties in disadvantaged neighborhoods can succeed at reducing local crime rates, especially for crimes that are not driven by a monetary incentive. I test this hypothesis by analyzing a community health policy implemented in a quasi-random fashion in Barcelona city. *Barcelona Salut als Barris* (BSaB), meaning "Health in the Neighborhoods", was deployed in some of the city's most disadvantaged neighborhoods to reduce local disparities. It was run by the local health center with local social agents and the community itself. To analyze it, I apply a staggered difference-in-differences methodology combined with a battery of socioeconomic controls and time and space fixed effects. Regarding data, I use a unique geocoded criminal offense dataset from the Local Police which is enriched with Barcelona City Hall sociodemographic controls.

Estimates suggest that the observed reduction in criminal actions can be attributed to the implementation of BSaB. Specifically, I find that the offense rates for young individuals drop in neighborhoods that benefit from BSaB. The policy also reduces crimes against the person and those with a very close personal link between offender and victim, which I label as intimate crimes. The reduction is close to 25% and only occurs in the short term. I also find a reduction in drug crimes one year after the policy is implemented. Finally, evidence is suggestive that results are not due to health or unemployment improvements in the participating neighborhoods. Instead, it indicates that the effects are linked to a more robust social fabric. This result is supported by an increase in the number of per capita associations.

The novelties of this research reside in many factors: (1) The policy deployment provides a conditionally exogenous variation in the drivers of community ties at a small geographical level, which allows me to determine causal links. In this way, I answer a crucial question adding to the existing causal evidence on the effects of social ties on crime. (2) This research uses a geocoded and highly detailed database that includes registered victims, offenders, and crime typologies. Added to socioeconomic variables, I assemble detailed data on local crime and other characteristics within Barcelona city. This data adds to the analysis' accuracy and richness as I can carry out several heterogeneity exercises. (3) This work contributes to research conducted outside the United States and considers a city whose residents are heterogeneous in terms of economic and demographic characteristics. Together, these features constitute the external validity of my exercise. Findings contribute to academic research and offer specific guidance for policy-making to deter criminal activity, moving beyond traditional approaches. (4) This case study benefits other cities, given that the policy recommendations that emerge apply to similar urban settings.

The rest of the chapter is organized as follows. In Section 2, I analyze the link between community capital and crime. Section 3 describes the institutional framework of the initiative I analyze. Then in Section 4, I present the data I use, and I define my main variables. Section 5 lays out the methodology I follow as well as my empirical model. After presenting my main results in Section 6, in Section 7, I provide conclusions and policy recommendations.

2.2 Brief review on community ties and public interventions

Crime and social interactions have been extensively studied in economics. In their seminal paper on the subject, Glaeser et al. (1996) (and also Glaeser et al. 2002) detect a large number of social interactions in criminal behavior. The authors present a model in which social interactions explain the high cross-city variation in crime rates in the United States. Additionally, their model provides an index of social interactions, namely the proportion of potential criminals who respond to social influences. The index suggests that the number of social interactions is highest in petty crimes, moderate in more serious crimes, and almost negligible in murder and rape.

Crime economics is a field in which there is room for interdisciplinary contributions. There are different approaches towards crime prevention in such a framework, and measures to fight crime can broadly be split into either "hard" or "soft" policies. While the first one advocates for heavy policing and sturdy prosecuting measures, the second focuses on reducing crime-triggering disparities. In that respect, contributions to the literature have shown that in many circumstances, "tough-on-crime" measures can lead to a worsening of the initial situation and imposing a high cost to society, both in monetary and welfare terms. As an alternative, innovative strategies to prevent crime have been carried out, in which new societal agents play a crucial role. Lewis and Salem (1981) indicate that programs with a social control perspective strengthen the local community's capacity to exert social control. Cozens (2008) argues that crime prevention through environmental design has potential benefits for public health and in delivering safer environments. That last set of strategies is of particular importance in deprived areas, as social interventions are most needed, and a strong police presence may have a disruptive effect. Crowley (2013) states that policymakers wishing to install effective and efficient developmental crime programs should invest in interventions that deliver prevention programs as well as engage innovative mechanisms for investing in crime prevention efforts. Lawless (2006) analyzes The New Deal for Communities program, an English area-based initiative that aims to transform deprived neighborhoods. While outcomes indicate modest changes against benchmarks, the author concludes that working with other agencies helps change, and having the community at the heart of the initiative enhances outcomes. Machin et al. (2011) analyze a law that changed the compulsory school leaving age in England and Wales and show significant decreases in property crime. In this way, the authors find that improving education can enhance social benefits and reduce crime.

Meanwhile, there has been extensive debate in the literature regarding social capital: what it is and how to measure it. Putnam et al. (1994) set the stage for such considerations when analyzing the effects of social engagement. Since then, social capital has been defined and measured in several different ways. Jackson (2019) considers seven forms of social capital. The author defines community capital as "the ability within a community to sustain cooperative behavior in transacting, the running of institutions, the provision of public goods, the handling of commons and externalities, or collective action". This last definition is the one that serves as a reference for this chapter.

Most certainly is the case that community capital can play an important role in many economic spheres. The economics of crime is a significant one. On this, a number of papers focus on social capital as a driver of crime at the local geographical level, as Hirschfield and Bowers (1997), Lederman et al. (2002), Buonanno et al. (2009) and Akçomak and Ter Weel (2012). However, the results do not present clear conclusions. While Buonanno et al. (2009) find that associational networks have a negative and significant effect on property crimes, Lederman et al. (2002) state that trust has a significant and negative effect on violent crime rates, and Akçomak and Ter Weel (2012) find a negative correlation between social capital and crime rates. Importantly, Hirschfield and Bowers (1997) state that there is a significant relationship between social cohesion and crime levels in disadvantaged areas.

More recently, and regarding the causal impact of social capital on crime, Damm and Dustmann (2014) state that social interactions are an important channel through which neighborhood crime affects individual criminal behavior, particularly in violent crimes for young males. Additionally, Sharkey et al. (2017) incorporate the so-called systemic model of community life[2] and estimate the causal effect on violent

[2]Sociologists also have devoted efforts to understanding the link between social capital and crime rates. These rely on social disorganization theory and systemic models of community attachment. Social disorganization is defined as the inability of a community structure to realize the shared values of its residents and maintain adequate social controls (Sampson 1988; Sampson and Groves 1989). This theory has recently been linked to the concept of social capital, defined as those features of social organization (networks, norms of reciprocity, and trust) that facilitate cooperation between citizens for mutual benefit. The systemic model of community attachment (Flaherty and Brown 2010) emphasizes the effect of community structural characteristics on neighborhood friendship and associational ties and their effect on informal social control and crime levels. The systemic model hypothesis is that more extensive social ties decrease crime rates since communities with more comprehensive friendship and associational ties have more significant potential for infor-

crime of non-profits focused on reducing violence and building stronger communities. The authors estimate that a higher presence of organizations focusing on crime and community life achieves significant reductions in violent and property crime. On its part, García-Hombrados (2020) investigates the 2010 earthquake in Chile and finds that it had a positive effect on community life's strength and ultimately led to a decrease in crime in the affected neighborhoods. The author presents robust estimates consistent with an informal guardianship mechanism reported after natural disasters. The improvement in social capital at the community level facilitated cooperation among neighbors and boosted the adoption of community-based measures to prevent crime. Regarding other initiatives, Gonzalez and Komisarow (2020) study the effect of community-based monitoring on crime in the context of a school safety initiative, finding that overall crime drops by 17% relative to non-treated blocks.

2.3 Institutional Setup: Barcelona Salut als Barris

In the framework of public policy analysis, the community component plays an important role. On this matter, the Local Government Association of the United Kingdom (LGA) defines community action as "any activity that increases the understanding, engagement, and empowerment of communities in the design and delivery of local services" (Local Government Association 2016). Even though the activities may differ, greater engagement of local citizens is vital in the planning, designing, and delivering of local services. According to the LGA, such action can help build a community and social capacity by creating social networks. Among its many benefits, improving community cohesion and safety are mentioned.

Moreover, Barcelona City Hall defines community action as "a process of stimulating cooperative social relationships between members of a community, a human collective that shares space and a sense of belonging that results in reciprocal links and support, and that motivates members to become central agents in the improvement of their own reality" (Ajuntament de Barcelona 2005). Therefore, the objective of community action is to improve social well-being by promoting active participation. Community action requires the empowerment of citizens to drive

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mal social control due to social cohesion. Regarding empirical contributions, Warner and Rountree (1997) analyze the role of local social ties in mediating between structural conditions and crime rates and find that the extent to which friendship networks decrease crime depends in part on the racial makeup of the neighborhood. Kawachi et al. (1999) argue that two sets of societal characteristics influence the level of crime: the relative degree of deprivation and the degree of cohesion in citizens' social relations. Takagi et al. (2012) find that generalized trust, reciprocity, supportive networks, and social capital within a neighborhood were inversely associated with the probability of becoming a victim of crime.

change and improvements beyond their spheres.

In 2005, local health authorities in the city of Barcelona (Barcelona Public Health Agency (ASPB)[3] and Barcelona Healthcare Consortium (CSB)), jointly with different actors from the ten districts of the city, started developing the community health program called "Health in the Neighborhoods" (*Barcelona Salut als Barris*, BSaB). The program aimed to improve health outcomes and reduce inequality between the disadvantaged neighborhoods and the rest of the city. The program developed uninterrupted since 2008[4]. BSaB is implemented through community-based interventions, and it targets neighborhoods where income is below 90% of the city median.

Local authorities have already performed some analysis of BSaB. While Díez et al. (2012) describe the experience, achievements, lessons, and challenges of the implementation of BSaB, Sánchez-Ledesma et al. (2018) characterize the BSaB prioritization procedure. These last authors state that the community perspective of health stimulates and empowers the community, encourages mutual support, and promotes their importance by making them responsible for improving their reality. Additionally, Barbieri et al. (2018) state the need to identify key indicators for measuring and characterizing community action for health and they devise an index for such tasks. However, this literature on BSaB primarily provides a descriptive analysis, and causal analysis is yet to be undertaken.

2.3.1 Description of the program

BSaB was deployed between 2008 and 2014 in 12 of the 49 neighborhoods potentially participating, out of the 73 in Barcelona city. Those 49 potentially included were those considered deprived, in which average income was below 90% of the city median[5]. Those 12 neighborhoods finally included in BSaB represent 15% of the city population and 25% of the potentially participating population[6]. A key feature is that the progressive roll-out of BSaB in the territory did not follow any specific pattern concerning socioeconomic or demographic characteristics. This feature al-

[3] All acronyms come from the original name in Catalan.

[4] The program kept running even though there were changes in the party in power, both at the local and city level. In 2005, the center-left Socialist Party was in power both in Catalonia (Local Government) and in Barcelona (Barcelona City Hall). It was ousted by the center-right *Convergència i Unió* coalition from both in 2010 and 2011 respectively. Since 2015, Barcelona City Hall is run by *Barcelona en Comú*, a left-leaning party.

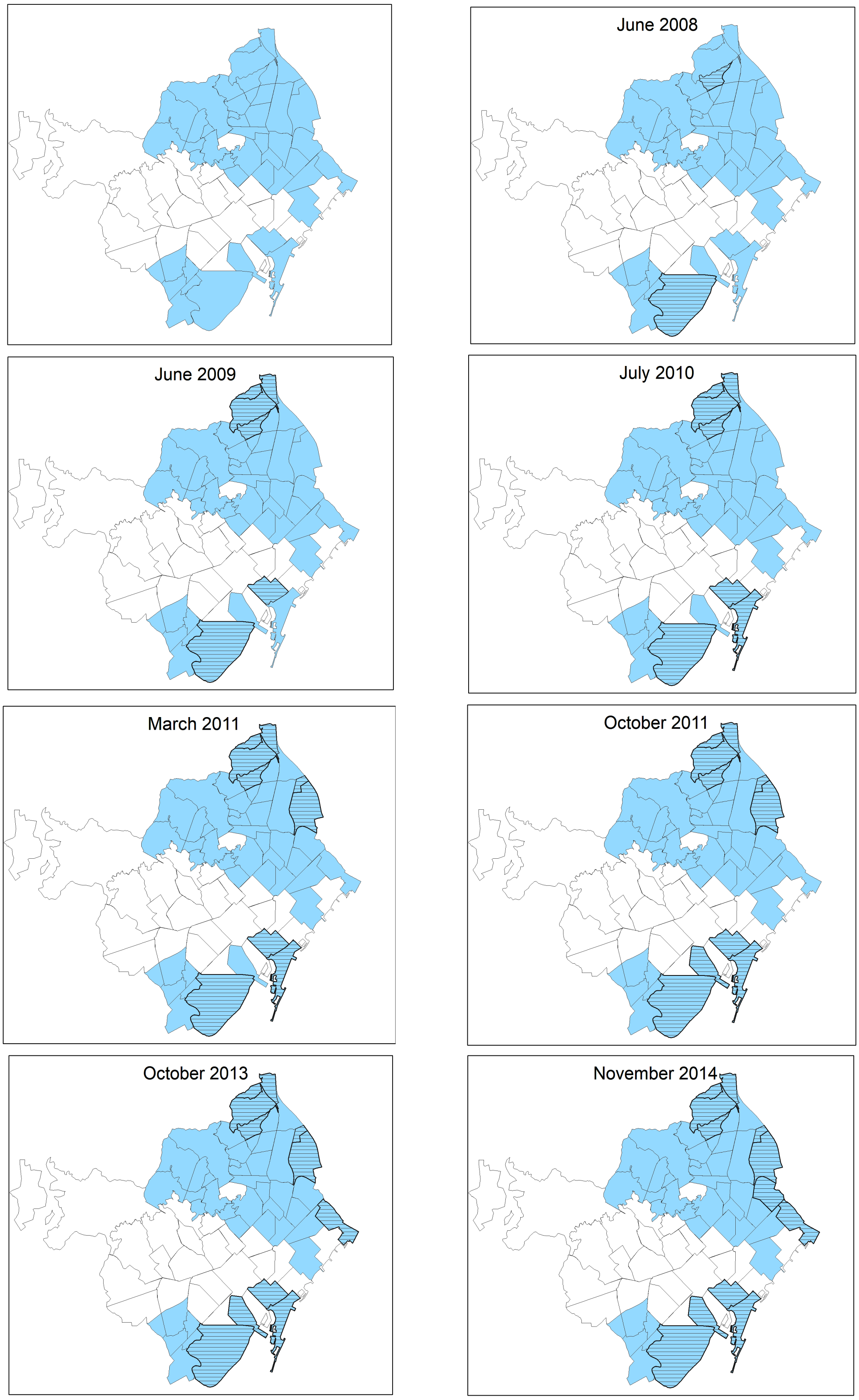
[5] Neighborhoods receiving BSaB would also be "deprived" in terms of social ties. See Table A2.3 in Appendix for correlation matrix between social ties (proxied by local associations) and socioeconomic indicators (income, unemployment, house prices, and other social conditions).

[6] See Table A2.1 in Appendix for population and income data of all neighborhoods in 2007 and 2014.

lows it to be regarded as a quasi-random experiment[7]. The deployment and timing of BSaB are shown in Figure 2.1 and Table A2.2 of the Appendix.

[7]The quasi-random deployment of BSaB was confirmed by the public authorities running the program. Importantly, they reported that crime levels were not considered when deciding BSaB implementation and deployment. This pattern is statistically assessed in later sections.

Figure 2.1: Deployment of BSaB interventions in the city of Barcelona.



Notes: The colored neighborhoods are those that were potentially included in BSaB due to their income characteristics (49 neighborhoods). Those that in addition have hatching were those that actually participated (12 neighborhoods by 2014).

As explained in Díez et al. (2012), in the implementation of BSaB, plurality, participation, sustainability, evidence, and evaluation were applied in the following phases:

1. Establishment of political alliances and a steering group to facilitate interventions (3 months, pre-intervention).
2. Construct qualitative and quantitative community knowledge to list perceived problems (1 to 3 months, pre-intervention).
3. Prioritization of problems and interventions by the local community and authorities (1 day, pre-intervention).
4. Drawing up of an intervention plan for previously defined lines of action. Intervention starts.
5. Evaluation of implementing the overall plan and each intervention (1 to 3 years, post-intervention).
6. Maintenance of the working group on health, after the intensive phase (3 to 4 years, post-intervention).

The interventions intended to facilitate non-competitive physical activity, social relationships, healthy recreation, health literacy, and sexual health. Interventions included attention to the use of addictive substances, training and job placement, sexual and reproductive health advice, parenting skills programs, mental healthcare, and healthy leisure workshops (Díez et al. 2012; Generalitat de Catalunya 2014; Comissionat de Salut 2016)[8]. However, each neighborhood had a unique combination of interventions, making a heterogeneous analysis by intervention type unfeasible.

For example, in the neighborhood of *Ciutat Meridiana*, one of the activities was named "Alternative Fridays". Targeted at adolescents aged 14-18, it aimed to provide healthy leisure activities. In its first edition, over 200 individuals participated, of whom 73% were men and around 60% were foreigners. In satisfaction surveys, respondents were very satisfied, and a quarter of participants stated that the activities should be more frequent. Another example is the "Syrian" program at *Bon Pastor* neighborhood. This program aimed to increase awareness of contraception, reproductive health, and public services available in the neighborhood, especially for the immigrant population. The program reached 745 individuals, and according to a survey of participants, satisfaction was very high (median of 9/10).

Another key factor in the policy roll-out is that these interventions were mainly managed and run in each neighborhood by the local health center (CAP) alongside a community group that included civic entities, community associations, and social

[8] See Table A2.4 in the Appendix for a complete list of activities run in the framework of BSaB.

workers. There are 70 local health centers citywide, and most of them exclusively relate to a neighborhood[9]. Each CAP has a specific area and population under its responsibility that the administration sets. Hence, spillovers from one neighborhood to another are highly unlikely[10]. Importantly, all of these interventions were run from the beginning under a community perspective, involving the steering group, the local community, and the authorities. This communal component of BSaB leads me to hypothesize that BSaB boosted community ties and through it, reduced local crime rates.

2.3.2 Potential mechanisms: the community component

Theoretically, the BSaB policy may affect criminal activity via different pathways. Initially, the most obvious may be the health channel, by which the improved health status of the affected population reduces criminal activity. In these lines, Bondurant et al. (2018) estimate the effects of expanding access to substance-abuse treatment on local crime for United States counties. They indeed find that it reduces violent and financially motivated crimes in a specific area, but not immediately.

However, due to the characteristics of BSaB, I argue and later show that improvements in health are not the primary outcome driver. Instead, I claim that a mechanism of community ties operates[11]. As previously mentioned, a body of research documents the association between community capital and becoming a victim of crime. The theoretical pathways via which community capital leads to crime prevention include both formal and informal mechanisms. Sampson and Laub (1995) state that communities with substantial social capital can exert informal social control and bolster the capacity to obtain services from public agencies and formal institutions. Due to the high degree of involvement that BSaB requires from neighbors, it is expected that closer links are built up within the neighborhood. As a result, informal social control may also arise, increasing the probability of being arrested, potentially leading to a fall in the area's crime rate. Following Putnam et al. (1994), Buonanno et al. (2009) and Guiso et al. (2011) among others, I use the number of associations per capita at the neighborhood level as a measure of community ties.

Several findings can help disentangle the underlying mechanisms in this setting.

[9] Every resident in Barcelona is assigned to a CAP according to their home address. In a sense, their area of influence (called the basic health area) can be seen as that of a school district in the United States. Basic health areas coincide to a large degree with neighborhoods.

[10] This was also confirmed by the authorities running the BSaB program.

[11] I also test as a possible mechanism whether the program improved local labor perspectives by analyzing if unemployment figures are significantly affected in treated areas as opposed to non-treated areas. Results are shown in the following sections.

Firstly, I estimate the timing of the effects in criminal activity through an event study exercise. I claim that if the response of the crime rate to the policy is relatively fast, it is harder to attribute the reaction to the population's improved health. If health is the mechanism behind the effects of BSaB on crime, the results would take some time to materialize, as in Bondurant et al. (2018). Secondly, I assess if BSaB impacts per capita local associations, my proxy for community ties. Thirdly, I examine whether there have been changes in the health status of individuals in participant and non-participant neighborhoods. Additionally, I analyze if there have been changes in registered unemployment, as some of the activities had such objectives and thus can affect engagement in criminal behavior.

Consequently, if I observe (1) a change in crime rates within a short interval of time after policy implementation, (2) a significant predictive power of the BSaB policy onto local associations, and (3) if no effect is found nor in health nor unemployment, potential impacts on crime are likely to be due to the community feature of the policy and stronger community ties. Moreover, if I find that the effects are homogeneous across neighborhoods, irrespective of the content or priorities set, the hypothesis that community ties lead the result is even more relevant.

2.4 Data

The primary data source in this chapter is a geocoded administrative dataset of all registered crimes in Barcelona from 2007 to 2014. This data is provided by the Local Police. It comprises all registered crimes with information on the exact time and place of the crime and crime type. In total, it contains over one million entries. Such detail allows me to estimate the effects of BSaB at a relatively high time-frequency (such as a month) and a low geographical level (such as a neighborhood) while maintaining the results' robustness. Moreover, the data provides information on the offenders and victims, when available. As BSaB is aimed at specific populations through different interventions, it is possible to evaluate whether the targeted groups are more or less likely to become offenders or victims of a crime.

Additional data sources come from the Catalan Health Department (ICS) and the Public Policy and Government Institute (IGOP), a research group at the Autonomous University of Barcelona (UAB; Barbieri et al. 2018). These data sources provide information on the neighborhoods potentially targeted, those treated, the policy's timing in each neighborhood, and details of the activities in each intervention. This information allows me to understand the setting in detail, build my primary explanatory variable, and justify the policy's roll-out quasi-random nature.

I also account for a set of socioeconomic variables that enrich my main analysis.

First of all, I have information on the registered local associations (registration date and aims), which allows me to understand the associations' relevance, my proxy for community ties. The Local Government provided this information. Moreover, and related to business cycles, I have information on registered unemployment rates, and housing prices per square meter[12]. Finally, I also account for a proxy for touristic pressure[13]. This last variable accounts for potential confounders resulting from the related economic activity, which is of great relevance in a city highly exposed to such inflows. These last three variables (registered unemployment, housing prices, and tourism pressure) are built from information provided by Barcelona City Hall. While local associations, housing prices, and registered unemployment are considered at the neighborhood level, the tourism pressure index is considered at the district level as a neighborhood may be too small of an influence area for it. All of these variables are available at the neighborhood-year-month level. A description of them is shown in Table A2.5 of the Appendix.

The final dataset of this study comprises 4,704 observations at the neighborhood-year-month level. The number of observations results from the 12 months in 8 years in the 49 neighborhoods potentially targeted. For each observation crime, offense, and victim rates per 1,000 inhabitants are built, and the socioeconomic variables previously mentioned are available.

2.4.1 Creating crime typologies

The database provided by the Local Police is rich in many aspects, one of which is the way crime is codified. There are over 300 types of crime recorded, covering more than 190 articles of the Spanish Penal Code. Even though having such a large amount of information can be of great value for research, this codification is not functional for the present analysis. Based on those 300 types, I construct 17 detailed crime categories, which I also group into 3 broad categories. Both categorizations cover the entire range of recorded crime types. Details of crime classifications are presented in Table 2.1.

[12]According to the National Statistics Institute (INE), 76% of all unemployed individuals appear in the unemployment register. Registered unemployment rates and housing prices are only available since 2009.

[13]I consider the number of tickets sold daily in every public museum in the city. This proxy is highly correlated (0.69) with the total number of tickets sold in every tourist outlet point in the city.

Table 2.1: Broad and detailed crime categories

Broad	Share	Detailed	Share
Against Property	86.6	Damages to Property	8.5
		Fraud	5.2
		Car Theft	11.4
		Robbery	14.5
		Theft	47.1
Against Person	8.9	Family	0.7
		Gender Violence	2.0
		Injuries	3.0
		Murder	0.1
		Sexual	0.3
		Threats	2.5
		Other	0.3
Other	4.5	Arson	0.0
		Drugs	0.7
		Environment	0.2
		Disobedience	1.8
		Road safety	1.8
Total	1		1

Notes: This table presents a categorization of all crimes available in my administrative database from the Local Police. I present both a broad categorization (left panel, 3 categories) and a detailed one (right panel, 17 categories). Source: Own construction from Local Police data.

Moreover, considering my setting I understand that different and more specific crime categories should be designed. To this end, I also construct two less traditional crime categories that are transverse to those previously defined, which is presented in Table 2.2. First, I create a crime category I named "intimate crimes", which covers the detailed categories of family, sexual and gender violence. The rationale behind this aggregation is that it summarizes all the crimes related to very close personal relationships. Secondly, following the description by Currie and Almond (2011), I define a crime category I named "anger crimes" that includes the detailed categories of damages to property, injuries, disobedience and threats. These are crimes that are not motivated by money or close links but still have some behavioral or personal component[14]. Except for damages to property, all the other categories correspond to crimes against the person. I understand that damages to property still needs to be included in such a category as it may result from anger, irritation, or rage. In this regard, the richness of the data allows me to depart from traditionally set crime typologies and analyze new ones that focus on the crime types I believe

[14]Currie and Almond (2011) state that temperamental skills are often proxied by psychological traits, social skills, and behavioral issues.

the BSaB policy may affect via the community channel. This classification helps to pinpoint the causal effects of community ties on crime better.

Table 2.2: New crime categories, and distribution by location

	Share Crime	Share Residence	Share Street	Share Other
Total crime	100	10	45	46
Intimate	3.0	62	25	13
Family	0.7	68	19	13
Gender Violence	2.0	64	26	10
Sexual	0.3	36	31	32
Anger	15.9	21	45	35
Damages to Property	8.5	21	41	38
Injuries	3.0	11	52	38
Disobedience	1.8	8	67	25
Threats	2.5	43	31	26
Drugs	0.7	3	87	10

Notes: This table presents the composition of the crime categories labeled as "intimate" and "anger", as well as its contribution to overall crime. It also indicates where these crimes took place, considering a residence, the street or other locations. Source: Own construction from Local Police data.

This last classification indicates that intimate and anger crimes account for almost one out of every five crimes and that anger crimes are much more frequent than intimate crimes. Even though it may seem that these do not represent an essential part of overall crime, they inflict a much higher disutility on their victims than other more frequent types of crime. Indeed, Dolan et al. (2005) indicate that while discounted QALY[15] losses resulting from rapes and sexual assaults are 0.561 and 0.160, while for a common assault, this figure is just 0.007. These facts demonstrate the importance of dealing with such offenses.

Additionally, Table 2.2 shows how crime types are distributed by location. There are some typologies with location patterns that are particularly attached to an address. These are indeed those which I included in the intimate crime category. Some others, such as threats (included in the broad anger category), also present a high share of being committed at a residence. Because of this location pattern and its relevance in light of the BSaB policy's characteristics, my analysis focuses on intimate and anger crimes. I also pay particular attention to drug offenses, as they are closely related to the initiatives carried out as part of BSaB.

Tables A2.6 to A2.9 in the Appendix show summary statistics for my dependent variables and controls. Results are shown both for Barcelona city (all 73 neigh-

[15]Quality-Adjusted Life Years.

borhoods) and for those neighborhoods potentially included in BSaB (49 neighborhoods).

2.5 Methodology

To evaluate the impact of BSaB on local crime, I adopt a staggered difference-in-differences approach (sDiD), where my observational unit is a neighborhood-year-month pair. The staggered term comes from the fact that treatment was implemented over different periods for the different observational units. This method quantifies the impact of a given program (in this case, BSaB) as the difference of outcome changes (post- vs. pre-intervention) between participants and non-participants. In this case, and to have comparable treatment and control units, the spatial units of analysis are the neighborhoods in Barcelona whose income was below 90% of the city median (those colored blue in Figure 2.1; the white areas are not part of my analysis). I quantify the BSaB policy's impact as the difference in crime before and after the implementation of BSaB for neighborhoods where BSaB took place (blue and with hatching in Figure 2.1) and those where it did not (blue but without hatching in Figure 2.1). The identification strategy relies on the fact that the roll-out of BSaB was quasi-random and not correlated with any observable characteristics. Thus, it can be seen as an exogenous change.

$$\begin{aligned} sDiD = & E[Crime(after) - Crime(before)|BSaB = 1] \\ & -E[Crime(after) - Crime(before)|BSaB = 0] \end{aligned} \tag{2.1}$$

Since the implementation of BSaB was staggered across neighborhoods, the before and after periods differ across treatment observations.

It should be noted that the artificial nature of the geographical boundaries may introduce the problem of potentially capturing spillover effects across neighborhoods. This problem is a general concern in the urban economics literature when dealing with geographically small treatment and control units. In order to address this issue, researchers have either chosen to focus on some types of crime that follow a more geographically concentrated pattern (Warner and Rountree 1997) or construct a unique exposure to the treatment measure (Takagi et al. 2012). In this analysis, I focus on crime types with a precise location pattern, such as those that mostly take place in residences, which above all are those I classify as intimate crimes. I also consider drug-related and anger crimes due to the nature of the policy. Restricting the study in such a way dispels potential spillover concerns. This focus is also supported by the functioning of the policy itself, run by local health centers that only deliver to the specific neighborhood in which they are placed.

Taking the previous points into consideration, my first set of estimations tests the impact of BSaB on criminal activity as follows

$$Crime_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 (T_{it} \cdot BSaB_i) + \theta X_{it} + \eta_i + \phi_t + \varepsilon_{it} \tag{2.2}$$

where the dependent variable is the victim/offense/crime rate per 1,000 inhabitants, and the observational unit is an "neighborhood-year-month" pair, i is the neighborhood, t is the time period (year-month), $BSaB_i = 1$ for participants, $T_{it} = 1$ for the post-treatment periods (different for each treatment unit), X_{it} is a vector of socioeconomic controls, η_i and ϕ_t are neighborhood and year-month fixed effects, and ε_{it} is the error term.

My main results also include interaction terms between baseline neighborhood characteristics and a time trend. Additionally, observations are weighted by population size. In the case of victims and offenders, I consider as dependent variables specific victim/offense rates per 1,000 individuals, considering the characteristics of the victims/offenders in terms of gender and age. In all cases, the estimation of the policy effect is given by β_2.

I also study responses over time following an event study approach. I perform fixed-effects regressions of the following type:

$$Crime_{id} = \beta_0 + \sum_{d \neq -1} \phi_d \cdot (BSaB_i \cdot Time_d)_{id} + \theta X_{id} + \eta_i + \varepsilon_{id} \tag{2.3}$$

where the dependent variable is the victim/offense/crime rate per 1,000 inhabitants, and the observational unit is an "neighborhood-distance to treatment" pair (measured in quarters), i is the neighborhood, d is the distance-to-treatment period. $BSaB_i = 1$ for participants, $Time_d = 1$ are distance to treatment indicator variables (different for each treatment unit), η_i is a neighborhood fixed effect, X_{id} is a vector of socioeconomic controls and ε_{id} is the error term.

I estimate $BSaB \cdot Time$ interactions, leaving $Time_{id} = -1$ as the reference period. Each of the ϕ_d coefficients quantifies the criminal activity difference between the $BSaB$ neighborhoods and the control group relative to the period -1. While coefficients $\{\phi_{-M}, ..., \phi_{-2}\}$ identify anticipation effects, coefficients $\{\phi_0, ..., \phi_M\}$ identify dynamic treatment effects. First of all, this allows me to test the existence of pretrends. Secondly, it helps me to determine the speed at which the policy may affect criminal activity (if at all), potentially leading to heterogeneous results among typologies. Also importantly, it will assist in disentangling potential mechanisms behind the results as explained in Section 2.3.2.

2.6 Results

2.6.1 Baseline results

First of all, to tackle possible endogeneity issues of treatment status (having BSaB), in Table 2.3 I present a set of t-tests performed on differences between treatment and control neighborhoods, previous to the intervention (in 2007). These indicate no significant differences between treatment and non-treatment neighborhoods in a set of observable socioeconomic and demographic characteristics. Regarding crime rates, differences appear at the level, but not in growth rates.

Table 2.3: t-tests on pre-existing crime rates and sociodemographics

	Mean Diff.	Std. Err.	p-value
Sociodemographics			
Population	749.11	4666.67	0.874
# Men	-207.26	2381.53	0.932
# Women	956.37	2300.37	0.682
# Teenagers	27.41	179.51	0.880
# Spanish	1316.47	1398.09	0.357
# Foreign	-2577.23	1921.53	0.205
Mortality rate	-57.25	76.40	0.457
Fecundity rate	-4.52	2.26	0.062
Housing prices	-1.62	1.86	0.402
# Retired	-45.68	41.95	0.297
Associations per capita.	0.04	0.045	0.440
Crime Rates			
All	-3.48	1.07	0.001
Against Property	-3.04	0.95	0.002
Against Person	-0.31	0.10	0.003
Intimate	-0.16	0.04	0.000
Anger	-0.19	0.17	0.275
Drugs	-0.04	0.02	0.026
Crime Growth			
All	0.01	0.03	0.702
Against Property	-0.03	0.04	0.525
Against Person	0.10	0.06	0.103
Intimate	0.15	0.13	0.275
Anger	0.03	0.06	0.592
Drugs	-0.49	0.13	0.000

Notes: This table presents balancing tests for sociodemographic (panel a) and criminal characteristics (panels b and c) between treated and control neighborhoods in 2007, before the BSaB policy was deployed. Source: Own construction from Barcelona City Hall and Local Police data.

Furthermore, I estimate a logit model where the dependent variable is the treatment indicator *BSaB*. I also estimate a panel logit, where the timing of the treatment is also considered. The results of these two exercises (in Tables A2.10 and A2.11 of the Appendix) show that socioeconomic variables do not seem to explain either the fact of being treated with BSaB or its timing. Thus, results in Tables 2.3, A2.10 and A2.11 provide evidence that the parallel trends assumption holds in this setting[16].

Table 2.4 presents results based on the estimation of Eq.(2.2) for crime rates while Table 2.5 present the results for offense and victim rates, in both cases clustering standard errors at the neighborhood level (Cameron and Miller 2015) and weighting each observation by population size. Each column indicates a different specification, each one being more stringent than the previous one. My preferred specification is that in column 4, including neighborhood-specific time trends. Overall, the results for the estimated impact of BSaB on local crime rates indicate that there was indeed a negative and significant impact on crime. Even if I do not see a decrease in criminal activity across all its different aspects studied after the policy implementation, I see significant reductions in aspects of crucial relevance in light of BSaB.

In the broad crime categories, reductions in crimes against the person and other crimes are observed. In other crimes, the effect is driven by crimes labeled as disobedience to agents of the law. Somewhat related to the reduction in crimes against the person, BSaB impacted intimate crime rates: BSaB reduces intimate crime rates by 0.07, which implies a decrease of 25% with respect to the mean. For this category, the results are mainly derived from gender violence crimes. It must be noted that crime rates for intimate crimes are much lower than for other criminal typologies, making percentage decreases of higher magnitude. Regarding drug crimes, which represent another vital result considering the policy, no direct effect of BSaB is found. For anger crimes, no significant results are found.

On the matter of offenders and victims, Table 2.5 evidences a reduction in criminal outcomes of significant sets of the population. Even if no widespread significant reduction of offenses is found, there is a significant reduction in the offense rates of those individuals under 18 years of age. Regarding victimization, I not find any significant impact. When analyzing these results by age and gender (see Table A2.12 in the Appendix), I observe that for offenders, the results are led by those of female offenders under 18 and male offenders aged 18-25.

[16] Such a feature was later confirmed informally by anecdotal evidence provided by the authorities running BSaB in the Barcelona Public Health Agency (ASPB). At informal meetings, I learned that neighborhoods' assignment to the intervention did not follow any rule-based procedure, and it was instead a quasi-random decision.

Table 2.4: Effect of BSaB on crime - crime categories

	(1)	(2)	(3)	(4)	Control mean
Against Property					
	7.897**	0.804	0.691	0.186	7.461
	(3.315)	(1.174)	(1.108)	(0.715)	
Against Person					
	0.373***	-0.087	-0.089	-0.088	0.760
	(0.115)	(0.074)	(0.071)	(0.056)	
Other					
	0.290**	-0.194	-0.206	-0.095*	0.539
	(0.115)	(0.164)	(0.153)	(0.051)	
Intimate					
	0.057**	-0.101***	-0.075**	-0.066***	0.239
	(0.026)	(0.032)	(0.031)	(0.024)	
Anger					
	0.663***	-0.089	-0.063	-0.098	1.497
	(0.186)	(0.107)	(0.093)	(0.090)	
Drugs					
	0.110*	-0.013	-0.017	-0.018	0.044
	(0.055)	(0.052)	(0.052)	(0.018)	
Observations	4,702	4,702	4,702	3,264	
Neighborhood FE		Y	Y	Y	
Year-Month FE			Y	Y	
Neighborhood-Time trends				Y	

Notes: This table reports the results of the difference-in-differences estimation following Eq. (2.2) for the 2008-2014 period. Each column presents a different specification according to the controls added, being each more demanding than the previous one. The observational unit is a neighborhood-year-month pair. Treated units are those in which the BSaB policy took place, while those in which it did not are controls. Treatment timing differs across units. The coefficient showed is that of interest in a difference-in-differences setting, being *Treated* · *Post*. Confidence intervals are based on standard errors clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.5: Effect of BSaB on crime - offender and victim categories

	(1)	(2)	(3)	(4)	Control mean
Off. U18					
	0.488***	-0.583**	-0.513**	-0.428***	0.897
	(0.161)	(0.249)	(0.228)	(0.154)	
Off. 18-25					
	8.917**	-0.801	-1.133	-1.632	8.751
	(3.421)	(2.105)	(1.991)	(1.403)	
Off. 25-35					
	2.729**	0.125	-0.105	-0.587	5.086
	(1.165)	(0.805)	(0.760)	(0.350)	
Off. 35-45					
	2.464**	0.755**	0.320	-0.166	3.914
	(0.968)	(0.333)	(0.313)	(0.267)	
Vict. U18					
	1.066*	0.278	0.099	0.209	1.241
	(0.582)	(0.199)	(0.192)	(0.128)	
Vict. 18-25					
	25.812*	5.346	6.237	5.805	13.970
	(13.458)	(5.369)	(5.389)	(4.495)	
Vict. 25-35					
	6.680**	0.034	0.736	1.018	8.143
	(2.979)	(0.656)	(0.573)	(0.814)	
Vict. 35-45					
	5.593**	0.848*	0.635	0.896	7.518
	(2.277)	(0.451)	(0.385)	(0.722)	
Observations	4,702	4,702	4,702	3,264	
Neighborhood FE		Y	Y	Y	
Year-Month FE			Y	Y	
Neighborhood-Time trends				Y	

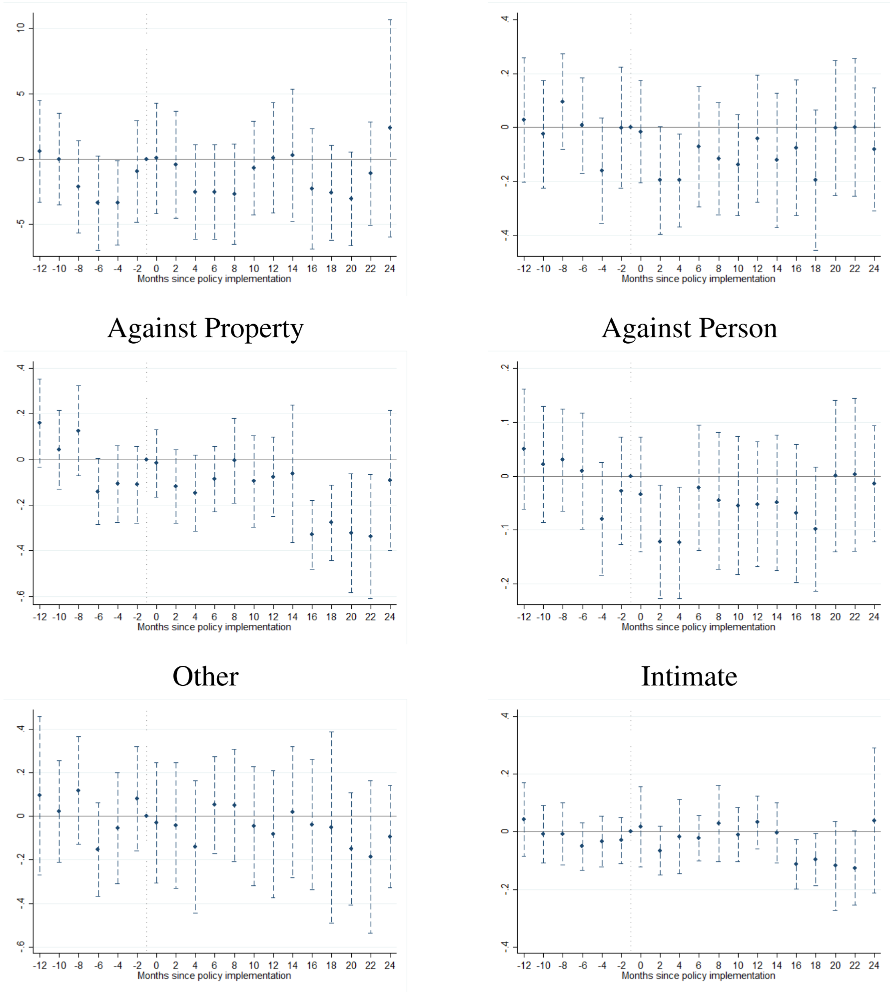
Notes: This table reports the results of the difference-in-differences estimation following Eq. (2.2) for the 2008-2014 period. Each column presents a different specification according to the controls added, being each more demanding than the previous one. The observational unit is a neighborhood-year-month pair. Treated units are those in which the BSaB policy took place, while those in which it did not are controls. Treatment timing differs across units. The coefficient showed is that of interest in a difference-in-differences setting, being $Treated \cdot Post$. Confidence intervals are based on standard errors clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Furthermore, I present estimations from Eq. (2.3), where I analyze the policy's dynamic treatment effects. I interact the treatment indicator with distance to treatment indicator variables, which are neighborhood-specific. For this analysis, period -1 is taken as a point of reference. I perform a binning of effect window endpoints as in Schmidheiny and Siegloch (2020). On this matter, the authors show that this exercise is critical for identifying dynamic treatment effects. In this case, I bin periods 12 months before and 24 months after BSaB interventions. The results are presented in Figure 2.2 for the crime typologies previously analyzed.

The first feature to highlight in Figure 2.2 is that there do not seem to be any anticipatory effects of BSaB on crime in all subfigures. This pattern strengthens the evidence found in Table 2.3 on the parallel trend assumption holding in this context. The second analysis corresponds to the dynamic treatment effects. As Figure 2.2 reflects, the impact of BSaB is different over time across crime rates. No dynamic treatment effects are found for crimes against property. There is an effect for crimes against the person in the short term (months 2-4). For other crimes, an effect is found in the medium-long term (months 16 and on). This pattern reflects what happens in the detailed crime categories that are of interest in this paper. Related to crimes against the person, the effect of BSaB on intimate crime rates occurs in the short run. The impact is quite immediate, showing a significant decrease two months after policy implementation. However, Figure 2.2 also shows that the impact is quite ephemeral, as, by month 6, the effect had already become diluted.

A very different picture is found for anger crime rates. In this case, no dynamic treatment effects are found. Nevertheless, even if confidence intervals are large and point estimates are not significant, I consistently see negative coefficients from the second semester onwards. Finally, for the case of drug crimes, a medium-long term effect is found, even if no significant effect was found in the difference-in-differences estimates. For this crime category, BSaB takes longer to affect local crime rates, as significant and reducing effects are found 16 months after deployment.

Figure 2.2: Effect of BSaB on crime - event study exercise, 95% confidence intervals



Against Property

Against Person

Other

Intimate

Anger

Drugs

Notes: This graph reports the results of an event study exercise following Eq.(2.3) the 2008-2014 period for crimes against property, against person, other crimes, intimate crimes, anger crimes and drug crimes. The observational unit is a neighborhood-year-month pair. Treated units are those in which the BSaB policy took place, while those in which it did not are controls. Treatment timing differs across units. Confidence intervals are based on standard errors clustered at the neighborhood level.

These results are also supported by the evidence shown in Table 2.6. In it, I present joint significance tests for all lag and lead coefficients. Results indicate that I cannot reject the hypothesis that all anticipatory effects are equal to zero. At the same time, it is possible to reject it for dynamic treatment effects in intimate and drug crimes. Finally, the results derived from an estimation following De Chaisemartin and d'Haultfoeuille (2020) do not differ significantly from the estimations presented in Figure 2.2[17].

Table 2.6: Effect of BSaB on crime - event study exercise, joint significance tests for anticipatory and dynamic effects

	F-stat anticipatory F(11,3093)	Prob > F	F-stat dynamic F(25,3093)	Prob > F
Intimate	1.28	0.229	1.39	0.093
Anger	1.18	0.296	0.84	0.697
Drugs	1.00	0.441	2.39	0.000

Notes: This table reports the results of joint significance test of the pre and post coefficients of the event study exercises shown in Figure 2.2. The observational unit is a neighborhood-year-month pair. Treated units are those in which the BSaB policy took place, while those in which it did not are controls. Treatment timing differs across units. F-stats columns present the statistic realization for the test that either all lag coefficients or all lead coefficients are jointly different from zero.

Finally, I present results from the safety and victim survey for Catalonia 2007-2014. In the survey, individuals are asked about safety and civility in their neighborhood and district and their experiences of being a victim of crime in the past 12 months. Specifically, individuals are asked whether they feel safety and civility has improved, worsened, or stayed the same in their neighborhood compared to the previous year. I use this question by running a logistic regression on safety and civility having improved, against BSaB in the neighborhood in that year. Estimates are presented in Table 2.7. The presence of BSaB significantly raises the probability of perceiving an improvement in safety by approximately 3%. From this result, I conclude that even if local crime rates do not drop for all the categories analyzed, individuals living in the participating neighborhoods feel that safety has improved. However, no significant results are found for perceptions of civility. I believe that the fact that civility is less specific than safety may influence these results[18].

[17] See Figure A2.1 in the Appendix.

[18] It could be that each respondent has a different concept of civility (as broadly specified in the Survey), and it may be more difficult to perceive.

Table 2.7: Effect of BSaB on perceptions in the neighborhood

	Civility	Security
BSaB	-0.007	0.032***
	(0.004)	(0.004)
Observations	21,779	21,779
Wald Chi2	225.98	160.9
Neighborhood FE	Y	Y
Year FE	Y	Y

Notes: This table presents difference-in-differences estimates of the BSaB policy in other outcomes besides crime, each presented in a different column. I show average marginal effect from logistic regression with district and year fixed effects and robust standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Overall, the results above are in line with those of previous studies, while in many ways, they represent improvements on some of the approaches previously adopted. Takagi et al. (2012) establish that support networks and social capital are inversely associated with crime. However, crime was only measured for any victim, making a broader analysis. My results are also related to those of Buonanno et al. (2009) and Lederman et al. (2002), although my findings differ in some aspects. Buonanno et al. (2009) find a clear effect of social capital on crime, but their dependent variable is property crime. I do not find a significant effect on all property crimes. Moreover, Lederman et al. (2002) state that trust (seen as social capital) has a significant and robust effect on violent crime, proxied by homicide rates.

My findings are of value in light of the policy evaluation. The type of crime that BSaB reduced is intimate crimes, that most likely will affect women. This result is highly relevant for two reasons. Firstly, many interventions aimed at empowering women and raising awareness of sexual health and education. Moreover, most of the actions targeted younger population groups, that seem to be those more positively affected (showing a lower offense rate) due to the program. Secondly, it is relevant as findings indicate that progress was achieved on such an essential issue as violence against women. According to the National Statistics Institute, in 2018, over 30 thousand cases registered as gender violence in Spain[19].

Results for alternative empirical strategies

Table 2.8 presents several robustness checks for the baseline estimates shown in Table 2.4. In Table 2.8, column 2 shows results clustering standard errors in a more stringent way - at the neighborhood-year-month level (Cameron and Miller 2015). Columns 3 and 4 show estimates when including other sociodemographic controls,

[19] https://www.ine.es/prensa/evdvg_2019.pdf

such as touristic pressure and housing prices, at the expense of losing observations. Finally, column 5 presents results of a placebo exercise in which I randomly assign a fake BSaB treatment across neighborhoods and time. I find that the coefficient estimated for BSaB of Table 2.4 are stable across these alternative specifications. Moreover, and very importantly, my falsification exercise (Column 5 of Table 2.8), which assigns random treatment in terms of neighborhoods and roll-out, reflects no significant results.

Table 2.8: Effect of BSaB on crime - robustness exercises

	Baseline	Twoway cluster Neigh-Month	Controls I Tourism	Controls II Tourism + Housing	Placebo
Against Property					
	0.186	0.186	0.169	0.113	0.088
	(0.715)	(0.487)	(0.628)	(0.891)	(0.085)
Against Person					
	-0.088	-0.088***	-0.088	-0.105*	0.007
	(0.056)	(0.030)	(0.053)	(0.060)	(0.005)
Other					
	-0.095*	-0.095*	-0.095*	-0.154***	-0.001
	(0.051)	(0.047)	(0.051)	(0.055)	(0.005)
Intimate					
	-0.066***	-0.066***	-0.066***	-0.073*	0.002
	(0.024)	(0.015)	(0.023)	(0.036)	(0.003)
Anger					
	-0.098	-0.098	-0.098	-0.201***	-0.008
	(0.090)	(0.060)	(0.090)	(0.054)	(0.009)
Drugs					
	-0.018	-0.018	-0.018	-0.018	-0.001
	(0.018)	(0.025)	(0.016)	(0.020)	(0.001)
Observations	3,264	3,264	3,264	2,377	3,264
Neighborhood FE	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y
Neigh.-Time Trend	Y	Y	Y	Y	Y
Control: Tourism			Y	Y	
Control: Housing				Y	

Notes: This table reports the results of alternative specifications for the difference-in-differences estimation following Eq. (2.2) for the 2008-2014 period. Each column presents a different specification. The observational unit is a neighborhood-year-month pair. Treated units are those in which the BSaB policy took place, while those in which it did not are controls. Treatment timing differs across units. The coefficient showed is that of interest in a difference-in-differences setting, being *Treated* · *Post*. Confidence intervals are based on standard errors clustered at the neighborhood level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Further consideration is given to column 4 in Table 2.8. In it, additional controls on tourism and housing prices are included to the specification shown in column 4 in Table 2.4. For this exercise, all results of Table 2.4 hold. Additionally, a reduction in anger crime is registered. Concretely, according to this specification, BSaB reduces anger crimes by 0.20, which roughly translates to a significant average decrease of 13.4%. When analyzing its components, I conclude that damages to property mostly drive the anger crime figures.

2.6.2 Mechanism analysis

My central hypothesis is that the BSaB policy reduces criminal activity at the local level through its community component. One way to test this hypothesis is to link per capita local associations to crime via BSaB. In other words, I assess if BSaB increased per capita local associations and then if this increase further translated into lower crime rates[20]. As already mentioned, information on the registered local associations accounts for registration date, aims, and place of action. The Local Government provides this information.

To rule out other potential mechanisms, I carry out similar analysis for health and unemployment outcomes to assess whether these acted as channels for lowering crime rates. For the first one, I use microdata from the Barcelona health survey (ESB) for the 2006-2016 period. Specifically, I use the "health status" question, which is based on self-perception. Answers range from 1 (very bad) to 5 (very good). I then compare individuals' answers in treatment and control neighborhoods in 2006 (just before BSaB) and 2016 (after BSaB). I also perform a similar analysis for a mental health indicator derived from the Goldberg scale GHQ-12. In the Goldberg Scale, a higher number (1 to 12) indicates a higher risk of bad mental

[20]For this, I set up a suggestive exercise to analyze potential channels. I perform this with a two-stage least square (2SLS) regression where I use the exogenous deployment of BSaB as an instrument for the number of local associations per 1,000 inhabitants that can be endogenous to local crime rates:

$$\begin{aligned} Crime_{it} &= \alpha_2 + \beta_2.\widehat{assoc\_pc}_{it} + \theta_2.X_{it} + \gamma_t + \delta_i + \varepsilon_{it} \\ assoc\_pc_{it} &= \alpha_1 + \beta_1.BSaB_{it} + \theta_1 X_{it} + \gamma_t + \delta_i + \varepsilon_{it} \end{aligned} \tag{2.4}$$

Regarding the validity of the instrument, it must hold that (1) BSaB highly correlates with per capita local associations (relevance), and (2) BSaB is exogenous to local crime (exogeneity). The first one is tested by regression of BSaB on local associations. The second one is backed up by a logit regressing the probability of being treated on several sociodemographic variables including crime (Tables A2.10 and A2.11) and a pretrends analysis (Figure 2.2). As in many Instrumental Variables, this condition is more difficult to pin down regarding the exclusion restriction. I argue that BSaB only affects crime through local associations as the design of the policy thought of local associations as the most important catalyst and mediator at the local level and the key ally to achieve its goals. Other potential influences are discarded using the same 2SLS exercise, hinting that BSaB does not affect crime through other variables.

health. For the case of unemployment, I use Barcelona City Hall information on the registered unemployment rate by neighborhood.

Table 2.9 presents results on the impact of the BSaB on per capita local associations, registered unemployment, health and mental status. First, results reported in Table 2.9 show a positive and statistically significant effect of BSaB on per capita local associations[21]. Second, results indicate no statistically significant impact of BSaB on local unemployment. Third, there is no evidence of significant differences in the means of health and mental status between individuals in treatment and control neighborhoods before and after BSaB implementation. In line with this last result, Palència et al. (2018) find no evolution of self-rated health for men and women in treatment and control neighborhoods.

Table 2.9: Effect of BSaB on other socioeconomic variables - potential mechanisms

	Per capita Associations	Registered Unemployment	Health Status	Mental Health
BSaB	0.504***	-0.003	-0.087	-0.064
	(0.171)	(0.003)	(0.081)	(0.157)
Observations	3,264	3,264	3,716	3,653
Neighborhood FE	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y
Neighborhood-Time trends	Y	Y	Y	Y

Notes: This table presents difference-in-differences estimates of the BSaB policy in other outcomes besides crime, each presented in a different column. The observational unit is a neighborhood-year-month pair. Treated units are those in which the BSaB policy took place, while those in which it did not are controls. Treatment timing differs across units and the specification is the same that in my baseline specification for crime. Confidence intervals are based on standard errors clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Given that BSaB positively affects per capita local associations, I perform an Instrumental Variables exercise. I use BSaB as an instrument for per capita local associations to then study its impact on local crime rates. I compare this exercise's results to my baseline estimates (that of column 4 in Table 2.4). Results are shown in Table 2.10. The Instrumental Variables exercise provides evidence in the same direction as my reduced-form estimates of Table 2.4. Still, the F-stat reported for the first stage of this exercise shows a somehow weak instrument. For this reason, I take the results of this exercise with caution and do not rely on them for my main analysis. Nonetheless, I take results of Table 2.9 and Table 2.10 as suggestive evidence that the mechanism behind the effectiveness of BSaB towards crime is more

[21] Also see Figure A2.2 for the event study exercise on the impact of BSaB on per capita local associations.

likely to be related to community ties than to any other of the analysed potential mechanisms.

Table 2.10: Effect of BSaB on crime - Instrumental Variables estimates

	Reduced Form	Instrumental Variables
Against Property		
	0.186	0.368
	(0.715)	(1.344)
Against Person		
	-0.088	-0.174
	(0.056)	(0.125)
Other		
	-0.095*	-0.189*
	(0.051)	(0.098)
Intimate		
	-0.066***	-0.131**
	(0.024)	(0.061)
Anger		
	-0.098	-0.194
	(0.090)	(0.191)
Drugs		
	-0.018	-0.036
	(0.018)	(0.033)
Observations	3,264	3,264
Neighborhood FE	Y	Y
Year-Month FE	Y	Y
Neighborhood-Time trends	Y	Y
F-stat First Stage		8.645

Notes: This table reports the results of the Instrumental Variables estimation for the 2008-2014 period. Each column presents a different type of crime and the specification mimics that of column (4) in Table 2.4. The observational unit is a neighborhood-year-month pair. Treated units are those in which the BSaB policy took place, while those in which it did not are controls. Treatment timing differs across units. The coefficient showed is that of interest in an IV setting, being $\widehat{assoc\_pc}$. Confidence intervals are based on standard errors clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Finally, I apply a Bacon decomposition to disentangle if there are heterogeneous effects across neighborhoods (Bailey and Goodman-Bacon 2015; Goodman-Bacon 2018) . Goodman-Bacon (2018) shows that a difference-in-differences estimator is a weighted average of all possible two-group/two-period difference-in-differences estimators and also shows which terms or groups matter most. For this case, results from the Bacon decomposition for intimate crimes are shown in Table 2.11. These results indicate that the estimates previously found are driven by comparing treated versus never treated observations, rather than from comparison of early versus late treated units. This evidence is shown by the weight such variation source has in comparison to the others. These last results indicate that differences between treated units are not the main driver behind the effect of BSaB on crime. Hence, heterogeneity in outcomes due to neighborhoods' different priorities does not seem to be a determinant feature of the analysis. Figure A2.3 in the Appendix provide further results of the baseline specification when removing neighborhoods one at a time to show that my results are not dependent on the inclusion or exclusion of a particular neighborhood. This builds to the fact that the policy's content is less relevant than the fact of connecting people. Such analysis reinforces the evidence in favor of the community ties hypothesis.

Table 2.11: Effect of BSaB on crime - Bacon decomposition of intimate crimes estimates

		Comparison type weight
Difference-in-Difference estimate	-0.075	
Earlier T vs. later C	-0.080	0.060
Later T vs. earlier C	-0.036	0.050
T vs. never treated	-0.077	0.891
T vs. already treated	-	-

Notes: This table presents the Bacon decomposition of the baseline difference-in-differences estimates of the BSaB policy. The observational unit is a neighborhood-year-month pair. Treated units are those in which the BSaB policy took place, while those in which it did not are controls. Treatment timing differs across units. The package shows three types of comparisons, which differ by control group: (1) Always treated, a group treated prior to the start of the analysis serves as the control group; (2) Never treated, a group which never receives the treatment serves as the control group. (3) Timing groups, or groups whose treatment stated at different times can serve as each other's controls: (3.1) those treated later serves as the control group for an earlier treatment group and (3.2) those treated earlier serve as the control group for the later group . Also shown are the component due to variation in controls across always treated and never treated groups, and the "within" residual component.

2.7 Conclusions

In this chapter, I estimate the effect of bolstering community ties on local crime rates. To do so, I take advantage of the quasi-random nature of a community health policy rolled out in Barcelona from 2008 to 2014 (BSaB). The policy was implemented in 12 of the 49 potential neighborhoods and covered around a quarter of the targeted population. Even though the policy aimed to improve health outcomes in these underprivileged neighborhoods, I assess whether the community feature of BSaB led to an increase in community ties, and consequently, to reduce crime.

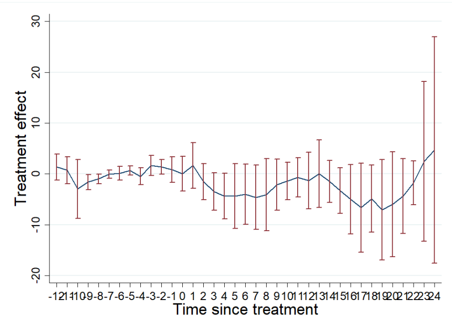
Using a staggered difference-in-differences approach and administrative records from the Local Police, I find that this is the case. Concretely, there is a reduction in crimes against the person related to reducing intimate crimes. These fall by 25% but only in the short term. Drug crimes also see a reduction but in the longer term. For outcomes on offense rates, there is a reduction in that of younger individuals. Results also indicate that BSaB increases per capita associations in participating neighborhoods but does not affect self-rated health, mental health, and unemployment rates across treatment and control neighborhoods. For this, I support that the strengthening of community ties is likely to be a key mechanism. This statement is also backed up by a Bacon decomposition of the results, which indicates no heterogeneity on outcomes between treated units, making the meetings themselves more important than their contents.

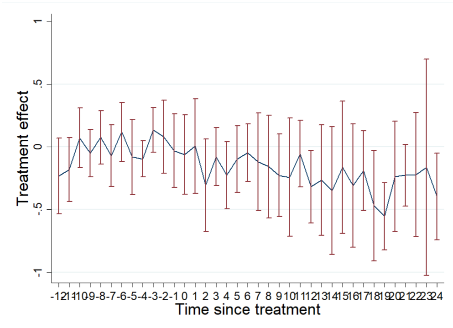
Despite crime not being one of the policy's specific targets, it indirectly links to them, as they reflect local disparities. For this, I understand that the policy is successful in achieving one of its goals. However, I further understand that policy design improvements are needed, as some key crime categories are not affected by the program. In light of the results on the underlying mechanisms, if new initiatives are to be carried on, cooperation with existing local institutions is crucial.

This chapter thus indicates that not only traditional policies against crime work and that new means of reducing criminal activity in disadvantaged neighborhoods can be effective. Additionally, these policies speak from an efficiency angle. Concretely, BSaB had an annual cost of 500,000 euros in 2015. This number implies a cost of 5,000 euros per annual activity, 70 euros per active participant, and 2 euros per potential participant. Hence, from a cost-effectiveness perspective, the policy also evidences positive points. Even if constructing community ties is more challenging than deploying traditional policing, these alternative policies may work better in several contexts. Buonanno et al. (2009) state that a policy of promotion of associational life may usefully complement traditional anti-crime policies. Moreover, Takagi et al. (2012) argue that policy-makers should not neglect policies aimed at reducing inequalities to promote social cohesion, social stability, and safer neighborhoods. A better understanding of the interactions between social cohesion and public policy is essential to reduce criminal activity induced by the lack of integration of some citizens facing substandard social and economic conditions.

2.8 Appendix

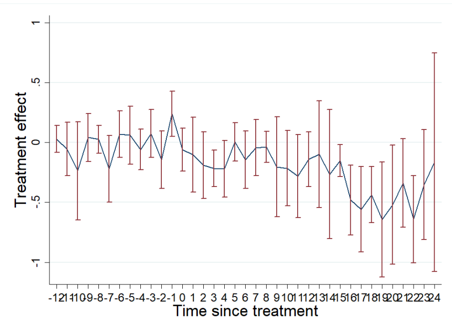
Figure A2.1: Effect of BSaB on crime - event study exercise à la De Chaisemartin and d'Haultfoeuille (2020), 95% confidence intervals

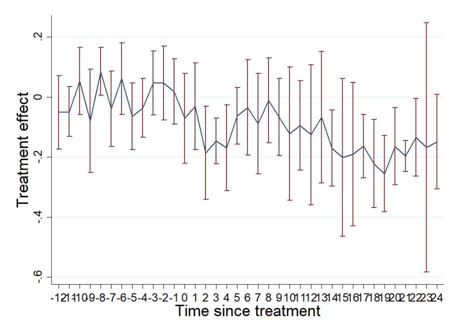




Against Property

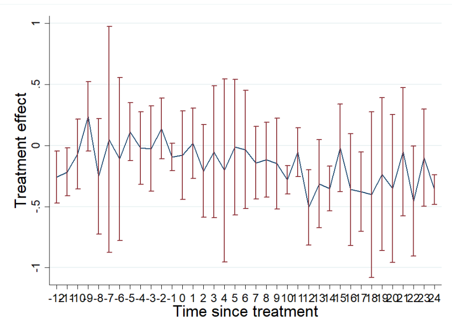
Against Person

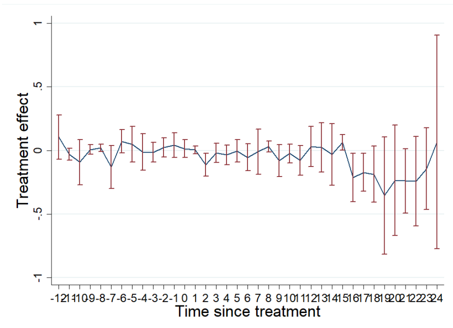




Other

Intimate



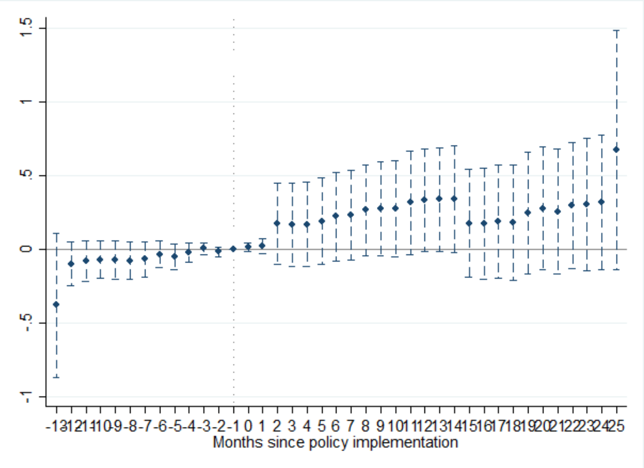


Anger

Drugs

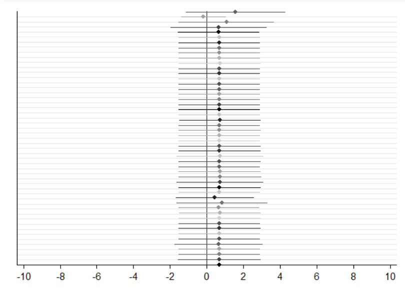
Notes: This graph reports the results of an event study exercise derived from the difference-in-differences estimation for the 2008-2014 period for crimes against property, against person, other crimes, intimate crimes, anger crimes and drug crimes considering the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020). The observational unit is a neighborhood-year-month pair. Treated units are those in which the BSaB policy took place, while those in which it did not are controls. Treatment timing differs across units. Confidence intervals are based on standard errors clustered at the neighborhood level.

Figure A2.2: Effect of BSaB on local associations - event study exercise, 95% confidence intervals

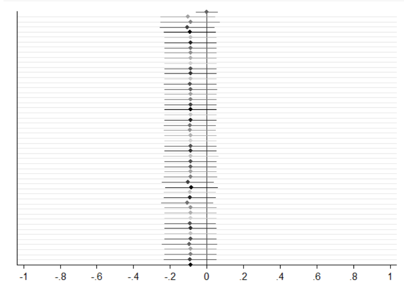


Notes: This graph reports the results of an event study exercise derived from the baseline difference-in-differences estimation for the 2008-2014 period for per capita local associations. The observational unit is a neighborhood-year-month pair. Treated units are those in which the BSaB policy took place, while those in which it did not are controls. Treatment timing differs across units. Confidence intervals are based on standard errors clustered at the neighborhood level.

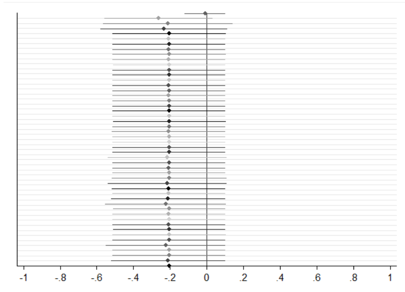
Figure A2.3: Effect of BSaB on crime - removing neighborhoods one at a time



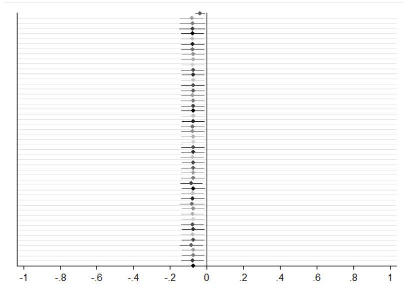
Against Property



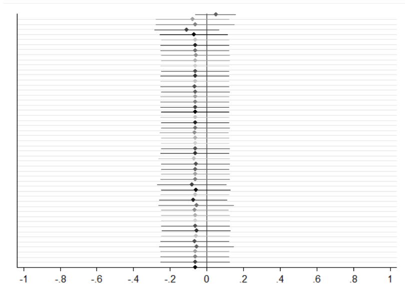
Against Person



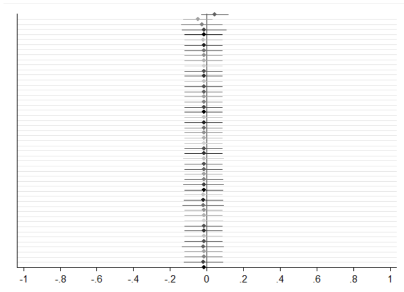
Other



Intimate



Anger



Drugs

Notes: These graphs report the results of the difference-in-differences estimation removing neighborhoods one at a time. The specification follows equation (2.2) for the 2008-2014 period, with controls as those of column 4 in Table 2.4. The coefficient showed is that of interest in a DiD setting, being *Treated* · *Post*. Confidence intervals are based on standard errors clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

Table A2.1: Neighborhood characteristics: population and rent

District		Neighborhood	Pop 07	Pop 14	Rent 07	Rent 14	Low Inc.	Treatment
0	0	Barcelona City	1.603.178	1.613.393	100	100	NA	NA
1	1	el Raval	46.595	48.471	64,7	65,9	Y	Y
1	2	el Barri Gotic	27.946	15.911	86,5	98,5	N	N
1	3	la Barceloneta	15.921	15.181	66,7	84,5	Y	Y
1	4	Sant Pere, Santa Caterina i la Ribera	22.572	22.674	80,2	92,5	Y	Y
2	5	el Fort Pienc	31.521	31.785	107,9	104,5	N	N
2	6	la Sagrada Família	52.185	51.562	101,8	92,4	N	N
2	7	la Dreta de l'Eixample	42.504	43.749	137,6	165,3	N	N
2	8	l'Antiga Esquerra de l'Eixample	41.413	41.975	126,5	127,8	N	N
2	9	la Nova Esquerra de l'Eixample	58.146	57.863	116,9	109,1	N	N
2	10	Sant Antoni	37.988	38.369	103,8	97,8	N	N
3	11	el Poble Sec - Parc Montjuic	39.579	40.674	73,3	66,3	Y	Y
3	12	la Marina del Prat Vermell - Zona Franca	1.005	1.151	80,4	39,4	Y	N
3	13	la Marina de Port	29.327	30.286	80,2	72,0	Y	N
3	14	la Font de la Guatlla	10.064	10.406	90,4	77,6	Y	N
3	15	Hostafrancs	15.771	15.919	82,7	76,8	Y	N
3	16	la Bordeta	18.592	18.451	81,9	76,0	Y	N
3	17	Sants - Badal	24.085	24.245	85,9	79,6	Y	N
3	18	Sants	40.272	41.102	89,5	85,8	Y	N
4	19	les Corts	46.400	46.205	130,4	125,4	N	N
4	20	la Maternitat i Sant Ramon	23.938	23.735	127,9	112,6	N	N
4	21	Pedralbes	11.413	11.670	193,6	251,7	N	N
5	22	Vallvidrera, el Tibidabo i les Planes	4.038	4.615	146,4	162,8	N	N
5	23	Sarria	23.316	24.691	174,9	195,2	N	N
5	24	les Tres Torres	15.325	16.381	215,3	217,8	N	N
5	25	Sant Gervasi - la Bonanova	23.634	25.378	182,2	191,8	N	N
5	26	Sant Gervasi - Galvany	46.454	46.648	187,0	192,1	N	N
5	27	el Putxet i el Farro	28.990	29.041	150,2	140,2	N	N
6	28	Vallcarca i els Penitents	15.381	15.454	113,2	101,6	N	N
6	29	el Coll	7.190	7.307	91,7	81,6	Y	N
6	30	la Salut	13.072	13.256	113,0	107,3	N	N
6	31	la Vila de Gracia	50.409	50.680	101,9	118,1	N	N
6	32	el Camp d'en Grassot i Gracia Nova	34.535	34.146	104,3	103,7	N	N
7	33	el Baix Guinardo	25.816	25.587	96,6	86,6	Y	N
7	34	Can Baro	8.998	8.887	81,2	77,4	Y	N
7	35	el Guinardo	35.038	35.698	93,0	82,0	Y	N
7	36	la Font d'en Fargues	9.621	9.467	103,5	102,0	N	N
7	37	el Carmel	32.745	31.728	72,0	56,6	Y	N
7	38	la Teixonera	11.332	11.379	72,2	69,6	Y	N
7	39	Sant Genis dels Agudells	7.069	6.865	85,7	80,0	Y	N
7	40	Montbau	5.105	5.082	85,5	70,0	Y	N
7	41	la Vall d'Hebron	5.476	5.422	96,5	86,9	Y	N
7	42	la Clota	445	529	89,9	90,1	Y	N
7	43	Horta	26.638	26.591	85,9	82,2	Y	N
8	44	Vilapicina i la Torre Llobeta	25.672	25.500	83,0	64,0	Y	N
8	45	Porta	23.470	24.424	75,3	58,3	Y	N
8	46	el Turo de la Peira	15.102	15.471	65,4	50,6	Y	N
8	47	Can Peguera	2.143	2.288	49,8	51,0	Y	N
8	48	la Guineueta	15.394	15.090	82,0	56,0	Y	N
8	49	Canyelles	7.539	7.014	76,7	61,0	Y	N
8	50	les Roquetes	15.756	15.668	60,9	50,8	Y	Y
8	51	Verdun	12.301	12.239	63,8	50,8	Y	N
8	52	la Prosperitat	26.696	26.171	72,6	53,7	Y	N
8	53	la Trinitat Nova	8.011	7.462	53,0	34,7	Y	N
8	54	Torre Baro	2.105	2.682	58,0	45,6	Y	Y
8	55	Ciutat Meridiana	10.929	10.356	59,4	39,2	Y	Y
8	56	Vallbona	1.267	1.353	51,6	39,9	Y	Y
9	57	la Trinitat Vella	9.992	10.268	74,8	45,9	Y	N
9	58	Baro de Viver	2.397	2.508	44,5	60,5	Y	Y
9	59	el Bon Pastor	12.332	12.758	66,2	59,6	Y	Y
9	60	Sant Andreu	55.171	56.496	85,9	76,6	Y	N
9	61	la Sagrera	28.469	28.914	88,1	74,9	Y	N
9	62	el Congres i els Indians	13.896	14.076	86,5	72,7	Y	N
9	63	Navas	21.454	21.949	92,9	83,3	Y	N
10	64	el Camp de l'Arpa del Clot	38.604	38.130	93,4	80,9	Y	N
10	65	el Clot	26.796	27.082	88,5	81,0	Y	N
10	66	el Parc i la Llacuna del Poblenou	13.104	14.814	103,2	88,6	N	N
10	67	la Vila Olimpica del Poblenou	8.783	9.391	132,8	150,8	N	N
10	68	el Poblenou	30.181	33.425	94,5	95,4	Y	N
10	69	Diagonal Mar i el Front Marítim del Poblenou	9.775	13.351	101,1	168,8	N	N
10	70	el Besos i el Maresme	22.652	23.191	61,7	58,9	Y	Y
10	71	Provençals del Poblenou	18.731	20.184	85,7	91,7	Y	N
10	72	Sant Marti de Provençals	26.261	26.018	81,5	67,6	Y	N
10	73	la Verneda i la Pau	29.452	28.903	74,8	57,2	Y	Y

Source: Own construction from Barcelona City Hall data.

Table A2.2: BSaB deployment by neighborhoods

Neighborhood	Start Date
Roquetes	Jun-2008
Poble Sec	Jun-2008
St. Pere, Santa Caterina i la Ribera	Jun-2009
Torre Baró	Jun-2009
Ciutat Meridiana	Jun-2009
Vallbona	Jun-2009
Barceloneta	Jul-2010
Baró de Viver	Mar-2011
Bon Pastor	Mar-2011
Raval	Oct-2011
El Besòs i el Maresme	Oct-2013
Verneda i La Pau	Nov-2014

Notes: The table presents the 12 treated neighborhoods by the BSaB policy in the city of Barcelona from 2008 to 2014, ordered chronologically. It also displays the start date of the program on each of them. Source: Barcelona Public Health Agency (ASPB).

Table A2.3: Correlation matrix - social and economic deprivation measures

	Income	Unemploy.	Housing Prices	Vehicles	Teen pregnancy	Assoc.
Income	1					
Unemploy.	-0.7854*	1				
Housing prices	0.8117*	-0.6568*	1			
Vehicles	0.4774*	-0.3823*	0.2182	1		
Teen pregnancy	-0.5899*	0.5904*	-0.4489*	-0.4311*	1	
Assoc.	0.2712*	-0.1809	0.219	0.7006*	-0.1932	1

Notes: This table presents pairwise correlation between socioeconomic measures of deprivation for all neigborhoods in Barcelona prior to BSaB implementation. Source: Own construction from Barcelona City Hall data.

Table A2.4: BSaB activities by scope

Intervention	Target population	Neighborhoods
Childhood		
Healthy sports leisure	Primary school	Poble Sec
Healthy sports leisure	Middle school	Roquetes, Bon Pastor, Baro de Viver
Parenting skills	Parents of kids 3-5	El Born, Torre Baro, Ciutat Meridiana, Vallbona, Barceloneta
Healthy cooking	Parents of kids 3-17	Poble Sec
Extracurricular activities	Primary school	Roquetes, Barceloneta
Adolescents		
Healthy sports leisure	High school	Roquetes, Poble Sec, El Born, Torre Baro, Ciutat Meridiana,Vallbona
Healthy leisure at night	14-18	Torre Baro, Ciutat Meridiana, Vallbona
Sexual health counseling	14-25	Torre Baro, Ciutat Meridiana, Vallbona, Raval
Education on contraception	Under 20	Torre Baro, Ciutat Meridiana, Vallbona, Bon Pastor, Baro de Viver
Drug counseling	Under 21	Roquetes, Poble Sec, Raval
Drugs, violence, groups	15-29 at risk	Bon Pastor, Baro de Viver, Raval
Empowerment, integration	14-21 foreign women	El Besos i el Maresme
Adults		
Sex education for adults	Women 20-50	Torre Baro, Ciutat Meridiana, Vallbona, Bon Pastor, Baro de Viver
Tai chi in the park	Above 40	Roquetes, Poble Sec, El Born, Torre Baro, Ciutat Meridiana, Vallbona, Bon Pastor, Baro de Viver, El Besos i el Maresme
Obesity, stress, anxiety, depression	Adults	Bon Pastor, Baro de Viver
Elderly		
Memory Groups	The elderly	Roquetes
Take a walk in the neighborhood	The elderly	Poble Sec, El Born, Torre Baro, Ciutat Meridiana, Vallbona, El Besos i el Maresme
How to be healthy	The elderly	El Born, Bon Pastor, Baro de Viver, El Besos i el Maresme
All interested		
Alcohol abuse	Everyone	Barceloneta
Tobacco addiction	All smokers	Roquetes, Poble Sec
Home-made remedies	Everyone	Roquetes

Notes: This table presents all initiatives undertaken under the BSaB scope. They are categorized by the aim of the intervention, they indicate who is they target population and in which neighborhoods they took place. Source: Own construction from Barcelona Public Health Agency (ASPB) data.

Table A2.5: Description of main variables

Variable	Description	Source	Frequency availability
Crime counts	Registered criminal acts	Local Police	Geocoded; Exact time
Offender counts	Registered offenders	Local Police	Geocoded; Exact time
Victim counts	Registered victims	Local Police	Geocoded; Exact time
Population	Registered inhabitants	Barcelona City Hall	Neighborhood; Year
Crime rate	Crime counts per 1,000 inhabitants	Police and City Hall	Neighborhood; Month
Victim rate	Victim counts per 1,000 inhabitants	Police and City Hall	Neighborhood; Month
Associations	Per capita local associations	Local Government	Neighborhood; Month
House prices	House market prices per square meter	Barcelona City Hall	Neighborhood; Month
Unemployment	Registered unemployment rate	Barcelona City Hall	Neighborhood; Month
Tourism	Per capita visitors to neighborhood tourist sites	Barcelona City Hall	Neighborhood; Month

Notes: This table presents a description of the main variables under analysis. It contains a brief description of how each is constructed, its sources and the frequency for which they are available. Source: Own construction from Local Police, Local Government and Barcelona City Hall data.

Table A2.6: Descriptive statistics, crime rates per 1,000 inhabitants. 2007-2014

	All Neighborhoods		Potentially participating	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
All	10.235	15.790	8.758	13.088
Against Property	8.957	14.150	7.459	11.116
Against Person	0.735	0.882	0.759	0.987
Other	0.543	1.445	0.540	1.641
Intimate	0.216	0.258	0.239	0.299
Anger	1.465	1.916	1.497	2.195
Drugs	0.065	0.271	0.044	0.181
Family	0.052	0.108	0.057	0.125
Gender Violence	0.140	0.208	0.158	0.243
Injuries	0.284	0.476	0.271	0.500
Disobedience	0.176	0.424	0.167	0.436
Sexual	0.024	0.073	0.023	0.083
Threats	0.205	0.339	0.222	0.401
Obs	7,008		4,704	
Income <90% median	0.671		1	
Treatment group			0.245	

Notes: This table presents descriptive statistics for different crime rates under analysis for the 2007-2014 period. Mean and standard deviation are shown for the whole city of Barcelona (73 neighborhoods) and for the potentially treated units (49 neighborhoods). Source: Own construction from Local Police data.

Table A2.7: Descriptive statistic, offense rates per 1,000 inhabitants. 2007-2014

	All Neighborhoods		Potentially participating	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Men	4.703	8.990	4.492	9.417
Women	1.229	2.278	1.150	1.922
Men under 18	1.387	3.178	1.274	3.331
Men 18-25	14.755	28.065	13.322	28.519
Men 25-35	7.744	19.940	7.717	23.226
Men 35-45	6.038	14.700	6.177	16.887
Men 45-55	4.119	8.677	4.048	9.206
Women under 18	0.540	1.764	0.487	1.575
Women 18-25	4.399	9.488	4.001	9.555
Women 25-35	2.048	4.773	2.045	5.303
Women 35-45	1.584	3.351	1.581	3.611
Women 45-55	1.165	2.934	1.221	3.307

Notes: This table presents descriptive statistics for different offense rates under analysis for the 2007-2014 period. Mean and standard deviation are shown for the whole city of Barcelona (73 neighborhoods) and for the potentially treated units (49 neighborhoods). Source: Own construction from Local Police data.

Table A2.8: Descriptive statistics, victim rates per 1,000 inhabitants. 2007-2014

	All Neighborhoods		Potentially participating	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Men	7.743	10.888	6.848	10.650
Women	6.526	9.311	5.519	7.701
Men under 18	1.366	2.425	1.260	2.563
Men 18-25	16.492	33.832	13.163	32.469
Men 25-35	9.630	16.159	8.584	16.977
Men 35-45	9.167	15.149	8.694	17.224
Men 45-55	14.133	21.686	12.709	22.073
Women under 18	1.545	3.886	1.228	3.528
Women 18-25	19.318	39.312	15.172	37.343
Women 25-35	8.603	12.291	7.620	12.024
Women 35-45	7.015	9.390	6.354	9.275
Women 45-55	11.198	17.678	9.856	16.704

Notes: This table presents descriptive statistics for different victimization rates under analysis for the 2007-2014 period. Mean and standard deviation are shown for the whole city of Barcelona (73 neighborhoods) and for the potentially treated units (49 neighborhoods). Source: Own construction from Local Police data.

Table A2.9: Descriptive statistics, control variables. 2007-2014.

	All Neighborhoods			Potentially participating		
Variable	Obs.	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Associations (per capita)	7,008	1.896	1.763	4,704	1.192	1.21
Tourism (tickets/population)	7,008	1.92	7.98	4,704	2.39	9.54
Reg. unemployment (rate)	5,256	0.07	0.02	3,528	0.08	0.02
House prices (euros/sqm)	4,762	2,362	1,005	3,087	2,023	893

Notes: This table presents descriptive statistics for different explanatory variables of my analysis for the 2007-2014 period. They include local associations per capita, registered unemployment, housing prices and a proxy for touristic pressure. Mean and standard deviation are shown for the whole city of Barcelona (73 neighborhoods) and for the potentially treated units (49 neighborhoods). Source: Own construction from Barcelona City Hall data.

Table A2.10: Logit regression pre-intervention

P(Treated)=1	Coef.	Std. Err.	z	P>z
Income	-0.12	0.15	-0.64	0.520
Population	0.00	0.00	0.69	0.490
Mortality	0.06	0.06	1.11	0.68
Teenage birth rate	0.01	0.34	0.03	0.976
Non-Spanish population	0.00	0.00	0.97	0.333
Pensions	-0.02	0.03	-0.61	0.544
House prices	0.52	0.71	0.74	0.461
Overall crime	0.00	0.00	0.05	0.958
Per capita assoc	-0.41	0.62	-0.66	0.509
Tourism	0.07	0.11	0.61	0.540
Prob LR>chi2 =0.0000 ; Pseudo R2=0.7554				

Notes: This table presents the results of a logistic regression of the probability of a neighborhood being treated on several sociodemographic characteristics in a pre-treatment period (average in year 2007). Robust standard errors. Source: Own construction from Barcelona City Hall data.

Table A2.11: Panel logit regression for intervention timing

P(BSaB)=1	Coef.	Std. Err.	z	P>z
Income	0.03	0.29	0.090	0.925
Population	0.00	0.00	-0.880	0.377
Mortality	0.02	0.02	1.350	0.178
Teenage birth rate	0.40	0.34	1.180	0.239
Non-Spanish population	0.00	0.00	0.880	0.378
Pensions	-0.04	0.04	-1.200	0.230
House prices	-0.51	0.19	-2.730	0.006
Overall crime	0.00	0.00	1.140	0.253
Associations	0.42	0.55	0.770	0.440
Tourism	0.04	0.13	-0.06	0.956
/lnsig2u	5.26	0.53		
sigma_u	13.89	3.66		
rho	0.98	0.009		
Prob W>chi2 =0.01056 ; Prob LR (rho=0)>chi2 =0				

Notes: This table presents the results of a panel logistic regression of the probability of a neighborhood being treated on several sociodemographic characteristics, for the 2007-2014 period. Robust standard errors. Source: Own construction from Barcelona City Hall data.

Table A2.12: Effect of BSaB on crime - offender and victim categories by age and gender

	O.U18		O.18-25		O.25-35		O.35-45	
	M	F	M	F	M	F	M	F
BSaB	-0.212	-0.656***	-1.634***	-1.169	-0.816	-0.185	-0.063	-0.332
	(0.143)	(0.235)	(0.562)	(0.948)	(0.547)	(0.165)	(0.321)	(0.300)
	V.U18		V.18-25		V.25-35		V.35-45	
	M	F	M	F	M	F	M	F
BSaB	0.158	0.275	5.455	6.108	1.346	0.592	1.031	0.763
	(0.199)	(0.213)	(4.022)	(5.005)	(0.910)	(0.781)	(0.684)	(0.825)
Obs.	3,264	3,264	3,264	3,264	3,264	3,264	3,264	3,264
Neigh. FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Neigh-Time Trends	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports the results of the difference-in-differences estimation following Eq.(2.2) for the 2008-2014 period, with controls as those of column 4 in Table 2.4. The observational unit is a neighborhood-year-month pair. Treated units are those in which the BSaB policy took place, while those in which it did not are controls. Treatment timing is differs across units. The coefficient showed is that of interest in a DiD setting, being *Treated* · *Post*. Confidence intervals are based on standard errors clustered at the neighborhood level. *** p<0.01, ** p<0.05, * p<0.1.

3 Sweeping up gangs: The effects of tough-on-crime policies from a network

3.1 Introduction

Since the 1980s, efforts to detect criminal organizations involved in drug trafficking have intensified, and sanctions have toughened (Mansour et al. 2006; Sweeten et al. 2013; Lessing 2016). At the same time, research has shown that individual choices regarding crime participation are affected by existing norms and networks (Glaeser and Sacerdote 1999) by providing role models, learning opportunities, and information diffusion. Crime-targeting policies should take such influences into account. The role of norms and networks in crime is particularly relevant when dealing with gangs. These are defined as "any durable, street-oriented youth group, whose involvement in illegal activities is part of their group identity"[1]. These criminal groups raise concerns for several reasons, such as 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 dialogue and integration. The former has been more popular concerning gangs, and interventions such as sweeps or crackdowns have been the most common. However, little is known about how they work. For a better understanding, it is crucial to understand the network structure of the gangs.

This chapter studies the effects of police sweeps against gangs. Specifically, this chapter answers the following research questions: Are sweeps successful at reducing crimes committed by arrested individuals? Do they also diminish the crimes committed by peers? Can a network analysis provide insights to improve gang sweep design? To answer these questions, I study the Metropolitan Area of Barcelona (MAB), where a drastic policy change towards gangs took place.

[1] Eurogang Network: www.umsl.edu/∼cj/eurogang/euroganghome

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 sweeps. To analyze the sweeps' effects, I follow a staggered difference-in-differences strategy by comparing criminal records for arrested individuals and known peers with those of other group offenders. I also study outcomes in the 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. Finally, I conduct a counterfactual policy exercise that compares crime changes caused by the sweeps with a prediction based on removing key players. Results evidence significant crime reductions for arrested individuals and known peers. For the first group, the drop in crime is almost 100% and persistent. For the second one, the reduction is 25% and only takes place in the short term. The biggest fall occurs in crimes against the person. Additionally, the areas of the sweeps experience improvements in crime, health, and education. Nonetheless, if sweeps 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. 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 (Blanco 2012). While this phenomenon's level does not compare to other settings, the rapid increase is a worrisome characteristic. Additionally, security has become the primary non-economic concern of citizens (Barometer of the city of Barcelona). In this setting, a drastic policy change occurred. 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). Additionally, the judiciary system implemented sturdier prosecution of criminal groups. This policy change was not concurrent with any other crime policy, providing an exogenous shock to gang arrests and a clean identification strategy.

In this analysis, I use administrative and confidential police records provided by the Local Police for the 2008–2014 period. This dataset has very detailed information on the crimes registered in the MAB and the offenders arrested, 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 offender. I exploit the level of detail of the data in two ways. Firstly, a unique identification number allows me to follow individuals over time and map out their criminal careers. Secondly, by matching information on the exact date, hour, place, and type of crime, I retrieve criminal network structures. Finally, I match these records with confidential information on the sweeps provided by the gang-specialized police unit (UGOV). This last information allows me to label individuals involved in sweeps and their peers.

To identify the causal effects of the policy change on crime, I implement a staggered difference-in-differences strategy. I compare criminal records for arrested individuals and their known peers before and after the sweeps to other group offenders' criminal records. By doing so, I estimate the treatment effects of the gang sweeps. I follow a similar strategy to study crimes and other relevant socioeconomic factors in a broader sense. In this case, I define a treatment indicator at the area level, which takes a value equal to one for the districts in which a sweep took place. This analysis allows me to assess its effects on crimes regardless of whether individuals are arrested, as well as examine other welfare determinants.

I also 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 of peer effect estimates derived from potential identification and endogeneity issues. I also use these peer effect estimates to identify key players in each gang. The key player in a criminal group is the individual that leads to the 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). Finally, I conduct a counterfactual policy exercise in which I compare the variation in crime caused by the sweeps with the theoretical prediction of a policy that removes the key players. Since the sweeps were of a larger scale, I cannot compare them with a scenario where I remove one individual. For this reason, I construct a predictive Cumulative Crime Reduction (CCR) measure as a function of the number of key players removed. I compare the contraction in crime after the sweeps with this CCR benchmark.

The results indicate significant reductions in the criminal activity of those arrested in the sweeps and their peers. Specifically, for arrested offenders, there is an average reduction in criminal activity of 96%. This effect is immediate and persistent, consistent with these individuals' incapacitation, as 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 in crime involves crimes against the person but not against the property. This result 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. This outcome would imply that peers are committing fewer crimes rather than being arrested less. Finally, I compare crime outcomes at the gang level after the sweeps with a theoretical benchmark derived from a policy that would have removed key players. For this, I estimate peer effects, identify key players, and compute the predicted reduction in criminality as a function of the number of key players removed. The results of this counterfactual policy exercise indicate that all sweeps 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.

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

This study contributes significantly to the research on criminal networks in several ways. Firstly, it provides a picture of gangs' network structure, providing a better understanding of 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 first 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 such an issue, Lindquist and Zenou (2019) provided an overview of policy lessons. However, there have been few studies involving counterfactual policy exercises from which recommendations could be extracted. Specifically, this chapter 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 nowadays, when police funding and interventions are in the spotlight.

More broadly, this chapter 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 chapter 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 chapter 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.

3.2 How to tackle gangs? Policy answers

When designing crime-fighting strategies, different paths can be taken. Without being too general, they can be split into two groups. The first and more traditional is labeled as the hard approach. Starting in the 1970s, safety policies in the United States have followed this "tough-on-crime" approach. Although 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, loosely labeled as soft, focuses on reducing crime-triggering disparities. Soft approaches are 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, as outlined in Chapter 2, 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 these approaches and whether they can serve different purposes and tackle different criminal profiles due to each one's specificities.

3.2.1 The case of the Metropolitan Area of Barcelona

Gangs were detected for the first time in the Metropolitan Area of Barcelona in 2002. Over the following decade, there was a steady increase in the presence of such criminal groups. Their public notoriety increased significantly in 2004, after the murder of a teenage boy[2]. In chronological terms, the first block to consolidate included the gangs known as the *Latin Kings* and *Ñetas*, linked to migratory flows originating in Ecuador. The second block included the *Black Panthers* and *Trinitarios* and was linked to migratory flows from the Dominican Republic. The third block, composed by *Mara Salvatrucha* and *Barrio 18* from El Salvador and Honduras, was the last to consolidate. Estimates indicate that while in 2003 there were around 70 members, after 2009 the number of members stabilized at around 2,500[3]. In 2012, around 15 gangs were detected. Most members are young men between 12 and 25 years old. Although most of them trace their origins to Latin America, Spaniards and individuals of other nationalities are frequently involved as well[4]. The factors mentioned in the sociological literature influencing involvement

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

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

[4]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 Blanco (2012), they mostly follow behavioral patterns present in Ecuador. This pattern refers to the organization inside the group (hierarchical structure) and behavior outside

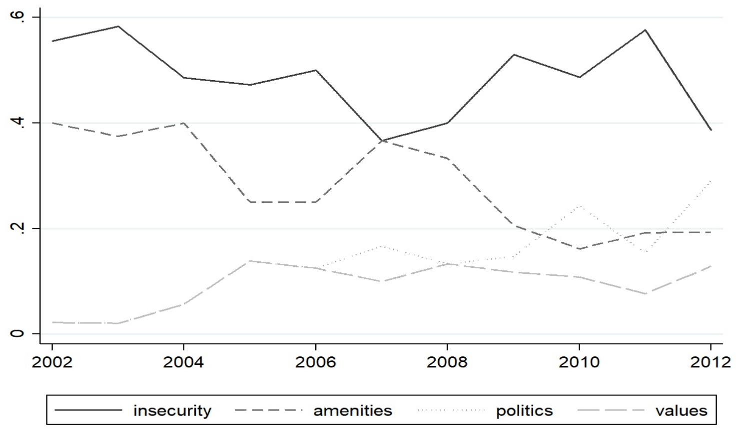
in gangs include, among others: social disorganization, presence of gangs in the neighborhood, barriers or lack of social and economic opportunities, lack of social capital, family disorganization, problems at school, and socialization in the street (e.g., Feixa 2012). However, what makes gangs deserve attention is their connection with criminal activities and the violence embedded in their behavioral patterns.

The expansion of this social phenomenon was conditioned to the specific context in which it occurred. Firstly, Spain underwent a widespread demographic change in the 2000s. The arrival of substantial migratory flows increased the immigrant population's percentage from less than 3.6% in 2000 to 14.3% in the year 2012[5]. South America contributed the most foreign citizens (around 350,000 individuals in 2012 and 300,000 in 2019). Secondly, there was an important change related to security enforcement. Between 1994 and 2008, the 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 crimes, in 2010 this percentage had increased to 19.4%. Finally, according to the barometer of the city of Barcelona, among non-economic concerns, citizens saw insecurity as the most concerning, with increasing weight given to this from 2007 onwards. This pattern is shown in Figure 3.1.

the group and rivalries.

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

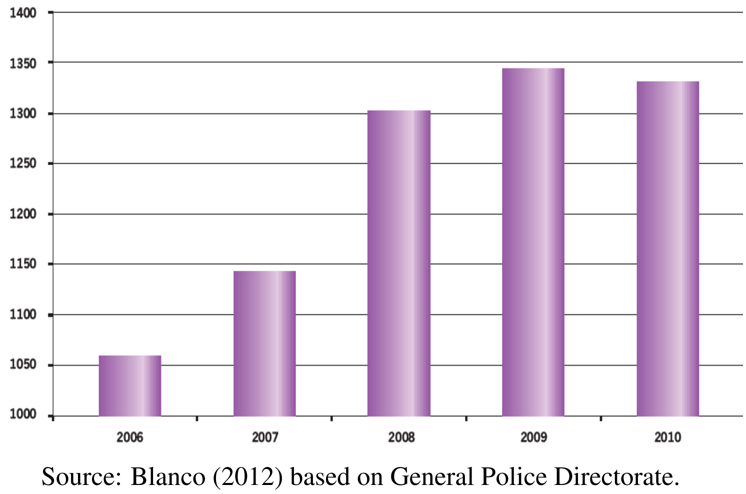
Figure 3.1: Main concerns for Barcelona residents, excluding the economy



Source: Own construction from Barometer of the City of Barcelona

In this context, the rise of gangs and criminal acts carried out by them took place. Figure 3.2 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 3.2: Arrests of gang members in Catalonia



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

From a policy perspective, two apparent periods can be distinguished in how the Local Public Sector (Local Government and Barcelona City Hall) decided to tackle the existence and operation of gangs.

1. From 2004 until 2012, a lenient approach was followed. In 2004, Barcelona City Hall commissioned a report on the gang situation (Feixa 2012). At this

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

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 (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 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 or crackdowns, which consisted of large-scale police interventions that arrested several and important gang members in a coordinated fashion. This change in the police was accompanied by 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.

Hence, in 2012, there was a drastic change in how the gang situation 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[10]. This context provides an excellent scenario to assess the effectiveness of a sturdier punishment policy towards gangs. It must be noted that the outcomes analyzed are due to the compound effect of

[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.

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

concomitant policy modifications (police and judiciary), as, from the public sector viewpoint, they were coordinated and seen as one.

3.3 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 the previously explained migration phenomenon in the early 2000s in Spain and large cities' attractiveness for the incoming population. The MAB is composed of 36 municipalities and comprises 4 million inhabitants. It is the fifth largest and the densest metropolitan area in Europe. Within the MAB, Barcelona municipality is the largest in population and territory (see Figure A3.1 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) mentions 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 formalized offenders during that period. It includes information on the exact time (yy-mm-dd; hh-mm) and place of the crime (X-Y geographical coordinates) as well as on the type of crime, and basic individual characteristics of the offenders (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 offenders are arrested alongside others. This matching allows me to identify criminal peers and thoroughly describe criminal networks.

Secondly, I have information about all sweeps carried out by the UGOV unit. The unit was created in 2012, and sweeps are still taking place. However, due to the availability of administrative police records only 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 are included in the records. During these first three years (2012–2014), several sweeps took place, leading to 151 individuals being arrested[11].

Using these data sources, I build a panel dataset for the MAB at the individual-

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

quarter level for the 2008–2014 period. This dataset includes 7,349,804 observations, coming from 262,493 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 partners they have[12] [13]. Demographic information about the individual as well as on the crimes committed is also included. Descriptive statistics are presented in Table 3.1.

Table 3.1: Descriptive statistics, offenders in the MAB 2008-2014

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

Source: Own construction from Local Police data.

3.4 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 results 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.

[12]If there are no arrests, a zero is imputed for the criminal actions committed by that individual in that quarter. This imputation allows building a balanced panel.

[13]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 offenders who were not arrested. This issue is common when dealing with crime data and is not easy to resolve. Still, the data provides a solid base to build this analysis.

3.4.1 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 described in the previous section, the primary analysis in this subsection estimates the following staggered difference-in-differences specification

$$\begin{aligned} Crime_{it} &= \beta_0 + \beta_1.Post_{it} \\ +\beta_2.(Arrested.Post)_{it} &+ \beta_3.(Peer.Post)_{it} + \eta_i + \phi_t + \varepsilon_{it} \end{aligned} \tag{3.1}$$

where 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. $Arrested_i$ and $Peer_i$ indicate whether an individual i was arrested in a sweep or if it is an known peer of someone that was. $Post_{it}$ is an indicator variable that takes a value equal to one after each sweep and is sweep-specific. η_i and ϕ_t are individual and year-quarter fixed effects, respectively. The observational unit is an individual-quarter pair, and the principal coefficients of interest are β_2 and β_3.

For my main analysis, control units are individuals 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' criminality when the sweeps took place in comparison to all group offenders.

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

$$Crime_{id} = \beta_0 + \sum_{d \neq -1} \phi_d \cdot (Treated_i \cdot Time_d)_{id} + \eta_i + \varepsilon_{id} \tag{3.2}$$

where the observational unit is an "individual-time to intervention" pair (measured in quarters). I estimate $(Treated \cdot Time)_{id}$ interactions, leaving $Time = -1$ as the reference period. Each ϕ_d coefficient quantifies the difference in criminal activity between the $Treated_i$ individuals (either $Arrested_i$ 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 check for the parallel trend assumption and understand the equation's post-treatment dynamics of Eq. (3.1).

I also take a continuous treatment approach in addition to the one shown in Eq. (3.1). For this exercise $Treated_i$ takes values $\in$ [0,1] according to different criteria.

The first criteria attributes a $Treated_i = 1$ to arrested individuals ($Arrested_i = 1$) and $Treated_i \in (0,1]$ to known peers ($Peer_i = 1$) based on the number of links to arrested offenders, after a min-max normalization[14]. Lastly, $Treated_i = 0$ for all others. Hence

$$Crime_{it} = \beta_0 + \beta_1.Post_{it} + \beta_2.Treated_i + \beta_3.(Treated.Post)_{it} + \phi_t + \varepsilon_{it} \tag{3.3}$$

where

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

The second criteria I take is assigning a [0,1] treatment indicator to individuals according to different network centrality measures. In this setting, I consider outcomes regarding two other centrality measures: closeness and alpha 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.

Finally, I run similar exercises to Eq. (3.1) 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 thus shows the effect on crime at a broader level. The second exercise indicates whether other socioeconomic outcomes change after sweeps occur, indicating whether their benefits exceed those related to criminal outcomes.

3.4.2 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

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

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

Peer effect estimates

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 and to rank them. In this setting, agents choose how many crimes to commit to maximize their utility, which depends on all agents' crime profiles and the network architecture. In this game, the utility function of individual i is given by

$$u_i(y,G) = \alpha_i y_i + \phi \sum_{j=1}^{n} g_{ij} y_i . y_j - c y_i - 1/2 y_i^2 \tag{3.4}$$

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[15] (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 agent maximizes her utility, and the best-reply function can be written in matrix form as

$$Y = \phi GY + \beta_0 + X\beta_1 + \bar{X}\beta_2 + u \tag{3.5}$$

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

where Y is a vector of the individual outcomes (crimes), G is a diagonal adjacency matrix[16], GY is a vector of the individual outcomes for peers, X is a vector of agents' characteristics and $\bar{X}$ is a vector of peers' average characteristics. Peer effects are given by ϕ, β_1 captures observable individual heterogeneity and β_2 reflects the contextual effects.

Threats to identification The identification of peer effects is not straightforward and suffers several problems (Bramoullé et al. 2009). The first of these is the well-known 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 is presumed to be endogenous. When this is the case, it is impossible to identify whether the correlation of behavior among peers results from the network or just of homophily.

As stated in Lee et al. (2020), both issues can be solved by an Instrumental Variables approach in three stages. Firstly, the observed adjacency matrix G needs to be replaced by a predicted adjacency matrix $\hat{G}$. The latter is based on exogenous covariates of the individuals. A logistic regression model on link formation is estimated considering matches on available observable characteristics, and a predicted probability of link formation is obtained for each element of $\hat{G}$. Secondly, peers' criminal outcomes (GY in equation (3.5)) are regressed against the IV matrix $\hat{Z} = [1, X, \hat{\bar{X}}, \hat{G}1, \hat{G}X, \hat{G}\hat{\bar{X}}]$. Thirdly, equation (3.5) is run with the predicted value of GY to obtain peer effect estimates, $\hat{\phi}$.

Centrality measure and key player ranking

Once peer effects are adequately identified and estimated, it is possible to compute the centrality of each individual in each gang. In order to compute such a measure, two assumptions are made. First, the gang is fixed; this implies assuming it does not vary after an individual is removed, meaning 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 peer effects ϕ, individual heterogeneity of crime productivity α and for all gangs r and all individuals i, Ballester and Zenou (2014) propose a

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

contextual intercentrality measure, which is built as follows

$$\delta_i(r,\phi,\alpha) = b_{\alpha_{\langle i\rangle}}(r,\phi)\cdot\frac{\sum_{j=1}^{n} m_{ji}(r,\phi)}{m_{ii}(r,\phi)} + b_{\alpha}(r,\phi) - b_{\alpha_{\langle i\rangle}}(r,\phi) \tag{3.6}$$

where $\alpha_{\langle i\rangle} = (X_i, \alpha^{[-i]})'$ describes the situation in which player i has not yet been removed (so she has her attribute X_i) but she does not affect or is affected by other players' abilities α_j. In this situation, the vector α is computed from the network r when individual i is removed ($r^{[-i]}$), that is $\alpha^{[-i]}$. $b_{\alpha,i}(r,\phi)$ is the centrality of individual i in network r and $b_{\alpha}(r,\phi)$ is the total centrality in network r. m_{ji} and m_{ii} are the corresponding elements of matrix $M = (I-\phi G)^{-1} = \sum_{k=0}^{\infty}\phi^k G^k$. M tracks the number of walks in network r starting from i and ending in j, where walks of length k are weighted by ϕ^k.

The contextual intercentrality measure of Ballester and Zenou (2014) considers two effects. The first effect is a network effect derived from the centrality measured by Ballester et al. (2006). This effect, corresponding to the first term in Eq.(3.6), captures the direct effect on crime from removing an individual and the indirect effect on others' criminal activity from the removal of that individual 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.(3.6), and stems from the change 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.

Predicted reduction in criminality and policy comparison

Lindquist and Zenou (2014) show that the predicted crime reduction in each 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

$$CR_{ir} = \frac{100.\delta_i(r,\phi,\alpha)}{b_{\alpha}(r,\phi)} \tag{3.7}$$

As Eq. (3.7) indicates, as $\delta_i(r,\phi,\alpha)$ is highest for the key player in each gang, so is the crime reduction at the gang level. However, it must also be noted that Eq. (3.7) computes the predicted crime reduction when a single individual is removed from the gang. For this reason, by itself, it is not a good benchmark with which to compare the outcomes of the sweeps as they were of a larger scale.

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

$$CCR_{nr} = CR_{1r} + CR_{2r}(1 - CR_{1r}) + ... + CR_{nr}(1 - CR_{1r} - ... - CR_{(n-1)r}) \quad (3.8)$$

where $i = 1, 2, ..., n$ are the individuals in the network r sorted by contextual intercentrality measure, being $i = 1$ the top-ranked individual, and $i = n$ the lowest-ranked individual.

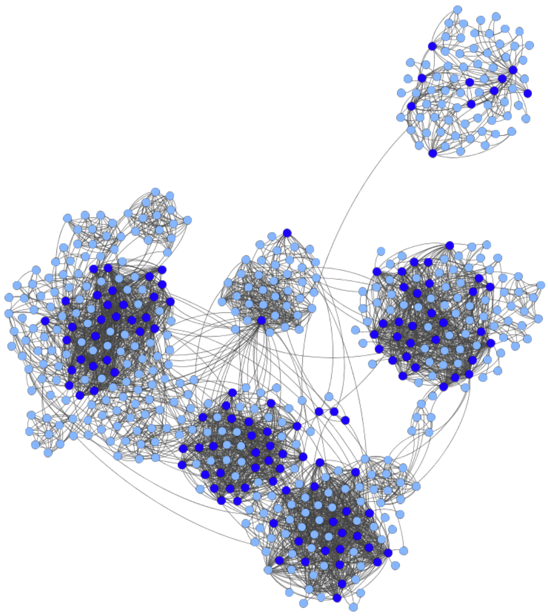
Firstly, this requires computing the predicted crime reduction when the key player is removed as in Eq.(3.7), CR_{1r}. Secondly, the additional reduction when removing the second-top-ranked individual is determined by computing their centrality over the remaining criminal activity after the first individual is removed. The second exercise is performed as many times as there are individuals in the gang. As a result, a map of the predicted crime reduction at the gang level as a function of the number of key players removed is obtained. Such predictions are compared with those observed after the sweeps. The resulting potential deviation speaks in terms of the effectiveness of the interventions.

3.5 Results

3.5.1 Sweeps analysis

Out of the 151 individuals arrested in the sweeps, 127 individuals are identified in the data. 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. For those 127 individuals identified, 413 first-order peers were identified, matching them in date, time, geographical coordinates, and crime type in Local Police records on arrests. As a result, a total of 540 individuals are considered treated by UGOV's sweeps, either directly ($Arrested = 1$) or indirectly ($Peer = 1$). The network structure of these 540 individuals is shown in Figure 3.3. This graph presents the network structure of individuals arrested in the sweeps and first-degree known peers. Each dot is an individual; darker dots are individuals arrested in the sweeps, whereas lighter dots are peers. Each line between individuals indicates that those two individuals had committed at least one crime together before the sweeps. Concretely, 3,463 criminal links are identified among these individuals.

Figure 3.3: Recovered criminal gang structure, before sweeps



Note: This graph presents the network structure of individuals arrested in the sweeps and first degree known peers. Each dot is an individual: 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 UGOV's sweeps information.

A description of the data used in this analysis is presented in Table 3.2, indicating the individuals' observed characteristics under analysis and their peers' ones. As expected, individuals treated by UGOV sweeps are, to a large extent, young males born in Latin America[17]. Table 3.3 shows the results of balancing tests regarding crime characteristics for treated (arrested individuals and peers) and control individuals (all other group offenders). This data indicates that while there may be differences in the number of crimes committed by treated individuals compared to control individuals, it is not possible to rule out that the variation in the number of crimes is the same for both groups. This data, therefore, provides the first piece of evidence in favor of the parallel trend assumption holding in this context.

[17]See Figure A3.2 in the Appendix for homogeneity measures inside gangs for the most extensive sweeps in the sample.

Table 3.2: Descriptive statistics – characteristics of individuals arrested in sweeps and their known peers

	Mean	Std. Dev.	Min	Max
Own characteristics				
Female	0.124	0.330	0	1
Spanish	0.298	0.458	0	1
Latin	0.622	0.485	0	1
Age	22.41	7.02	13	63
# Crimes	4.526	4.737	1	30
Peers	12.83	12.67	1	77
UGOV-arrested	0.235	0.425	0	1
Peer characteristics				
Female	0.091	0.162	0	1
Spanish	0.289	0.267	0	1
Latin	0.636	0.298	0	1
Age	22.01	4.63	14	41

Note: This table reports descriptive statistics for the 540 individuals linked to UGOV sweeps. Source: Local Police data and UGOV's sweeps information.

Table 3.3: Balancing tests on crime for treated and control individuals

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

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

Baseline estimates

Baseline estimates of Eq.(3.1) are presented in Table 3.4. Estimates are shown for individuals arrested in the sweeps as well as known peers. The probability of committing a crime, the total number of crimes for which they are arrested, and the number of group crimes they are arrested are shown. Control individuals are arrested in groups but are not part of any gangs arrested in the sweeps.

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; the number of crimes is reduced by 95%. For peers, reductions in criminality are of a smaller magnitude (26%) but also significant. Considering only crimes committed by groups, the drops in crime are even higher.

Table 3.4: Effects of sweeps on crime - baseline estimates

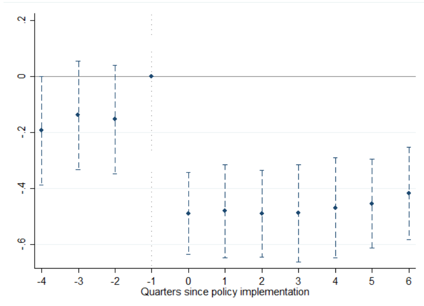
	P(crime)	Total crimes	Group crimes
Arrested·Post	-1.782***	-0.350***	-0.302***
	(0.211)	(0.028)	(0.023)
Peer·Post	-0.469***	-0.048***	-0.051***
	(0.117)	(0.019)	(0.015)
Obs.	3,544,535	3,544,535	3,544,535
Indiv.	126,968	126,968	126,968
Indiv. FE	Y	Y	Y
Year-Quarter FE	Y	Y	Y
% change arrested	-44%	-95%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

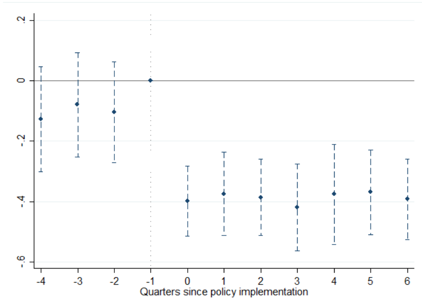
Notes: This table reports the results of the difference-in-differences (DiD) estimation following Eq. (3.1) for the 2008-2014 period. Each row presents estimates for different groups: arrested individuals and peers. The first column indicates the results for the probability of committing a crime, column two indicates the total number of crimes and column three indicates the number of group crimes. The observational unit is an individual–quarter pair and only individuals ever arrested in a group crime were included. Treated units are arrested individuals or peers. Treatment timing differed across individuals, according to the timing of the sweep. The coefficient shown is that of interest in a DiD setting, being $Treated \cdot Post$ for Arrested and Peer. Robust standard errors are shown in parentheses. p<0.01, ** p<0.05, * p<0.1.

Event study exercises allow effects to be seen over time. For arrested individuals, the crime reduction is sharp and immediate. Moreover, this reduction persists after one year and a half. For peers, a different pattern arises. The effect is short-lived as, after one year, the reduction in criminality is no longer significant. This pattern may relate to the average time taken to resolve a process legally. According to statistics from the Spanish Judiciary System, the average timescale for "brief procedures" in Catalonia is of 9.8 months or 7.1 for procedures involving underage offenders[18]. For peers, the crime reduction is no longer significant around this timescale.

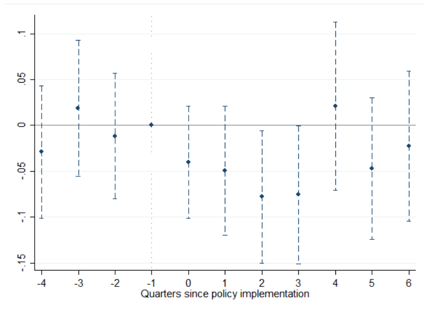
[18]The statistics are provided at the regional level. Because of this the Catalan average is used to approximate what takes place in the MAB. Source: http://www.poderjudicial.es/Informes-por-territorios-sobre-la-actividad-de-los-organos-judiciales/

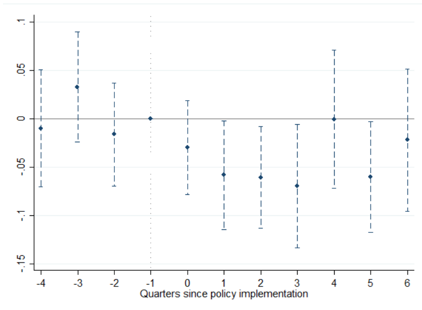
Figure 3.4: Effects of sweeps on crime - event study exercises, 95% Confidence intervals.





Total crimes of arrested individuals Group crimes of arrested individuals





Total crimes of peers Group crimes of peers

Notes: This graph reports the results of an event study exercise following Eq. (3.3) for total crimes (left panel) and group crimes (right panel). Results are presented for arrested individuals (upper panel) and peers (lower panel). The observational unit is an individual-quarter pair. Treated units are defined as in section 3.4.1, while treatment timing differed across units, according to intervention timing. Confidence intervals are based on robust standard errors.*** p<0.01, ** p<0.05, * p<0.1.

I also analyze the previous outcomes in terms of individual characteristics. The results are presented in Table 3.5 both for individuals arrested in the sweeps and their peers. These results indicate that the reduction in total criminality for arrested individuals is more considerable for offenders 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: female offenders show a more considerable decrease in crime following sweeps.

Table 3.5: Effects of sweeps on crime - individual demographics heterogeneity estimates

	Total Crimes	Group Crimes
Arrested·Post	-0.445***	-0.353***
	(0.062)	(0.048)
Arrested·Post·Underage	-0.197**	-0.114
	(0.077)	(0.088)
Arrested·Post·Female	0.122***	0.057
	(0.041)	(0.042)
Arrested·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. (3.1) for the 2008-2014 period. Each row presents estimates for different groups: arrested individuals and peers by heterogeneous individual characteristics. The first column indicates the results for the total number of crimes and the second column indicates the results for the number of group crimes. The observational unit is an individual-quarter pair and only individuals ever arrested in a group crime were included. Treated units are defined arrested individuals or peers. Treatment timing differed across units, according to the timing of the sweep. The coefficient shown is that of interest in a DiD setting , being $Treated \cdot Post$ for Arrested and Peer. Robust standard errors are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

The network structure remaining after the sweeps indicates that some small crime structures persists after the sweeps. This certain persistence is consistent with the small and short-term reduction in crime for peers. However, the network graph is much smaller and sparse than before the sweeps in observed individuals and criminal links. Before the sweeps, 540 individuals (127 arrested in sweeps and 413 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[19].

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

[19] See Figure A3.3 in the Appendix for a comparison of before and after network graphs.

Continuous treatment estimates

For the continuous treatment estimates, two approaches are followed. First, the number of links to arrested individuals is considered in a min-max standardized way, as described in section 3.4.1. The second approach takes two network centrality measures amongst arrested individuals and peers: alpha-centrality and closeness. The first is a measure of a node's influence in a network; the second measures the average length of the shortest path between the node and all other nodes in the graph.

Results of these exercises are presented in Table 3.6. 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 13%. 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 crimes by 3.2%, whereas for closeness, there is a 2% reduction[20].

[20] 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).

Table 3.6: 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)
% change	-5.3%	-13.0%	-11.4%
Panel B: alpha-centrality	-1.501***	-0.224***	-0.204***
	(0.151)	(0.025)	(0.020)
% change	-3.7%	-3.2%	-2.9%
Panel C: closeness	-1.172***	-0.156***	-0.143***
	(0.120)	(0.019)	(0.015)
% change	-2.9%	-2.0%	-1.9%
Obs.	3,544,535	3,544,535	3,544,535
Indiv.	126,968	126,968	126,968
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. (3.1) for the 2008-2014 period. Each panel presents estimates for different continuous treatment indicators: number of links, alpha-centrality and closeness measures. The first column indicates the results for the probability of committing a crime, column two indicates the total number of crimes and column three indicates the number of group crimes. The observational unit is an individual–quarter pair and only individuals ever arrested in a group crime were included. Treated units are defined as individuals who were either arrested or a peer, with heterogeneous treatment intensity according to each measure. Treatment timing differed across units, according to the timing of the sweep. The coefficient shown is that of interest in a DiD setting, being $Treated \cdot Post$. Robust standard errors are shown in parentheses. Robust standard errors shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Event study exercises using the number of links, alpha-centrality and closeness measures indicate a similar pattern for all crimes and group crimes as in Figure 3.4[21]. For all three, the reduction in criminality is immediate but fades over time. After six quarters, the effects are still present.

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 await-

[21] See Figure A3.4 Appendix for the same exercise considering continuous treatment measures.

ing 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.

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 3.7 summarizes the evidence on this regard.

Table 3.7: Effects of sweeps on crime - crime typologies heterogeneity estimates

	Against Property	Against Person	Other Crimes
Arrested·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. (3.1) for the 2008-2014 period. Each row presents estimates for different groups: arrested individuals and peers. The first column indicate results for the number of property crimes, column two indicates results for the number of crimes against the person and column three indicate results for all others. The observational unit is an individual–quarter pair and only individuals ever arrested in a group crime were included. Treated units are arrested individuals or peers. Treatment timing differed across individuals, according to the timing of the sweep. The coefficient shown is that of interest in a DiD setting, being $Treated \cdot Post$ for Arrested and Peer. Robust standard errors are shown in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

When analyzing outcomes by type of crime 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[22]. These patterns 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.

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, offenders 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 3.8, where the effect is distinguished according to the individuals' position in the distribution of committed crimes. For this exercise, I follow a triple differences strategy (treatment/time/crime level) and find no significant difference between high and low offenders. This holds considering different thresholds for what is defined as a high offender (above median, 75, 90, 95, and 99 percentiles). This result is in line to that in Philippe (2017).

[22]See Table A3.1 in the Appendix for a more exhaustive division of crime categories.

Table 3.8: 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 peers. Treatment, timing and criminal intensity are the differences considered. Each column presents different estimates according to which threshold is taken to define high crime offenders.The observational unit is an individual–quarter pair and only individuals ever arrested in a group crime were included. Treated units are peers. Treatment timing differed across individuals, according to the timing of the sweep. The coefficient shown is that of interest in a triple DiD setting, being $Treated \cdot Post \cdot High$ for Peer. Robust standard errors are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

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 shows no statistically significant differences between groups[23]. Hence, the results point towards a targeting strategy rather than a profiling one.

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. 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

[23] See Table A3.2 in the Appendix.

for a period 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-crime period.

Differential effect of sweeps vs. any arrest Finally, there is the possibility that UGOV 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 (versus the 127 identified by UGOV sweeps) and 56 peers (versus the 413 identified linked to those arrested by UGOV sweeps). I include these individuals in the pool of treated individuals. I then perform the same baseline analysis while 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 Metropolitan Area of Barcelona's crime-fighting strategy derived from the sweeps and Act 6/2009 has a differential effect on criminal outcomes.

The results of this analysis are shown in Table 3.9. They indicate a significant reduction in the criminal activity of arrested individuals and their known peers regardless of whether they were linked to a sweep or 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 sweeps: the reduction in the criminal activity of individuals arrested in the 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. 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 3.9: Differential effect of sweeps on crime

	P(crime)	Total crimes	Group crimes
Arrested·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)
Arrested·Post·Sweep	-0.453	-0.145***	-0.087**
	(0.343)	(0.050)	(0.041)
Peer·Post·Sweep	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: arrested individuals and peers. The first column indicates the results for the probability of committing a crime, column two indicates the total number of crimes and column three indicates the number of group crimes. The observational unit is an individual–quarter pair and only individuals ever arrested in a group crime were included. Treated units are peers. Treatment timing differed across individuals, according to the timing of the sweep. The coefficient shown is that of interest in a triple DiD setting, being $Treated \cdot Post \cdot Sweep$ for Arrested and Peer. Robust standard errors are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

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 units. To overcome potential issues derived from negative weights, De Chaisemartin and d'Haultfoeuille (2020) propose another estimator that solves them. Results following De Chaisemartin and d'Haultfoeuille (2020) do not differ significantly from the linear regression estimator presented previously[24]. This outcome reflects the fact that negative weights are not an issue in this analysis[25], 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. Specifically, I modify the control group to consider criminals

[24]See Figure A3.5 in the Appendix.

[25]Concretely, no negative weights are identified in this setting.

arrested for any crime, crimes against the person, other crimes, and drug crimes. Additionally, I estimate Eq. (3.1) with Poisson regression. As the dependent variable in this analysis, namely the number of total crimes, has a count data structure, this modeling type might be better suited. The results generally hold for both arrested individuals and peers across specifications.

Table 3.10: Effects of sweeps on crime - alternative specifications estimates

	Baseline	Control: All criminals	Control: Against Person	Control: Other	Control: Drugs	Poisson IRR
Total Crimes						
Arrested·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						
Arrested·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: arrested individuals and peers. Each column indicates a different specification, considering different control groups for columns 2 to 5 and a Poisson model in column 6. The observational unit is an individual–quarter pair and only individuals ever arrested in a group crime were included. Treated units are peers. Treatment timing differed across individuals, according to the timing of the sweep. The coefficient shown is that of interest in a DiD setting, being $Treated \cdot Post$ for Arrested and Peer. Robust standard errors showed in parentheses. p<0.01, ** p<0.05, * p<0.1.

Area Level Outcomes

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

I therefore examine the impact of sweeps at a broader level. To do so, I look at the evolution of different outcomes in the area in which the sweeps took place. For 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 an 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 3.11.

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 a crime reduction for specific typologies and involve other socioeconomic variables. Table 3.11 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 3.11: 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	57.42314	1.03	(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.(3.1) for the 2009-2014 period, incorporating an AR(1) disturbance term. Each column presents results for different outcomes. The observational unit is an area-year pair. Treated units are defined as those in which an UGOV sweep took place. The coefficient showed is that of interest in a DiD setting, being $Treated \cdot Post$. Robust standard errors are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

3.5.2 Key player benchmark

While the previous section analyzes the effect of the UGOV sweeps on arrested individuals' criminality and known peers, this section aims to compare such outcomes with those that network theory predicts would derive from targeting the key player in each gang. To do this, I first estimate a peer-effects model, as described by Eq. (3.5). On the matter of model estimation, and as previously explained, I consider the 3SLS estimator of section 3.4.2 for Instrumental Variable regressions. For this, I obtain $\hat{G}$ by running a logistic regression to predict link formation probabilities. For each potential link in each gang (that took empirical values of 0 or 1), the outcome is regressed on the difference in each pair of individuals' observable characteristic available (age, gender, nationality). For link formation probabilities, there is strong evidence of homophily as matches in characteristics increase the probability of committing a crime together for the individuals under analysis[26]. 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 $\hat{G}$ is likely to be a weak instrument to the actual links.

The estimation results for peer effects as outlined in Eq.(3.5) are reported in Table 3.12. The first column presents OLS estimates, column 2 presents IV estimates with IV matrix Z, column 3 shows IV estimates with IV matrix $\hat{Z}$, and column 4 presents GMM estimates. Regarding the estimates of the first two columns, they may suffer from endogeneity issues derived from the reflection problem and the fact that the network itself is not exogenous. Moreover, the overidentification test for the 2SLS-G estimation rejects the null hypothesis. Given these issues, it is necessary to instrument the 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, peer effects are 0.007[27]. This result 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, the first authors conduct their analysis on suspected Swedish criminals, and 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 10% ($\frac{1}{1-13\hat{\phi}}$).

[26] See Table A3.3 in the Appendix for results of the link formation model.

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

Table 3.12: Peer effect estimates - gangs in the Metropolitan Area of Barcelona

	OLS	2SLS-G	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 criminal networks following Eq. (3.5). 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 criminal. The coefficient of interest (that of peer effects) is provided by ϕ. Robust standard errors are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Under the invariant network assumption (that is, that the network does not rewire after an agent is removed), the key player is the agent with the highest contextual centrality measure in the network (Ballester and Zenou 2014). As explained by the authors, failure to include contextual effects can lead to spurious inference on social network effects as individuals adjust behavior because of shared influences. Using the GMM estimates reported, the contextual centrality measure is calculated for each agent following Eq. (3.6), and the key player is identified for each gang.

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

Finally, following Ballester and Zenou (2014) and Lindquist and Zenou (2014), I compute the predicted reduction in crime that would have been achieved by removing the key player. In this case, the model predicts that removing the key player in each gang would lead to a weighted average crime reduction for the mean gang 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 also verified in the current study. On average, targeting the key player would achieve a crime reduction that would outperform targeting the most active criminal by 2.3%, targeting the most central individual (considering the measure by Bonacich (1987)) by 2.9% and the most connected individual by 0.7%[28]. This set of results is consistent with those of Lindquist and Zenou (2014) and Philippe (2017). Even if some of the current results differ from their results, the focus of the current study is on a different type of networks: youth criminal groups (Lindquist and Zenou (2014) consider all types of crime and Philippe (2017) focuses on pairs or groups of 7 or less). Hence, the outcomes and policy comparisons may differ.

3.5.3 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, the sweeps achieve a crime reduction of 61% in the year following the intervention. This reduction outperforms the key player strategy by 43.3%. However, the comparison between the two strategies is not straightforward. While the prediction of the removal of the key player is based on catching just one individual, sweeps affect more individuals[29]. Thirdly, it is possible that being arrested is positively and significantly correlated with the contextual centrality 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[30].

To overcome the difficulties in comparison, I perform a sequential exercise by removing more than one key player[31]. According to the key player theory predictions, this exercise indicates that a similar reduction in crime to that achieved by

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

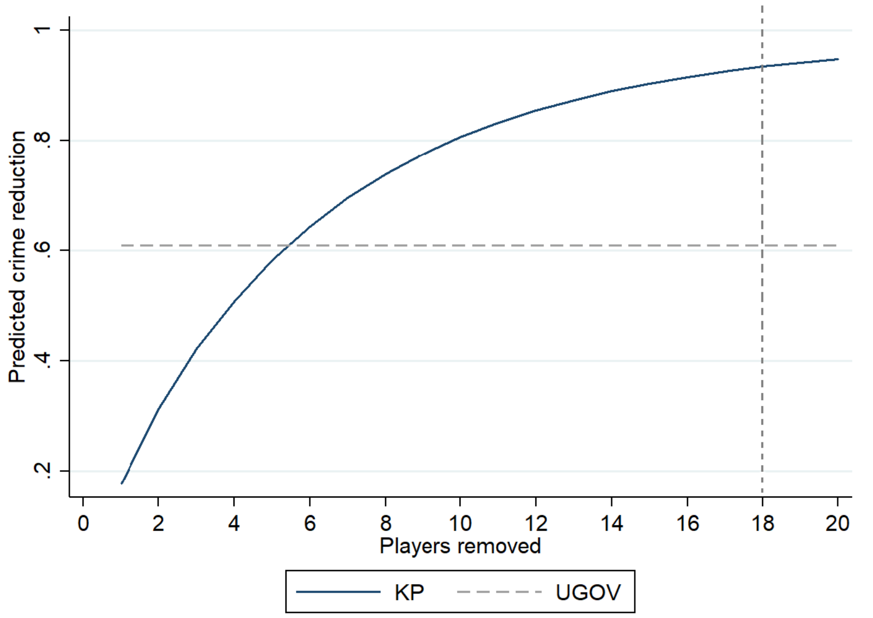
[29]They arrest on average 18 individuals per gang, or 24% of the gang.

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

[31]As previously explained, I first compute the classical key player exercise: I remove the highest contextual centrality individual and estimate the predicted reduction in crime in the gang. After this, I compute the same exercise for the second-ranked individual and compute the predicted crime reduction in the fraction of crime that would remain after removing the first key player. I do this in several steps, as outlined in Eq. (3.8).

the sweeps would have been achieved by removing the top six individuals sorted by the contextual centrality measure. This number of arrests corresponds to a third of the average actually arrested. The exercise also 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 centrality instead of the actual arrests. This outcome implies a 50% increase in reduced criminality compared to the one recorded. Hence, by adequately identifying, targeting, and catching the key players in each network, the sweeps could have achieved the same crime reduction with a smaller deployment or a more considerable reduction in crime if arrests were held constant.

Figure 3.5: Predicted reductions in criminality, by number of key players removed



Note: This graph presents the predicted crime reductions as a function of the number of agents removed, ordered by contextual centrality. Such outcomes were 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, the key player is not identifiable by either observable or gang characteristics. The second comparison is that between targeting strategies and other approaches, such as general tough-on-crime policies. In this case, the sweeps achieve a significantly higher crime reduction than that predicted by the key player theory. Still, this strategy involves a more extensive police deployment and does not always catch the most relevant individuals in terms of intercentrality. Indeed, by catching the key players in each gang, the sweeps would have achieved a 50% more considerable reduction in the affected networks' criminal activity. From the analysis above, it can be concluded that, in comparison with the sweeps, removing only one key player would be less effective. However, identifying and tackling a group of key players in each gang can 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 (if there is no availability) and data analysis (since, as mentioned, the key player is not easily identifiable by sociodemographic, criminal, or network characteristics). Secondly, under the invariant network assumption, the key player predictions are only valid in the short term. It is unlikely for the remaining agents 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 long-run 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 agents. It hence would be more difficult for police resources to reach. Additionally, networks would respond endogenously to the key player's extraction by restructuring or re-grouping to continue committing a crime. Hence, a key player strategy might not be the optimal strategy for police forces if their cost is too high in terms of investment or not low enough in 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.

However, this does not mean that tough-on-crime interventions are always the approaches to follow. Previous literature indicates how costly these approaches may be in many dimensions. Firstly, the direct cost for the police in terms of human resources, training, and deployment. Secondly, the indirect costs to society, 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.

3.6 Conclusions

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

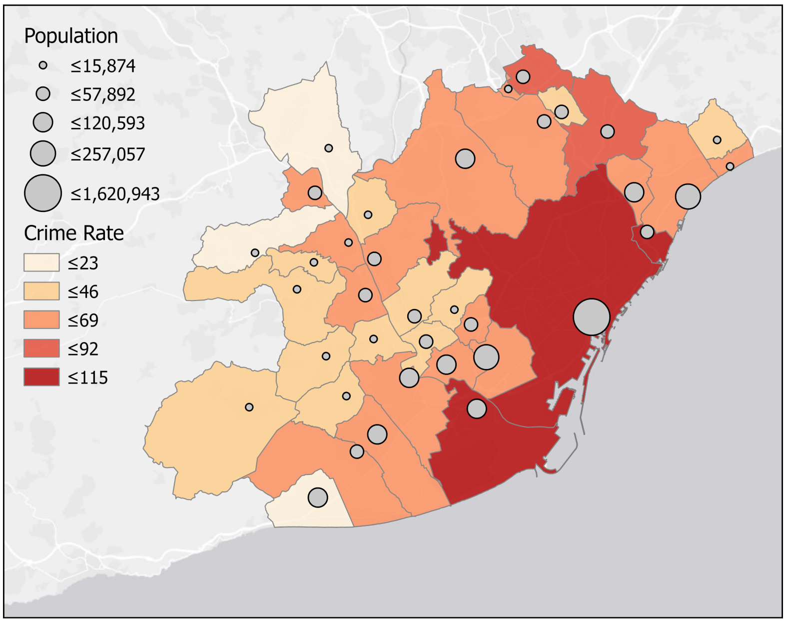
My results indicate significant reductions in the criminal activity of those arrested in the sweeps and their known peers. For the former, there is an immediate and sharp drop in criminal activity. This result, alongside average trial and prison times, is consistent with an incapacitation effect. In 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.

The peer effects estimations indicate that, on average, crime increases by 10% when an individual is part of a gang compared to when committing crimes alone. Based on 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.

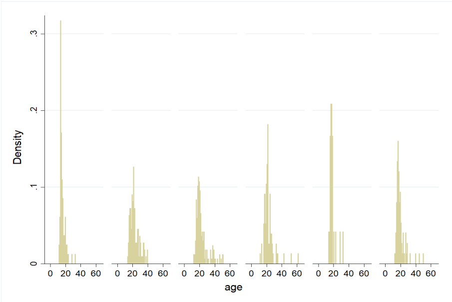
3.7 Appendix

Figure A3.1: Metropolitan Area of Barcelona and corresponding municipalities

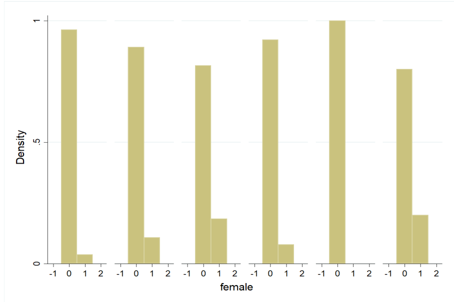


Source: Own construction from Local Police and National Institute of Statistics data.

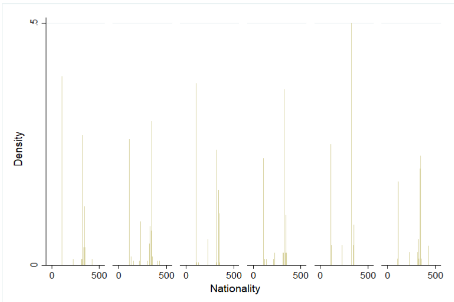
Figure A3.2: Histogram of frequency of individual characteristics within gangs. Top sweeps.



Age



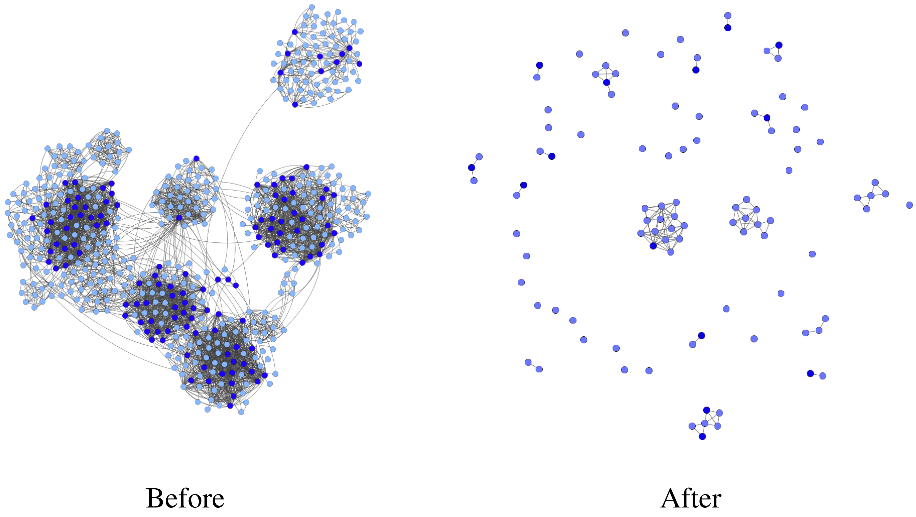
Gender



Nationality

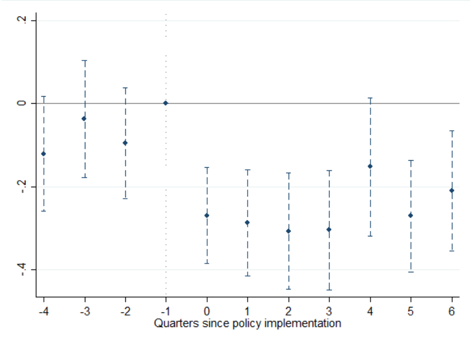
Source: Own construction from Local Police data.

Figure A3.3: Recovered criminal gang structure, before and after UGOV sweeps.

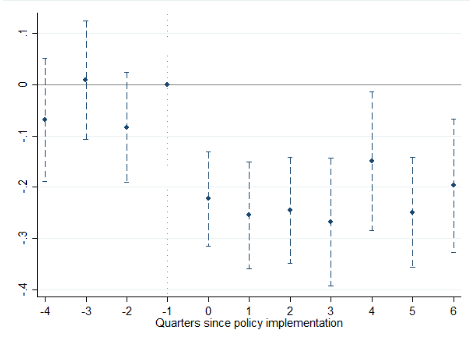


Note: This graph presents the network structure of individuals arrested in the sweeps and first degree known peers before and after the sweeps were carried out. Each dot is an individual and each line indicates a link. Source: Own construction from Local Police data.

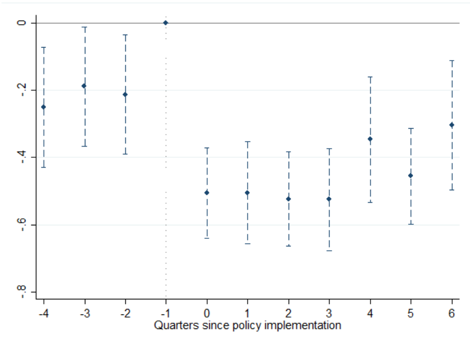
Figure A3.4: Effects of sweeps on crime - event study exercise with a continuous treatment indicator, 95% confidence intervals.



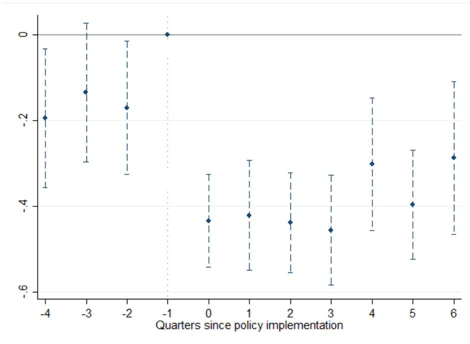
Total crimes, alpha centrality



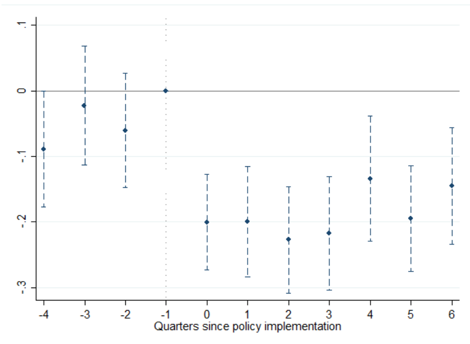
Group crimes, alpha centrality



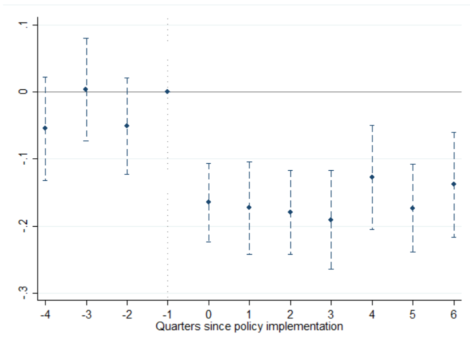
Total crimes, closeness



Group crimes, closeness



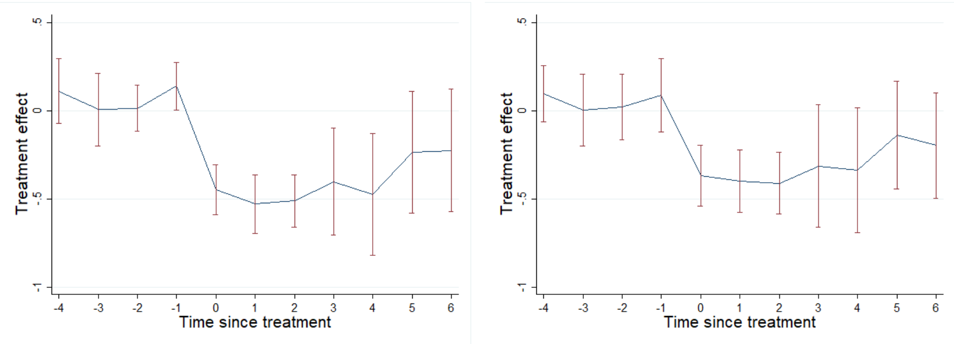
Total crimes, number of links



Group crimes, number of links

Notes: This graph reports the results of an event study exercise following Eq. (3.3) for total crimes (left panel) and group crimes (right panel). Results are presented for pooled arrested individuals and non-arrested co-offenders, with heterogeneous treatment intensity according to the alpha-centrality, closeness and number of links criteria. The observational unit is an individual-quarter pair. Treated units are defined as in section 4.1, while treatment timing differed across units, according to intervention timing. Confidence intervals are based on robust standard errors.*** p<0.01, ** p<0.05, * p<0.1.

Figure A3.5: Effect of sweeps on crime - event study exercise à la De Chaisemartin and d'Haultfoeuille (2020), 95% confidence intervals



Total crimes of arrested individuals Group crimes of arrested individuals

Notes: This graph reports the results of an event study exercise following Eq. (3.3) and De Chaisemartin and d'Haultfoeuille (2020) for total crimes (left panel) and group crimes (right panel). Results are presented for arrested individuals. The observational unit is an individual-quarter pair. Treated units are defined as in section 4.1, while treatment timing differed across units, according to intervention timing. Confidence intervals are based on robust standard errors.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3.1: 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. (3.1) for the 2008-2014 period for peers. The observational unit is a individual-quarter pair and only individuals ever commiting a group crime were included. Treated units are defined as in section 3.4.1, while treatment timing differs across units, according to intervention timing. The coefficient showed is that of interest in a DiD setting, being Peer·Post. Robust standard errors are shown in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3.2: 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 by UGOV interventions (potentially profiled) with other individuals perceived as "high crime" prone, before and after the unit creation. The observational unit is a individual-quarter pair and only individuals ever committing a group crime were included. Treated units are defined as those potentially profiled, while the post period is that after the UGOV creation. The coefficient showed is that of interest, being Profile·Post. Robust standard errors are shown in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3.3: 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.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4 Behind closed doors: Crime composition in gang territory[1]

4.1 Introduction

Criminal organizations and their presence carry important effects on welfare for many other agents. Even if it has been documented that their presence can provide certain public goods in some specific and very limited situations (Blattman et al. 2021), their impact on welfare is by far detrimental. For this reason, efforts to detect and dismantle criminal organizations have intensified worldwide since the 1980s (Mansour et al. 2006; Sweeten et al. 2013; Lessing 2016). Within the scope of criminal organizations, gangs are of great concern. According to the Eurogang Network, a working group of the European Society of Criminology, they are defined as "any durable, street-oriented youth group, whose involvement in illegal activities is part of their group identity." Gangs are particularly worrisome as they mostly affect youngsters at risk of social exclusion or with low prospects. Still, their impact surpasses their members: it affects family, friends, and neighbors of their area of influence. This effect is due to their functional structure, in which territory is an important part. While in some contexts territorial control is absolute (Melnikov et al. 2020), in others, gangs exert a very high level of influence (Magaloni et al. 2020b).

It is also important to highlight that gang crime differs from overall crime. This distinction relates to the fact that the two phenomena stem from different drivers. As stated in Curry and Spergel (1988) and Bursik and Grasmick (1993), crime rates are primarily associated with deprivation and poverty, while in gang crimes (and particularly homicides), special consideration is addressed to the role of social disorganization theories. However, despite having documented these different criminal patterns, economics literature has not devoted much effort to analyze non-gang crime in gang-controlled areas. Gang and non-gang crime patterns might also depend on the strength and model of gang territorial control and their interaction with other agents. On this, gangs can choose to cooperate or compete with other criminal

[1]Research coauthored with Daniel Montolio.

organizations and the police. They can also choose to coerce the population living under their influence or win their "hearts and minds".

In this chapter, I study gangs' presence and influence in an urban area in a developed country at a small geographical level. I analyze whether there is a threshold in gang presence that affects criminal patterns, and I test for discontinuities in crime levels and composition across such threshold if it exists. For such an analysis, the Metropolitan Area of Barcelona (MAB) provides an appealing setting for several reasons. It is a context in which gangs (particularly latin ones) rapidly unfolded at the beginning of the 21st century. Starting from the almost complete absence of latin gangs in 2002, ten years later, 2,500 individuals were identified by local authorities as belonging to a latin gang (Blanco 2012). Concretely, estimates by Blanco (2012) indicate that between 2003 and 2009, gang membership grew at a compound annual growth rate of 81.5%. While this phenomenon's level does not compare to other settings, such as Chicago or Detroit, the rapid increase was a troublesome characteristic. The statement from the police side was one of being "worried but not alarmed" [2].

For this analysis, I exploit a highly detailed dataset for the MAB built from Local Police administrative records for the 2008–2014 period. This is a geocoded dataset that has information on the crimes registered and their typology. Moreover, it accounts for registries on the offender and victim and few demographic characteristics when available. Based on Chapter 3 and information provided by the gang-specialized police unit (UGOV), I can link offenders to their status on gang membership. Once gang members and their crimes are identified, I construct a gang intensity score across the MAB using the Local Getis-Ord statistic (G^*, Ord and Getis 1995). I then identify a tipping point in criminal patterns to gang intensity, and I map it into territorial support to construct a gang boundary. Finally, I test whether crime patterns change significantly across such a boundary, using a regression discontinuity design as in Angrist and Lavy (1999), Card et al. (2008) and Keele and Titiunik (2015).

Results indicate that the number of crimes is not significantly different across the gang boundary. Nonetheless, there are significant differences in its composition. Across the gang boundary, evidence shows a higher share of crimes against the person in detriment of crimes against property. Additionally, there is also a higher share of male offenders to female victims. Even if there is no change in the number of crimes, the compositional change across the gang boundary carries crucial welfare implications. An examination of potential mechanisms suggests that results are driven from the existing territorial control from gangs that leads to underreporting

[2] https://www.ABC.es/cataluna-tiene-jovenes-bandas.html

in petty property crimes. However, the increase in interpersonal violence against women would be explained by the existing gender role models in gangs. This factor is seldom explored in the economics of crime literature.

The contribution of this research is threefold. Firstly, I identify gangs' areas of influence at a very small geographical level, as in Lessing (2016), Blattman et al. (2021), and Kennedy et al. (1996). In this case, I perform the analysis in an urban area in a developed country, a still understudied context with a stronger state capacity that could derive from different policy actions. Secondly, I assess the impact of organized crime on welfare. On this matter, literature is already abundant both on all criminal organizations (Pinotti 2015; Dell et al. 2019; Dell 2015) and gangs (Bruhn 2019; Melnikov et al. 2020; Blattman et al. 2021). Still, I document the importance of gangs beyond their crimes to state their disruptiveness. Finally, I outline potential mechanisms apart from territorial control as a cause of non-gang crime in areas with high gang intensity. Following research such as Miller (1998), Miller and Decker (2001), and Trickett (2016), I explore the influence of gender roles in gangs and their social surroundings.

The remainder of the chapter is structured as follows. Section 2 states the role of gangs in urban settings in general and the Metropolitan Area of Barcelona. Section 3 presents the data used for the empirical analysis. Section 4 outlines the methodological approach. Section 5 presents the results. Finally, Section 6 contains concluding remarks.

4.2 Gangs in urban settings

Gangs are present in many cities worldwide. They are both in developed and developing countries, and low and high violence cities. In some cities, gangs have institutionalized and have been present for decades while in others their operations are newer (Hagedorn 2005; Jensen and Arnett 2012; Muggah 2012; Van Hellemont 2012). Their spread mostly took part by cultural diffusion patterns, adapting to local circumstances (Small Arms Survey 2010).

Their presence is not trivial for a city's adequate functioning, as their direct and indirect effects on welfare are very harmful. Literature has shown this in several ways. At a macro level, Pinotti (2015) documents that organized crime associates with significantly lower per capita economic output levels, and Olivera (2006) states that the proliferation of gangs is linked with poverty, unemployment, and lack of prospects for young people. Moreover, Melnikov et al. (2020) show that individuals living under gang-controlled areas have significantly less education, material wellbeing, and income. Focusing on gangs in urban settings, Bruhn (2019) reports that isolated gangs do not cause violent crime, yet when two gangs operate in close vicinity, violence increases. On its part, Huebner et al. (2016) indicate how communities with more gang members also have higher gun assault rates. Moreover, and related to preventive policies, Grogger (2002) finds that after gang injunctions are imposed, violent crime decreased in the first year by at least 5%. Owens et al. (2021) identify how injunction areas also experience house price reductions as negative police interactions would be more common.

As outlined in Skaperdas (2001), the traditional view on organized crime indicates that it proliferates when state enforcement is null. Criminal groups' rule provides essential public goods that states do not, such as security, at a higher cost than if provided by a modern state. Under this hypothesis, the deployment of public services where criminal groups operate could crowd them out. Nonetheless, Magaloni et al. (2020a) outline that state interventions against criminal groups sometimes improve security, but they can also worsen violence patterns. The authors indicate that police intervention poses different challenges according to the criminal governance regime that the criminal organization follows. Magaloni et al. (2020b) enumerate factors that shape gangs strategies' toward the population, other criminal organizations, and governments and that each would relate with different security outcomes. Furthermore, as recently uncovered by Blattman et al. (2021), the aforementioned traditional view does not consider other incentives that criminal groups might have to rule a territory and keep the state out. Concretely, such a scenario helps certain businesses going unnoticed, while it also helps to gain civilians' "hearts and minds" against the state.

Despite the efforts of the existing literature to understand the role of gangs in crime in an urban setting (Levitt and Venkatesh 2000; Levitt and Venkatesh 2001; Pedersen 2014; Huebner et al. 2016), much remains to be learned about their spatial distribution and other consequences of residential gang membership. First, it is still needed to study further their scope of action in developed contexts outside the United States, as their violence and territorial control patterns differ (Small Arms Survey 2010). Second, it is necessary to study non-gang crime in areas where gangs exert their influence. As stated by Curry and Spergel (1988), gang and global crime rates are conceptually different community problems. Among the issues that often go unnoticed, gender violence is a crucial one. As early explored by Miller (1998) and Olivera (2006), understanding the version of masculinity enacted by the young men in gangs is crucial: misogyny is a recurrent trait in gangs. Thus, exploring other worrying phenomena in gang areas will help unravel other distorting factors of gang presence. The present study attempts to contribute to these pressing issues.

4.2.1 Gangs in the Metropolitan Area of Barcelona

The Metropolitan Area of Barcelona (MAB) is the fifth largest and the densest in Europe. It is also one with the highest crime rates[3]. Moreover, the MAB constitutes one of the most critical settings for latin gangs outside the American continent (Blanco 2012). This importance mainly relates to the migration phenomenon that took place in the early 2000s in Spain. The arrival of substantial migratory flows increased the percentage of the immigrant population. In the region of Catalonia, where the MAB locates, the share of migrant residents increased from 4.0% in the year 2000 to 17.7% in 2012[4]. Within a non-European migrant population, South America is the most frequent origin: in 2012, migrants from South America accounted for 350,000 individuals in Catalonia.

Gangs were detected for the first time in the MAB in 2002. Over the following decade, there was a steady increase in the presence of such criminal groups. Estimates indicate that while in 2003 there were around 70 members, after 2009 the number of members stabilized at around 2,500[5]. Most members are young men between 12 and 25 years old that trace their origins to Latin America. The factors mentioned in the sociological literature influencing involvement in gangs include, among others: social disorganization, presence of gangs in the neighborhood, barriers or lack of social and economic opportunities, lack of social capital, family disorganization, problems at school, and socialization in the street (e.g., Feixa 2012).

In chronological terms, the first block to consolidate included the gangs known as the *Latin Kings* and *Ñetas*, linked to migratory flows originating in Ecuador. The second block included the *Black Panthers* and *Trinitarios* and was linked to migratory flows from the Dominican Republic. The third block, composed by *Mara Salvatrucha* and *Barrio 18* from El Salvador and Honduras, was the last to consolidate. According to Blanco (2012), group dynamics mostly follow behavioral patterns present in Latin America and Ecuador in particular rather than those in the United States. This feature refers to the organization inside the group and behavior outside the group and rivalries.

However, the gangs' characteristic that deserves the most attention is their connection with criminal activities and the violence embedded in their behavioral patterns. Indeed, their notoriety in the MAB increased after the murder of a teenage boy that had particular impact on news outlets and civil perception of gangs[6]. Afterwards, several episodes of gang violence have been registered[7]. Regarding criminal

[3]https://ec.europa.eu/eurostat/databrowser/view/met_crim_gen/
[4]Catalan Institute of Statistics: https://www.idescat.cat/pub/?id=pmh
[5]https://www.eldiario.es/bandas-juveniles-estancan-cataluna.html.
[6]https://www.elperiodico.com/ronny-tapias
[7]https://www.elperiodico.com/pelea-mortal-entre-bandas-latin-king-y-blood-en-cornella;

activities, most illegal activity related to gangs' business is based on drug smuggling (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 are varied. They include crimes that traditionally relate to gangs functioning, such as injuries, threats, and even murder. Other interpersonal violent crimes have recently risen, among which sexual assault and gender violence are alarming[8]. In the following sections, a descriptive analysis of gangs' criminal offenses is outlined.

4.3 Data

This research's primary data source is a restricted administrative dataset of all registered crimes in the MAB from 2008 to 2014. Such data is provided by the Local Police and comprises all registered crimes with information on their exact date, time, and geocoded place of occurrence. It also records the type of crime it was classified as, which covers more than 190 articles of the Spanish Penal Code. In total, it contains over one million entries. Additionally, when identified, the dataset provides information on formalized offenders and victims and their basic demographic characteristics (gender, date and country of birth).

Moreover, I have information on the gang membership of all registered offenders. The gang-specialized police unit (UGOV) provided information on sweeps in the MAB against gangs during the analysis period. This specialized police unit, created in 2012, is an investigation police unit whose work solely attends to dismantling gangs. In this way, arrests taking place during sweeps are not a consequence of mere chance but rather the result of a thorough police investigation and planning in anticipation. Regarding these police actions, information on the place and time of occurrence was provided. In Chapter 3, registries of the administrative dataset are matched with the sweeps time and place. This data allows identifying individuals arrested in the sweeps and, in this way, label them as gang members. Moreover, looking at their criminal career and past arrests, it is also possible to identify the known criminal peers of the individuals arrested in the sweeps. These two sets of individuals (those arrested in gang sweeps and their known criminal peers) constitute my subset of gang members in the MAB.

Combining the two datasets mentioned above, I account for all registered crimes in the MAB and an identified subset of "gang crimes" which are all crimes perpe-

https://www.lavanguardia.com/tension-entre-bandas-Latinas-en-barcelona.html; https://elpais.com/catalunya/1333880884947336.html.

[8]https://www.abc.es/espana/madrid/banda-latina-mas-peligrosa.html

trated by individuals arrested on sweeps or their peers. The criteria to label gang crimes is broad: they are all crimes committed by a gang member. In this way, whether it was committed with other gang members or related specifically to gang militancy is not considered. A descriptive analysis of this data is presented in Tables 4.1 and 4.2.

As previously mentioned, Table 4.1 shows that all registered crimes account for over one million entries. Among these, crimes against the property represent the largest share, driven mainly by thefts and robberies. Regarding crimes against the person, they account for 18.9% of all registered crimes in the MAB. In this case, injuries and threats are the most common offenses. Considering other crimes, road safety offenses and disobedience for law officers are the most frequent misdemeanors. However, when analyzing those crimes identified as related to a gang, different patterns arise. Even if crimes against the property (and robbery and theft) are still the most frequent ones, for this subsample, crimes against the person are more significant, as they represent almost 30% of all these offenses. This point relates to the fact that injuries and threats are more frequent than when considering all crime registries. Regarding other crimes, the weight of disobedience for law officer offenses and drug crimes rises significantly. Moreover, murders committed by gang members represent almost 3% of all murders in the sample, while their weight in overall crimes is by far lower.

Such differential pattern for gang-related crimes is also noticeable when depicting offender and victim characteristics, as in Table 4.2. In all cases, there is a higher share of men than women involved, but in gang crimes, such a picture is exacerbated. Moreover, there is a higher share of individuals with origins in Latin America in gang-related crimes, both as offenders and victims. Finally, individuals involved in gang crimes are younger, especially offenders. Concretely, gang criminals are almost entirely men who are on average 21 years old, and most than half have origins in Latin America. Regarding their victims, young Latin American men are also the most common profile.

Table 4.1: Crime descriptives, Metropolitan Area of Barcelona 2008-2014

All crimes	1,021,588	100%	Gang crimes	2,512	100%
Against Property	719,930	70.5%	Against Property	1,347	53.6%
Theft	*392,418*	38.4%	*Theft*	*462*	18.4%
Robbery	*134,501*	13.1%	*Robbery*	*506*	20.0%
Fraud	*84,240*	8.2%	*Fraud*	*201*	8.0%
Car Theft	*56,188*	5.5%	*Car Theft*	*64*	2.5%
Damages to property	*52,583*	5.1%	*Damages to property*	*114*	4.5%
Against Person	193,473	18.9%	Against Person	743	29.6%
Injuries	*68,899*	6.7%	*Injuries*	*372*	14.8%
Threats	*55,857*	5.5%	*Threats*	*198*	7.9%
Gender Violence	*25,534*	2.5%	*Gender Violence*	*40*	1.6%
Others against Person	*19,913*	1.9%	*Others against Person*	*40*	1.6%
Family	*17,048*	1.7%	*Family*	*7*	0.3%
Sexual	*4,756*	0.5%	*Sexual*	*46*	1.8%
Murder	*1,466*	0.1%	*Murder*	*40*	1.6%
Other Crime	108,185	10.6%	Other Crime	422	16.8%
Road Safety	*46,515*	4.6%	*Road Safety*	*58*	2.3%
Disobedience	*44,437*	4.3%	*Disobedience*	*282*	11.2%
Drugs	*15,112*	1.5%	*Drugs*	*79*	3.1%
Environment	*1,749*	0.2%	*Environment*	*0*	0.0%
Arson	*372*	0.0%	*Arson*	*3*	0.1%

Source: Own construction from Local Police data and Chapter 3 identification of gang members.

Table 4.2: Offenders and victims descriptives, Metropolitan Area of Barcelona 2008-2014

All Offenders	Share	Gang crimes Offenders	Share
Male	76.7%	Male	91.0%
Spanish	50.7%	Spanish	31.5%
Latin	14.0%	Latin	56.5%
Age	36.0	Age	21.2
All Victims	Share	Gang crimes Victims	Share
Male	52.0%	Male	69.9%
Spanish	66.8%	Spanish	63.1%
Latin	8.6%	Latin	28.5%
Age	42.9	Age	33.1

Source: Own construction from Local Police data and Chapter 3 identification of gang members.

The previous analysis indicates that crimes labeled as "gang crimes" follow a different pattern than overall crime, as outlined by Curry and Spergel (1988). Crimes against the person (particularly violent ones) are more salient, mainly involving young men from Latin America. With this picture in mind, in the following sections, I further explore differential criminal patterns. Firstly, I consider the spatial distribution of gang crimes across the MAB to analyze gang intensity in the territory. I then consider gang intensity in the location of all offenses to assess if overall criminal patterns change in areas where gang intensity is high.

4.4 Methodology

4.4.1 Identifying gang intensity in an urban area

As outlined in the previous section, the data accounts for all registered crimes in the MAB, and it is geocoded. Translated into space, it constitutes a set of points distributed across the MAB surface.

The first issue I address is identifying gangs' areas of influence at a small geographical level. To do so, I follow an exploratory spatial data analysis, a methodology that generates patterns and associations in data without any prior assumptions. Focusing explicitly on spatial effects, I focus on local indicators of spatial association. Due to the data's detail, I can do so without incurring in biases deriving from the modifiable area unit problem.

In this case, I construct the New Getis-Ord G_i^* statistic. In Ord and Getis (1995), the authors present a series of statistics that can be used as spatial association measures. Their "new" local statistic G_i^* identifies partitions of spatial association that global statistics (as Moran's I or Getis and Ord's G) might not detect. Concretely, G_i^* informs if specific values of an indicator cluster spatially by looking at each observation within the context of its neighbors. If an observation has a high value and is surrounded by other observations with high values, it belongs to a cluster. The local sum for all observations and their neighbors is constructed and compared to all observations' summations to detect such local clusters. If a local sum is different from the expected local sum, and when that difference is too big to result from randomness, a local cluster is identified. The New Getis-Ord G_i^* is constructed as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{n\sum w_{i,j}^2 - (\sum w_{i,j})^2}{n-1}}} \tag{4.1}$$

where

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}; S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2 - \sum(w_{ij})^2}{n} - \bar{X}^2}$$

and x_j is a gang crime indicator for observation j, $w_{i,j}$ is the spatial weight between i and j and n is the number of observations.

In this case, I construct the Getis-Ord G_i^* statistic using only those observations (geocoded crimes) that I identified as a gang crime, as previously defined. As a result, I can map the spatial association of gang crimes in the MAB as a continuum across space[9]. I refer to the outcome measure as Gang Intensity (*GI*). In this way, given their geographical coordinates, all registered crimes j in the MAB territory, either labeled as gang crimes or not, have an associated *GI* value, namely GI_j.

4.4.2 Assessing crime pattern differentials

The second issue I analyze is whether there are crime differential patterns for different values of *GI*. To do so, I test for discontinuities in crime and its composition.

Testing for Tipping Behavior

Regarding the term "tipping point", Milkoreit et al. (2018) outlines a brief history of its coining. The term was firstly used in social sciences in Grodzins (1957). Studying the integration of neighborhoods in the United States, the author stated that when "one too many" black families arrived, the remaining white families would massively move out. That point was the one defined as a tipping point. The term stems from mathematics, and it refers to "qualitative change in a system described mathematically as a bifurcation." Afterward, the term has been applied in many fields and even subfields in Economics. Examples include research in climate change (Lemoine and Traeger 2012; Lemoine and Traeger 2016), labor (Pan 2015), taxation and debt (Traxler 2010; Caner et al. 2010; Gaspar et al. 2016), and urban economics (Card et al. 2008; Zhang 2011; Caetano and Maheshri 2017; Böhlmark and Willén 2020) among others. In this research, following the logic of Grodzins (1957), the existence of a tipping point would indicate that when "one too many" gang crimes occur, the remaining crime patterns will change significantly.

As stated by Card et al. (2008), the crucial obstacle is that the location of the tipping point ,labeled as GI^* (if existing), is unknown and must be estimated from the data. Since gang crime intensity is built as a continuum across the MAB territory, no natural break arises. For this, I follow Card et al. (2008) and the literature on structural breaks to identify potential tipping points. I select the point that yields the best-fitting model for crime counts and composition as a function of gang intensity

[9]Since the G_i^* statistic is already constructed as a Z statistic, I also consider its unstandardized value.

GI[10]. To obtain candidate values of GI^*, I follow a search technique as in Card et al. (2008) as follows

$$Crime_j = \alpha + \beta.\mathbf{1}[GI_j > GI^*] + \varepsilon_j \tag{4.2}$$

for $GI < GI_j < max\{GI\}$.

I set a value of GI to start, based on the empirical values of GI, and select the value of GI^* in the $[GI, max\{GI\}]$ interval maximizing the R^2 of Eq. (4.2). On this, Hansen (2000) shows that if Eq. (4.2) is correctly specified, this procedure yields a consistent estimate of the actual tipping point. I test whether there are tipping points in the number of overall crimes and the previously defined broad typologies, namely crimes against the property, against the person, and other crimes.

Such a tipping point, if existing, is identified in terms of GI and defined as GI^*. However, since GI is a measure of spatial association, I can also map GI^* into spatial support in the MAB and determine a geographical tipping point. This set of points identify a boundary in space for high gang intensity.

Discontinuity Analysis

Using the previous information on gang intensity GI and candidate values of tipping point GI^*, I identify a gang boundary in space in the MAB. I then carry out a regression discontinuity analysis in a similar fashion to Angrist and Lavy (1999) and Card et al. (2008). However, I translate the location of the tipping point from GI units to spatial support, and thus I explicitly consider space. As explained in Keele and Titiunik (2015), in this type of design, the discontinuity in treatment assignment is geographic: a geographic boundary splits units into treated and control areas. Concretely, I will consider as treated points those across the gang boundary, that is, those points in which $GI_j - GI^* = \delta_j > 0$.

$$Crime_j = \beta_0 + \beta_1.\mathbf{1}[\delta_j > 0] + \beta_2.distance_j + \beta_3.\mathbf{1}[\delta_j > 0].distance_j + \varepsilon_j \tag{4.3}$$

where the forcing variable is the distance to the gang boundary, measured in meters. $distance_j$ measures the distance (in meters) of point j to the closest boundary point where $\delta_j = 0$; values are above zero for those points where $\delta_j > 0$ and below zero for points where $\delta_j < 0$. The underlying identification assumption is that all other relevant factors (except crime) vary smoothly at the gang boundary.

Existing literature has already documented intra-city differences using spatial regression discontinuity designs. While Koster et al. (2012) estimate the costs of differences in within-city regulatory constraints for house owners using World War

[10] Card et al. (2008) also follow another methodology based on fixed points. The authors state that both methods yield very similar estimations of the estimated tipping point.

II bombing in Rotterdam, Hidano et al. (2015) analyse differentials in seismic hazard risk levels in Tokyo wards and their impact on housing prices. Even if in this case the variable of interest GI_j is continuous across space, I can identify a tipping point in criminal patterns, link such tipping point to spatial support, and run a spatial regression discontinuity exercise.

4.5 Results

4.5.1 Gang intensity in the Metropolitan Area of Barcelona

Figure 4.1 shows all registered crimes in the MAB labeled as gang crimes, with their exact location. These are all the registered crimes in which the offender can be linked to one of the latin gangs present in the area or is a criminal peer of a gang member. This highly detailed dataset is pooled for the 2008-2014 period. It stems from the Local Police and the identification of gang members in Chapter 3, using data from the gang-specialized police unit (UGOV) of the Local Police.

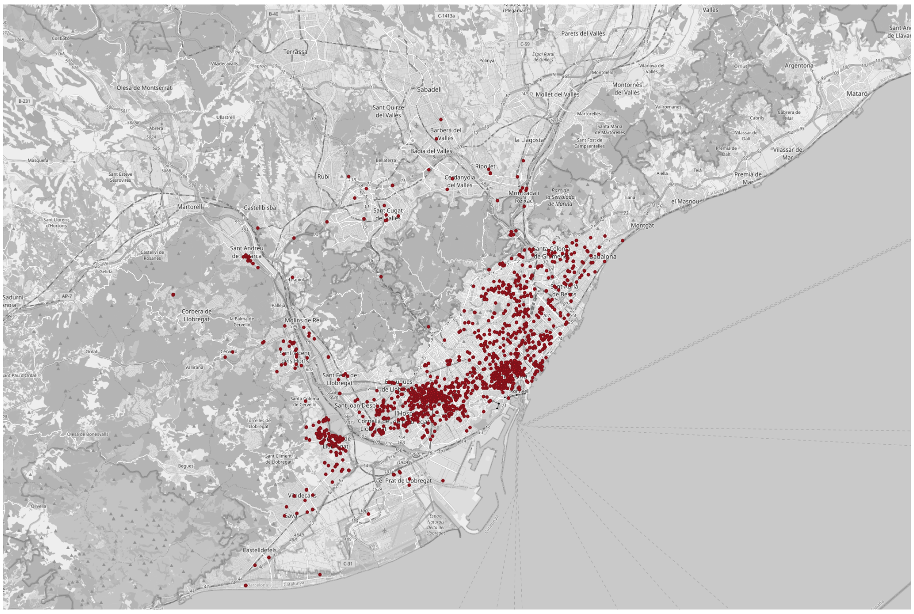
At first glance, it is possible to note in Figure 4.1 that gang crimes' spatial distribution is not uniform nor scattered across space. It instead seems that certain spatial association pattern takes place in some parts of the MAB. This concentration partly occurs in the city center, but it is also present in some outskirts' specific areas. The gangs identified as present in the MAB are *Latin Kings*, *Trinitarios*, *Black Panthers*, *MS-13*, *Bloods*, and *Los Menores*. Figure A4.1 in the Appendix shows these gang crimes with a color code for each gang. For each gang, as reflected in Figure A4.1, the spatial distribution is not uniform either. Instead, most gangs seem to evidence spatial concentration as well. To assess these assertions more rigorously, I construct the Getis-Ord G_i^* statistic for gang crimes, presented in Figure 4.2.

By construction, the higher values of the G_i^* statistic in Figure 4.2 take place where there is a higher density of points in Figure 4.1. The highest values of the G_i^* statistic are concentrated in two areas of the MAB. The first one (darker area on the right of Figure 4.2) is in a section of the historic city center (*El Born* neighborhood, Barcelona municipality). The second one (darker area on the left of Figure 4.2) takes place in a section of the outskirts (*La Torrassa* neighborhood, *L'Hospitalet de Llobregat* municipality). Moreover, in Figure 4.2 it is possible to see that the highest values of the G_i^* statistic are concentrated only around the two areas mentioned above. These two sets of points would be indicating two local maximums in gang intensity.

Regarding these local maximums, in the historic city center, there is a higher prevalence of the *Latin Kings* gang (originally from Ecuador) and the *MS-13* gang (originally from El Salvador). In *L'Hospitalet de Llobregat*, *Black Panthers* (originally from the Dominican Republic) and *Bloods* (originally from the United States) dominate. In these areas, gangs were dismantled through a police sweep from the gang-specialized police unit (UGOV). Since these interventions resulted from careful investigation of the aforementioned gangs, these indicate their areas of influence and where they operate.

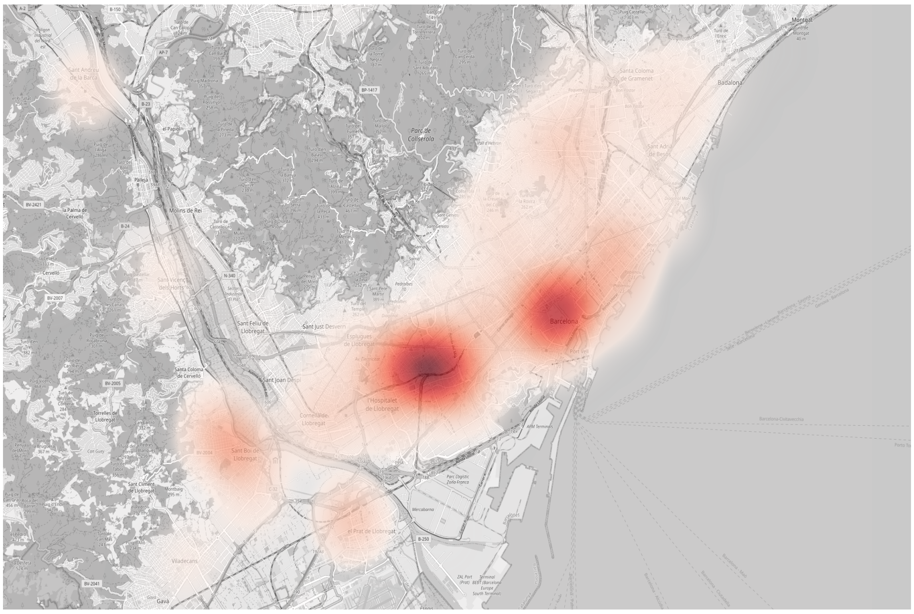
It must be noted that it is not the case in either one of the previously described areas that the entire neighborhood registers high values of the G_i^* statistic. Instead, this pattern is concentrated in a tiny portion of the MAB. Concretely, 50 census tracts in the MAB (which represent approximately 2.5% of all census tracts in the MAB) hold 90% of the points with the highest values (top 5%) of the Getis-Ord G_i^* statistic. In this way, the spatial association patterns reflected in Figures 4.1 and 4.2 indicate that gang intensity is highly concentrated in the MAB.

Figure 4.1: Gang crimes in the Metropolitan Area of Barcelona, 2008-2014



Source: Own construction from Local Police data and Chapter 3 identification of gang members.

Figure 4.2: Getis-Ord G_i^* score for gang crimes in the Metropolitan Area of Barcelona, 2008-2014



Source: Own construction from Local Police data and Chapter 3 identification of gang members.

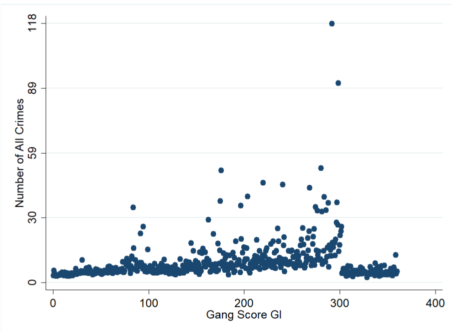
4.5.2 Tipping point estimation

I further want to test for tipping behavior in crime for gang intensity. The biggest obstacle to do so is that the location of the tipping point if existing is unknown. To assess this point, I first plot crime averages conditional on the Getis-Ord G_i^* statistic. This exercise provides a first visual inspection of possible discontinuities, and if so, it indicates where they might occur. Then, to test for the existence of a tipping point and defining it, I follow the structural breaks procedure outlined by Card et al. (2008). Concretely, I select the point that yields the best-fitting model for crime counts and their composition, as in Eq.(4.2). Finally, I map the location of the tipping point from a value of the Getis-Ord G_i^* statistic to spatial support.

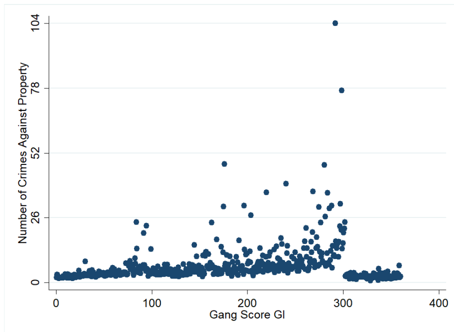
Figure 4.3 plots the average number of overall crimes, crimes against property, crimes against the person, and other crimes conditional on the Getis-Ord G_i^* statistic, which is my gang intensity measure. Figure 4.4 follows a similar spirit and plots the share of crimes against property, against the person, and other crimes, conditional on the Getis-Ord G_i^* statistic. These figures provide a first visual inspection to test whether there might be tipping behavior in crime.

Figure 4.3 indicates that the number of overall crime and crimes against property might follow a tipping behavior, as a discontinuity close to a value of 300 in the Getis-Ord G_i^* statistic might be present. For crimes against the person and other crimes, no clear evidence of this sort is found. Figure 4.4, which considers the shares of crimes against property, against the person, and other crimes, would provide more salient evidence in favor of a discontinuity. Figure 4.4 documents a sharp decrease in the share of crimes against the property. It also reflects a sharp increase in the share of crimes against the person. These changes would take place close to a value of 300 in the Getis-Ord G_i^* statistic. Thus, there is suggestive evidence in favor of a tipping point for crime patterns regarding gang intensity in the MAB.

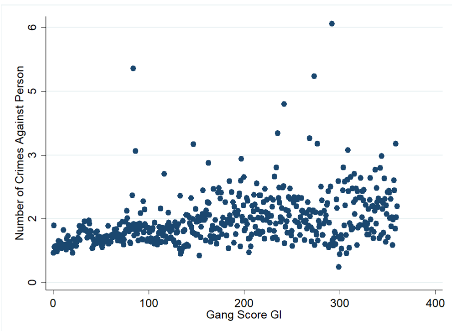
Figure 4.3: Crime counts and its composition by *GI* statistic



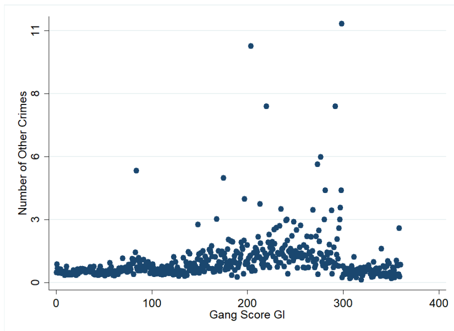
All crimes



Against Property



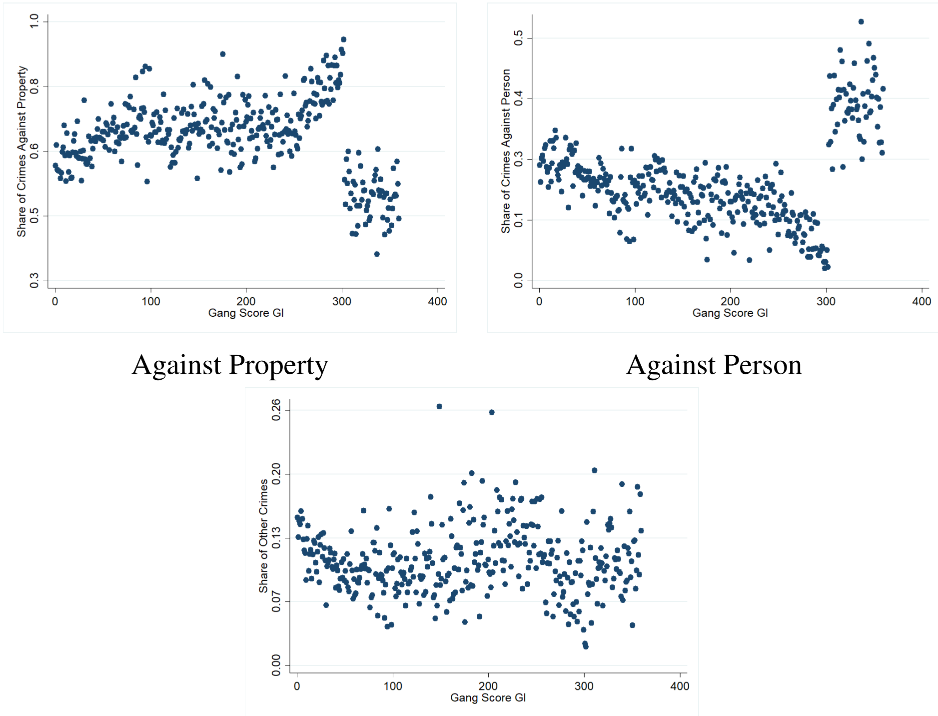
Against Person



Other crimes

Note: These graphs show the mean of the total number of all crimes, and of crimes against property, against person and other crimes, conditional on the *GI* statistic. The unit of observation is a crime, and each dot in the graphs reflects a conditional mean, binned by *GI* statistic.

Figure 4.4: Share of crimes by *GI* statistic



Against Property

Against Person

Other crimes

Note: These graphs show the mean share of crimes against property, against person and other crimes, conditional on the *GI* statistic. The unit of observation is a crime, and each dot in the graphs reflects a conditional mean, binned by *GI* statistic.

A visual inspection of Figures 4.3 and 4.4 reflects that there might be a tipping point and that it would be close to a *GI* value of 300. To identify the location of the tipping point in terms of the Getis-Ord G_i^* statistic or *GI* score, I follow the structural breaks method of Card et al. (2008). This method indicates to select the point that yields the best-fitting model for crime outcomes as a function of the *GI* statistic and an indicator variable for a structural break as in Eq.(4.2). The search technique in Card et al. (2008) carries out several regressions placing the indicator variable $1.[GI_j > GI^*]$ in different values of GI^*. Then, the selected value for GI^* is the one in which the R^2 of the regression is maximized, and where the tipping point locates.

Table A4.1 of the Appendix presents the adjusted R^2 values of several estimations of Eq.(4.2), considering different crime outcomes and several tipping point candidates. Table A4.1 displays that candidates for the tipping point would be closer to a GI^* value of 302 or 303, depending on which crime category is taken. Its location would be where the adjusted R^2 value is the biggest. Even if there is a difference on which would the tipping point be for the different crime categories, it is narrow considering that the GI statistic range is $[0,360]$. Based on evidence from Figure 4.3 that indicates neater evidence of discontinuity in all crimes and crimes against the property, I will follow the estimates for these categories. As a result, I place the tipping point in a value of $GI^* = 302$. In the following sections, I test for the robustness of these estimates.

To get a sense of what this GI^* value implies, in Table 4.3 I outline the average number of gang crimes per census tract, according to their average value of GI. Table 4.3 indicates that only 1.7% of the census tracts in the MAB evidence an average value of GI above the tipping point. These figures speak once again about the high spatial concentration of gang intensity across the MAB territory. Moreover, Table 4.3 shows that those census tracts that evidence a value of GI higher than 302 experience an average of 5 gang crimes throughout the period analyzed[11]. This gang crime value is much higher than the sample average of 0.83. It is also bigger than the average for the prior bracket. In this way, areas above the tipping point evidence a pretty different pattern regarding gang crimes in the MAB.

Table 4.3: Gang crime descriptives by census tract

Avg. *GI* Statistic	Avg. Number of Gang Crimes	SD of Gang Crimes	Number of Census Tracts
Below Tipping Point			
$[0-50)$	0.36	1.44	1,233
$[50-100)$	0.73	3.44	676
$[100-150)$	1.65	4.90	160
$[150-200)$	1.70	2.74	89
$[200-250)$	2.43	3.59	76
$[250-302)$	3.25	5.33	56
Above Tipping Point			
$[302-360]$	5.03	6.9	39
All	0.83	3.00	2,329

Note: In this table, the unit of observation is a census tract. The table shows summary statistics for gang crimes, according to the average *GI* score in the census tract.

Finally, I map the location of the tipping point from a value of GI to spatial support. Figure 4.5 marks the areas in the MAB in which the included points register GI values above the previously defined tipping point. In this way, the colored areas of Figure 4.5 show the points in the MAB in which $GI > GI^*$. On this, it must be noted that the boundaries delimited by points above the tipping point do not coincide with any other administrative boundaries in the MAB (municipality, district, neighborhood, or census tract). They also do not coincide with crime hotspots usu-

[11] Of these 39 census tracts, 4 experienced over ten gang crimes throughout the sample.

ally identified in the city and linked to pickpocketing in touristic areas. On this last point, the no-overlap is clear for the outskirts area. In the case of the historic city center, the boundaries outlined by the points above the tipping point do not cross any of the prominent streets highly attached to tourism in the corresponding district (*Las Ramblas*, *Via Laietana*).

In this way, in this section I describe gang intensity in the MAB, find a tipping point in crime conditional on such gang intensity, and outline the points in space above such tipping point. Combining all the previous results, Figure 4.5 plots the spatial gang boundaries for the MAB. Those inside are areas identified as above the gang tipping point. These are the gang boundaries for which I test for discontinuities in crime in the following sections.

Figure 4.5: Gang boundaries in the Metropolitan Area of Barcelona: points above the tipping point

Source: Own construction from Local Police data and Chapter 3 identification of gang members.

4.5.3 Regression Discontinuity Models

Results in crime

This section presents the results of a regression discontinuity (RD) analysis in crime across the spatial gang boundaries defined in the previous section. Recall that those areas inside the gang boundaries are those whose *GI* value is above the defined tipping point. These are areas in which $GI > GI^*$, roughly translating into at least five gang crimes per census tract. RD estimates are presented in Table 4.4.

In Panel A of Table 4.4, I present regression discontinuity estimates for the number of all crimes and the number of crimes by large categories, namely crimes against property, crimes against the person, and other crimes. Results show no statistically significant change in the number of all crimes, crimes against the person, and other crimes across the gang boundary. I do find a statistically significant reduction in the number of crimes against property across the gang boundary.

Since there is no statistically significant change in the number of all crimes, but there is one in the number of crimes against the property, I explore outcomes regarding crime composition across the gang boundary. To further explore these results, in Panel B of Table 4.4 I present regression discontinuity estimates for the share of crimes against property, against the person, and other crimes. In this exercise, I find a significant reduction in the share of crimes against property across the gang boundary. In contrast, the share of crimes against the person and the share of other crimes significantly increase. The increase in the share of crimes against the property is higher than the one in other crimes.

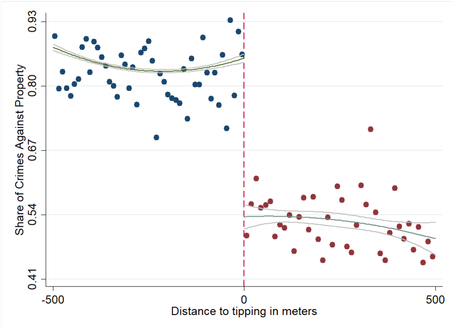
The two sets of results stemming from Panels A and B of Table 4.4 indicate that while there is no evidence that the number of all crimes changes across the gang boundary, its composition does change. A graphical analysis of the results of Panel B of Table 4.4 is shown in Figure 4.6. Those of Panel A of Table 4.4 are shown in Figure A4.2 in the Appendix.

Table 4.4: RD Regression analysis - crime across the gang boundary

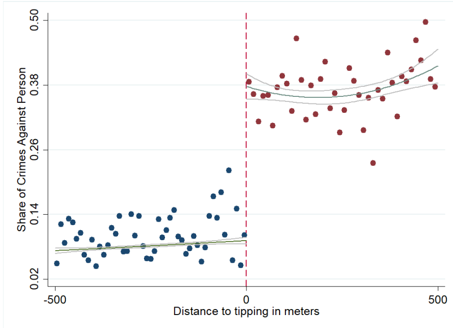
	All crime	Against Property	Against Person	Other
Panel A: Number of crimes				
Conventional	-9.954*	-11.494**	0.552	0.009
	(5.418)	(4.915)	(0.407)	(0.265)
Bias-corrected	-8.910	-11.511**	0.517	0.062
	(5.418)	(4.915)	(0.407)	(0.265)
Robust	-8.910	-11.511**	0.517	0.062
	(6.038)	(5.431)	(0.461)	(0.297)
Mean	10.821	8.393	1.544	0.884
Observations	6,333	6,333	6,333	6,333
Panel B: Share of Crimes				
Conventional		-0.387***	0.316***	0.093***
		(0.024)	(0.025)	(0.021)
Bias-corrected		-0.396***	0.324***	0.101***
		(0.024)	(0.025)	(0.021)
Robust		-0.396***	0.324***	0.101***
		(0.026)	(0.027)	(0.023)
Mean		0.705	0.189	0.106
Observations		83,505	83,505	83,505

Note: The table show estimates from a Regression Discontinuity Analysis following Eq. (4.3) for the 2008-2014 period for the MAB. Discontinuity is set at a $GI = 302$ and linked to a spatial support. The running variable is the distance in meters to the closest point where $GI = 302$. The unit of observation is a crime. Panel A presents estimates considering the number of crimes as the dependent variable, while Panel B presents estimates considering the share of crimes as the dependent variable, and observations are binned by GI statistic score. Standard errors are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

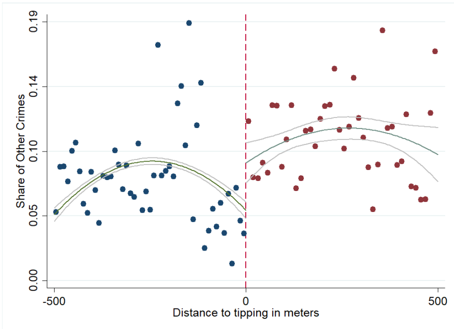
Figure 4.6: RD Graphical analysis - share of crimes across the gang boundary, by large crime categories



Against Property



Against Person



Other crimes

Note: These graphs show the share of crimes against property, against person and other crimes, conditional on the distance in meters to the gang boundary (closest point where $GI = 302$). The unit of observation is a crime, and each dot in the graphs reflects a conditional mean, binned by distance.

Regression discontinuity estimates for the detailed crime categories outlined in Table 4.1 are depicted in Table A4.2 and Figure A4.3 of the Appendix. These outcomes indicate that for crimes against property, the largest decrease across the gang boundary occurs in thefts, while there is no significant effect for robberies. For crimes against the person, there are significant increases across the boundary for all detailed categories. Results indicate increases in the shares of injuries and threats, which might be directly linked to gang activity in the area. Table A4.2 also shows evidence of an increase in the share of gender violence and family crimes across the boundary. This less obvious result is still relevant as it might reflect other gang characteristics seldom studied, as their gender role models. I will discuss this point in the following sections.

Regarding other crimes, it is worth highlighting two outcomes. The first one relates to the increase in the share of disobedience against law officers and the share of drug crimes, which might relate to gang activity in the area. The second point to mention is the no effect on crimes labeled as road safety. Due to the random nature of such crime typology, this no-result works as a first placebo indicating that no other factors relate to the outcomes mentioned above.

Results by offender and victim characteristics

I further explore crime discontinuities across the gang intensity boundary considering the offenders' and victims' demographic characteristics. I do so in light of the particular demographic characteristics associated with gang members and the significant increase in the proportion of crimes against the person documented in the previous section. I analyze this with the subsample in which I have information on both the offender and the victim[12]. I acknowledge that the reduction of sample size is not minor, but it is still a relevant exercise to perform.

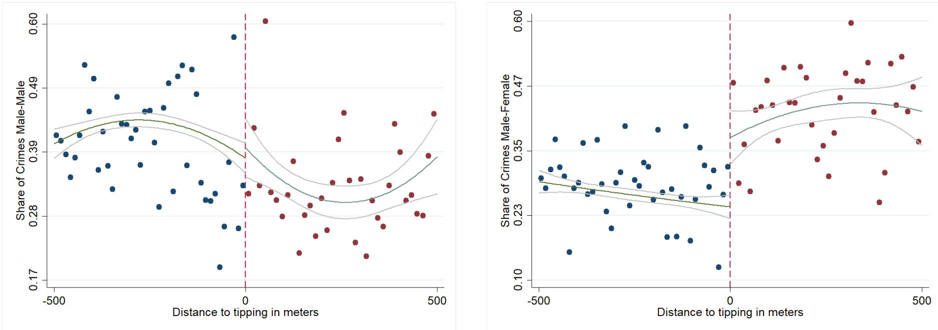
As previously outlined, the data accounts for a few demographic characteristics of those involved, namely gender, date, and country of birth. Since in the MAB context gang activity is associated with young latin men, I focus these heterogeneity exercises on testing for discontinuities on crimes in which men and foreign individuals are involved[13]. Figure 4.7 presents crimes by the victim's gender considering men offenders. Figure 4.8 presents crimes by the victim's nationality for foreign offenders.

Figure 4.7 points towards no discontinuities around the gang boundary for crimes in which both the offender and the victim are male. However, it also indicates that there seems to be a discontinuity for crimes in which the offender is male, and the victim is female. Concretely, across the gang boundary, there is a significantly larger share of crimes from males to females. This result is consistent with the findings in the previous section regarding an increase in gender violence. Regarding the analysis on nationality, Figure 4.8 shows a reduction in the share of crimes committed by a foreign offender to native victims across the gang boundary. At the same time, no discontinuity is present in crimes involving both foreign offenders and victims. Considering the average criminal pattern in the MAB, the first result would be linked to the reduction in thefts across the tipping point.

[12]For this analysis, n=141,793

[13]I perform these exercises taking only one demographic characteristic at a time. Namely, I only analyze crimes committed by men or crimes committed by foreigners.

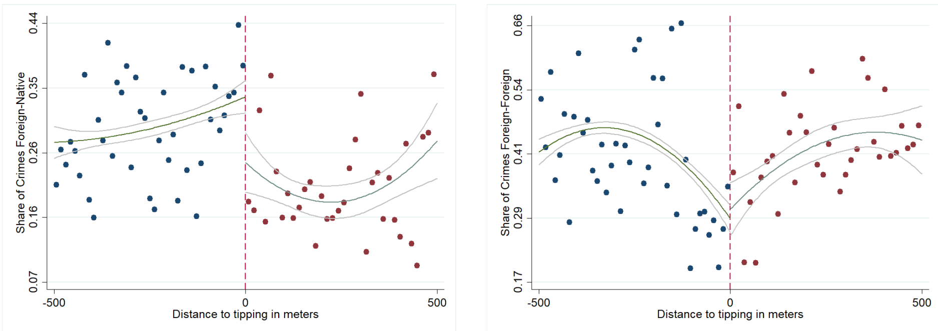
Figure 4.7: RD Graphical analysis - share of crimes across the gang boundary, male offenders by victims' gender



Male Offender-Male Victim | Male Offender-Female Victim

Note: These graphs show the share of crimes for different gender demographics of offenders and victims, conditional on the distance in meters to the closest point where $GI = 302$. The unit of observation is a crime, and each dot in the graphs reflects a conditional mean, binned by distance.

Figure 4.8: RD Graphical analysis - share of crimes across the gang boundary, foreign offenders by victims' nationality



Foreign Offender-Native Victim | Foreign Offender-Foreign Victim

Note: These graphs show the share of crimes for different nationality demographics of offenders and victims, conditional on the distance in meters to the closest point where $GI = 302$. The unit of observation is a crime, and each dot in the graphs reflects a conditional mean, binned by distance.

Furthermore, in Table 4.5 I present descriptive information on the top three crime categories for the subsets of crimes previously analyzed according to offender and victim characteristics. I present this tabulation for all crimes and those across the gang boundary (above the tipping point).

Clearly, Table 4.5 shows different crime compositions when considering all observations and when considering only for those across the gang boundary. These differences hold for all four analyzed cases of offender-victim combinations (Foreign Offender-Native Victim; Foreign Offender-Foreign Victim; Male Offender-Male Victim; Male Offender-Female Victim). The previously mentioned hypothesis for the analysis by gender is confirmed: across the gang boundary, 27% of crimes from men to women refer to gender violence, whereas this magnitude is 15% for all observations. Moreover, across the gang boundary, 22% of crimes among foreigners refer to gender violence. For all observations, this type of crime is not as large. Thus, across the gang boundary, there is a jump in the share of gender violence crimes, and it is most frequent in male to female crimes (as expected) and within the foreign population. Table 4.5 also reinforces the hypothesis that the drop in crimes from foreigners to natives across the gang boundary is linked to the reduction in thefts. For all observations, thefts represent 34% of crimes from foreigners to natives and 22% of crimes from men to men. Across the gang boundary, theft is not a meaningful crime category across any of the analyzed cases. However, robbery is for crimes from men to men. These patterns could speak on an escalation of violence across the gang boundary.

Table 4.5: Main crimes by offender and victim characteristics

All Obs.							
Foreign-Native		Foreign-Foreign		Male-Male		Male-Female	
Theft	33.9	Theft	35.3	Injuries	23.6	Threats	18.7
Robbery	12.7	Injuries	15.8	Theft	21.7	Theft	16.4
Injuries	11.7	Threats	11.2	Threats	12.5	Gender V.	15.0
$GI > 302$							
Foreign-Native		Foreign-Foreign		Male-Male		Male-Female	
Fraud	22.6	Injuries	24.7	Injuries	31.9	Gender V.	27.1
Robbery	19.2	Gender V.	21.8	Robbery	19.4	Threats	19.2
Injuries	15.6	Threats	17.0	Threats	15.3	Robbery	10.4

Note: This table shows the top three crime categories for different demographic characteristics of offenders and victims, and their corresponding shares over the total of crimes for that demographics combination. The unit of observation is a crime. Statistics are shown for all observations and for those observations across the gang boundary ($GI > 302$).

Robustness checks

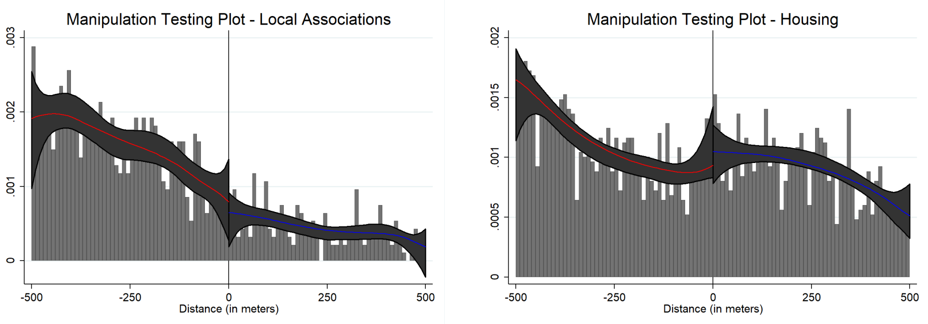
One of the critical identification assumptions of regression discontinuity methods is that other relevant factors vary smoothly at the boundary. In this case, there should be no jumps in other variables (except crime) across the gang boundary in order for such an assumption to hold. In Figure 4.9 I provide such evidence for the presence of local associations and housing transactions[14].

[14]Since I am not running the analysis at any set administrative boundary level, the set of variables to check for no other discontinuities is limited. For the MAB, local associations and housing transactions are available at a geocoded level.

A discontinuity analysis for housing transactions information reflects more financial features, while local associations account for more social factors in the areas close to the gang boundary. In this context, both issues are of relevance. As already mentioned, Coleman (1988) elicits both poverty and social disorganization as drivers of gang crimes. Moreover, there was an attempt to dismantle gangs through integration into the local social tissue between 2004 and 2012. This initiative might have affected the creation and spatial distribution of local associations. Thus, accounting for geocoded data on local associations is an essential part of the present analysis.

The panels of Figure 4.9 indicate that across the gang boundary, there are both fewer local associations and housing transactions. Still, this variation goes smoothly across it. Thus, there is no evidence of a jump at the gang boundary nor in local associations nor in housing transactions.

Figure 4.9: Density of local associations and housing transactions across the gang boundary



Local Associations Housing transactions

Note: These graphs show histograms for local associations and housing transactions, conditional on the distance in meters to the closest point where $GI = 302$. The unit of observation is an association or a housing transaction, and each bar in the graphs reflects a frequency, binned by distance.

I also examine the potential bias due to an error in the identification of the tipping point. Following the structural break literature, I concluded that the most likely candidate was a value of $GI^* = 302$. Still, it could be the case that the boundary was not precisely that for all crime typologies. I, therefore, conduct several doughnut exercises in which I exclude all observations within a distance D (in meters) of the previously defined gang boundary (Keele and Titiunik 2015; Keele et al. 2015). This exercise would exclude observations that could be set on the wrong side of the boundary if this one was misdiagnosed. On this, Table 4.6 shows that results remain mostly stable across these exercises, particularly when removing observations up to 50 meters from the defined boundary.

Table 4.6: RD Regression analysis - doughnut estimates

D=	0	10	30	50	70	90
Against	-0.396***	-0.401***	-0.263***	-0.311***	-0.544***	-0.617***
Property	(0.026)	(0.044)	(0.060)	(0.059)	(0.091)	(0.129)
Against	0.324***	0.371***	0.163***	0.043	0.091	0.310**
Person	(0.027)	(0.056)	(0.046)	(0.056)	(0.090)	(0.127)
Other	0.101***	-0.011	0.062*	0.275***	0.453***	0.308***
	(0.023)	(0.037)	(0.034)	(0.037)	(0.063)	(0.077)
Observations	83,505	81,792	79,135	75,261	73,691	71,558

Note: The table show robust estimates from a Regression Discontinuity Analysis following Eq. (4.4) for the 2008-2014 period for the MAB. Discontinuity is set at a $GI = 302$ and linked to a spatial support. The running variable is the distance in meters to the closest point where $GI = 302$. The unit of observation is a crime and observations are binned by *GI* statistic score. Each row presents results for a different crime category, and each column presents results for a different doughnut distance *D*. Robust Standard errors are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Evidence does not support that a potential error in identifying the tipping point goes further away from the distances presented above. Figures A4.4 and A4.5 in the Appendix indicate that a 50 meters distance corresponds to a distance of 10 in terms of *GI* score. On this, previous evidence outlines how the tipping point was at a closer range around a 300 *GI* score than such a distance.

Lastly, I carry out a set of falsification exercises. In them, I move the gang boundary and test for discontinuities across them. Figure A4.6 of the Appendix presents this series of exercises for crimes against the property, against the person, and others moving the gang boundary 100, 150 and 200 meters from the baseline specification. The panels of Figure A4.6 indicate no significant jumps in crime patterns across any other boundaries.

Potential mechanisms

I hypothesize that two underlying mechanisms explain the results of this research. The first one relates to the reduction in the share of crimes against the property, and thefts in particular. I argue that rather than picking up a crime reduction, results potentially capture a reduction in reporting of these crimes.

This assertion is based on two points. The first one relies on previous research on crime reporting. Studies as MacDonald (2002) indicate that theft is one of the most underreported crimes when studying crime against property. This feature is related to the fact that there is no use of violence in these acts and that usually, the amount of money involved is relatively low. On the other side of the spectrum, car thefts are the most reported crimes against property and overall. This trait relates to insurance companies' administrative procedures to cover the damages, in which the official crime report is required. The second one is based on Table A4.2 of the Appendix. In it, estimates indicate that while there is a significant reduction in theft across the gang boundary, there is a significant increase in car theft. Putting these two points together, I conclude that the drop in crimes against property across the gang boundary is likely due to the underreporting of petty crimes.

Such a result is also consistent with findings on the literature on organized crime and concretely on the role of territorial control. As outlined before, Blattman et al. (2021) indicate that by ruling a territory, criminal organizations have an easier time keeping specific issues unnoticed. In this case, not reporting a petty crime in the areas across the gang boundary would avoid unwanted police attention to more severe issues. Further analysis is be needed to detect whether this underreporting relates to the victims' extortion or winning their "hearts and minds." Casual evidence extracted from several news outlets would indicate that in this context, fear is the predominant feeling for those affected by gangs[15].

The second mechanism behind the results is linked to the increase in the proportion of crimes against the person. I distinguish between the increase in injuries, threats, and disobedience crimes, and that in gender violence. Still, both arise from the same factor of masculinity conceptions in gangs.

On this, Olivera (2006) indicates how misogyny is a recurrent trait of gangs. Moreover, Trickett (2016) interviews male gang members in the United Kingdom to analyze masculinity views within gang contexts, focusing on the attitudes and behaviors of male gang members towards the women with whom they are acquainted. Based on criminology theories of subcultures, symbolic interactions, and labeling, Trickett (2016) states that the behavior of those interviewed stems from a male honor code that validates two central characteristics of their masculine identities: toughness and heterosexuality. The first one demonstrates in physical violence, and the second one through their relationship with women. This pattern is consistent with the results of this research. Such patterns could even be exacerbated by the fact that most gang members in this context come from countries with more conservative gender norms. Based on survey data by Latin Barometer, Berniell et al. (2021) show how Latin American countries with more conservative gender norms are associated with more considerable differences between mothers' and non-mothers labor market outcomes. Ecuador, El Salvador, and Honduras, important origins for gang members in the MAB, are among the most conservative countries in the study. Then, the heightening of these features of masculinity role models in gangs follows quite

[15] https://www.20minutos.es/bandas/latinas/violenta/;
https://www.lavanguardia.com/bandas-Latinas-disputan-parques.html;
https://elpais.com/1366212803.html;
https://elpais.com/1349567312.html

well the empirical findings of this research.

4.6 Conclusions

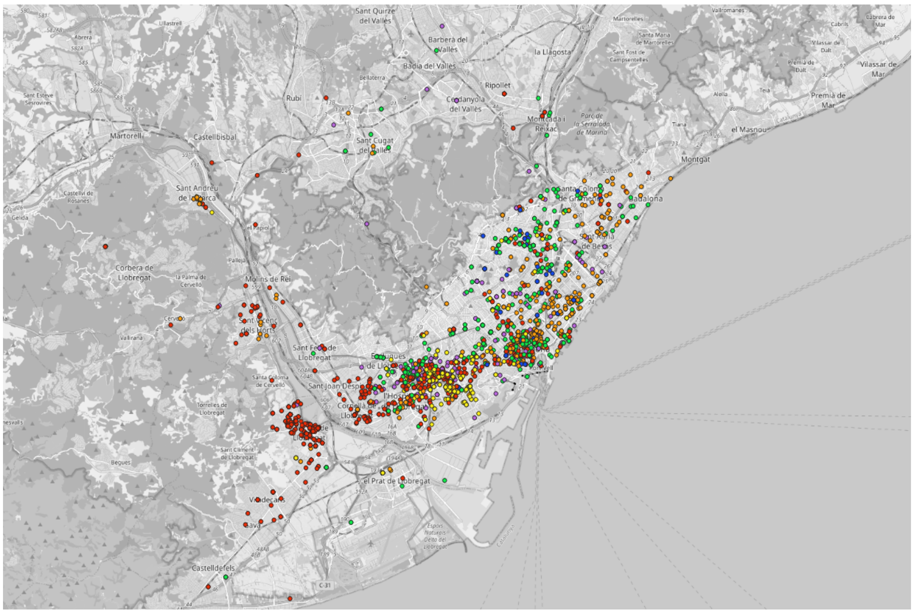
In this chapter, I study gangs' influence in an urban area at a small geographical level. Using granular data for the Metropolitan Area of Barcelona, I analyze the existence of a tipping point and define a spatial gang boundary. I then test for discontinuities in crime patterns across such gang boundaries. I document that across the gang boundary, the number of total crimes is not significantly different. However, there is a significant change in its composition. There is a lower share of crimes against property crimes and a higher share of crimes against the person. While a lower share of thefts drives the reduction for crimes against property, all categories rise for crimes against the person. There is a higher share of crimes committed by male offenders to female victims in terms of offender and victim characteristics. In terms of mechanisms, I postulate that two features are behind the results of this research. While the underreporting of property crime would be behind the results for thefts, the increase in crimes against the person would relate to the gender role models followed by gang members.

The compositional change in crime found in this research across the gang boundary carries significant welfare implications. While no significant change is found in overall crime across the gang boundary, there is a shift in crime composition towards more severe and violent crime patterns. The reduction in reported petty property crime, and particularly the increase in gender violence crimes, highlight the need for attention to critical issues seldom studied in areas with strong gang influence.

The chapter speaks of the importance of a mix of traditional and alternative policies to reduce crime. While tough approaches are still the most used strategy worldwide to tackle gangs (and sweeps in particular, as seen in Chapter 3), this research shows how in communities experiencing this type of place-based policies, other interventions are needed as well. Chapter 2 of this dissertation showed how community-based initiatives could reduce crime, particularly those involving close personal links. Furthermore, the area across the gang boundary in the historic city center benefited from a community-based health policy whose priority was set on drug problems. Furthermore, Trickett (2016) indicates how a policy response and a hefty budget were pledged to young women at risk of sexual violence by male gang members in the United Kingdom. From a policy point of view, hard and soft approaches towards fighting gangs need to be thought of as complementary rather than substitutes.

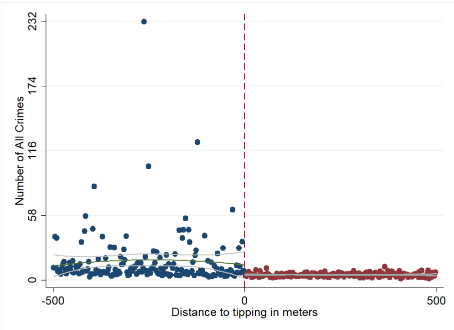
4.7 Appendix

Figure A4.1: Gang crimes in the Metropolitan Area of Barcelona by gang, 2008-2014

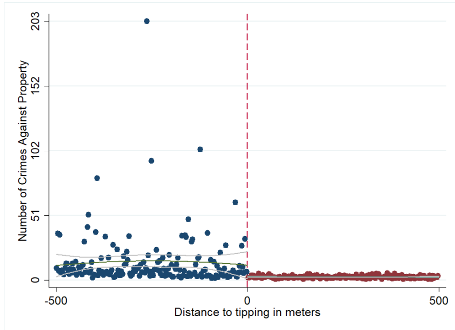


Source: Own construction from Local Police data and Chapter 3 identification of gang members.

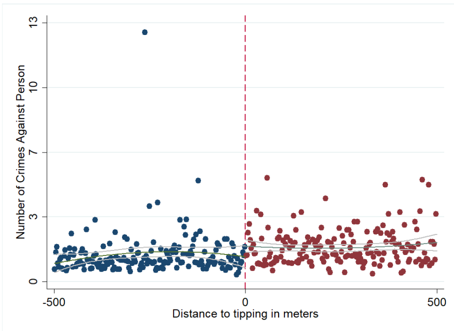
Figure A4.2: RD Graphical analysis - crime counts across the gang boundary, by large crime categories



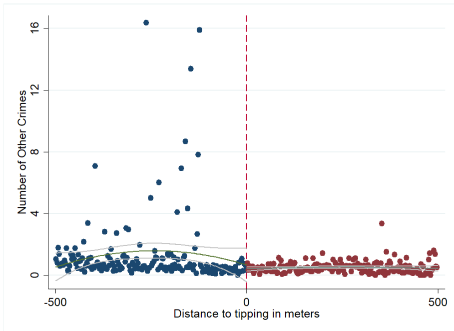
All crimes



Against Property



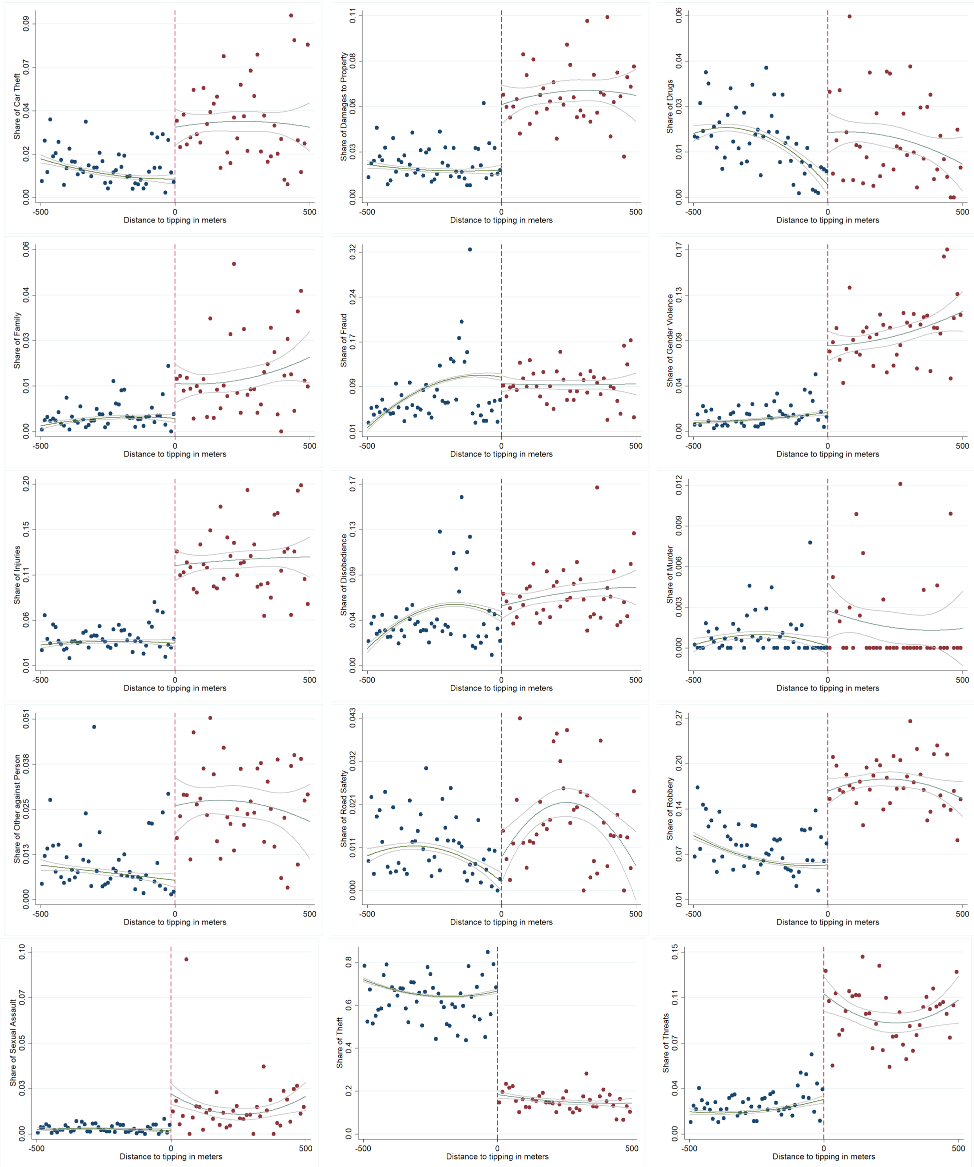
Against Person



Other crimes

Note: These graphs show the number of all crimes, those against property, against person and other crimes, conditional on the distance in meters to the closest point where $GI = 302$. The unit of observation is a crime, and each dot in the graphs reflects a conditional mean, binned by distance.

Figure A4.3: RD Graphical analysis - share of crimes across the gang boundary, by detailed crime categories



Note: These graphs show the share of different detailed crime categories conditional on the distance in meters to the closest point where $GI = 302$. The unit of observation is a crime, and each dot in the graphs reflects a conditional mean, binned by distance.

Figure A4.4: Relationship between *GI* distance and distance in meters around the gang boundary

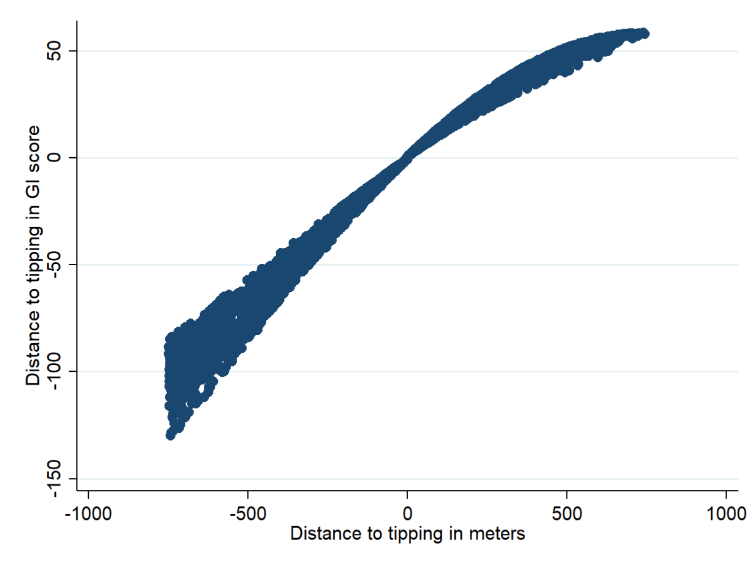


Figure A4.5: Relationship between *GI* distance and distance in meters around the gang boundary - zoom

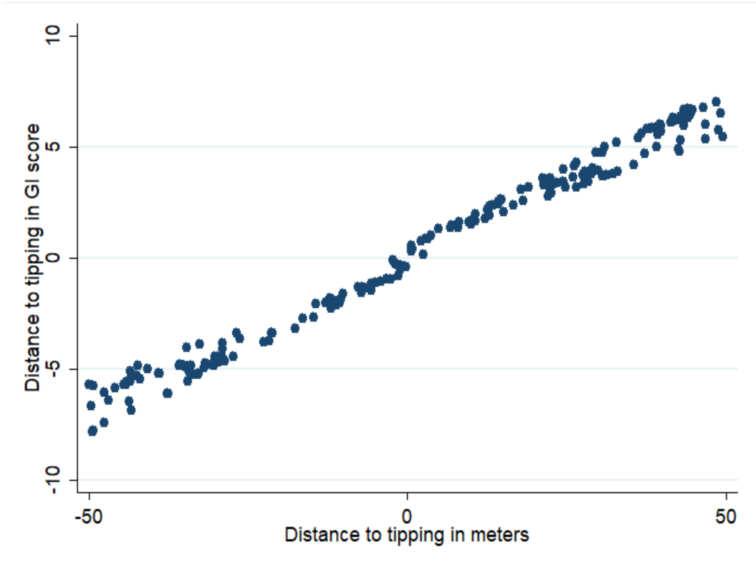
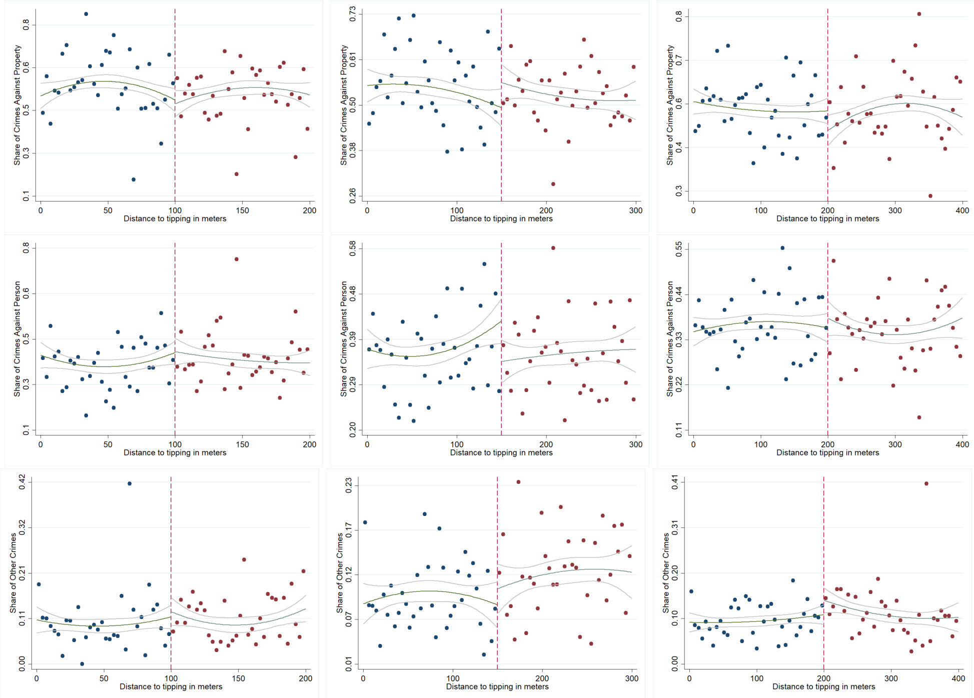


Figure A4.6: RD graphical analysis - gang boundary falsification exercises



Note: These graphs show the results of falsification exercises moving the tipping point. Each row presents results for different broad crime categories, and each column presents results for different falsification tipping points, at 100, 150 and 200 meters of the actual one respectively. Each graph shows the share of the crime category conditional on the distance in meters to the false tipping point. The unit of observation is a crime, and each dot in the graphs reflects a conditional mean, binned by distance.

Table A4.1: Adjusted R^2 statistic of structural break models for selected tipping point candidates GI^*

GI^*=	300	301	302	302.5	303	304	305
All crimes	0.0026	0.0027	0.0035	0.0034	0.0033	0.0032	0.0031
Against Property	0.0029	0.0032	0.0041	0.004	0.004	0.0039	0.0038
Against Person	-0.0001	0	0	0	0.0001	0	0
Other	0.0013	0.0012	0.0011	0.0011	0.0011	0.001	0.001

Note: The table shows the Adjusted R^2 statistic for OLS regressions following the structural breaks method of Card et al. (2008). While each row refers to a crime typology, each column presents results for different tipping point candidates GI^*.

Table A4.2: RD Regression analysis - share of crimes across the gang boundary, by detailed crime categories

Panel A: Against Property	All	Theft	Robbery	Damages to property	Car Theft
	-0.396***	-0.425***	0.036	0.045***	0.027**
	(0.026)	(0.031)	(0.024)	(0.013)	(0.011)
Panel B: Against Person	**All**	**Injuries**	**Threats**	**Gender Violence**	**Family**
	0.324***	0.109***	0.104***	0.082***	0.015**
	(0.027)	(0.016)	(0.019)	(0.015)	(0.006)
Panel C: Other	**All**	**Disobedience**	**Drugs**	**Road Safety**	**Arson**
	0.101***	0.048***	0.021**	0.007	0.000
	(0.023)	(0.017)	(0.009)	(0.006)	(0.000)
Observations	83,505	83,505	83,505	83,505	83,505

Note: The table show robust estimates from a Regression Discontinuity Analysis following Eq. (4.4) for the 2008-2014 period for the MAB. Discontinuity is set at a $GI = 302$ and linked to a spatial support. The running variable is the distance in meters to the closest point where $GI = 302$. The unit of observation is a crime and observations are binned by GI statistic score. Each row presents results for a different broad crime category, and each column presents results for a different detailed crime category inside each broad category. Robust Standard errors are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

5 Concluding Remarks

Crime is one of the most salient issues that negatively affect individual and societal welfare. The economics of crime focuses on the effect of incentives on criminal behavior and the use of a cost-benefit framework to assess alternative strategies to reduce crime (Freeman 1999), and is a relevant field as crime is noteworthy in current societies. However, some stylized facts about crime are not well explained by traditional cost-benefit analysis. Social interactions are a missing factor that could account for the excess crime in urban areas and the young. Being able to account for social interactions, local characteristics, and specific events that affect individual involvement in crime has been crucial for the economics of crime. The availability of better data, alongside the advances in causal inference, allowed for significant causal analysis advances over a relatively short time.

This Ph.D. dissertation provided new research on the role of networks on criminal outcomes in an urban context. While doing so, it shed light on the functioning of traditional and non-traditional preventive policies. The final goal of this dissertation was to improve the understanding of criminal drivers, how different networks deter or encourage them, and how they interact with socioeconomic factors. With these considerations, Chapter 2 studied the effects on crime of a non-traditional public policy that bolsters community ties. Chapter 3 analyzed the impact of a tough-on-crime policy on the criminal outcomes of the arrested individuals and their peers. Chapter 4 examined gangs' territorial influence and crime composition. Outcomes of this dissertation contributed to academic research and offered guidance for policy-making to deter crime.

Throughout the dissertation, the empirical analysis centered on the Metropolitan Area of Barcelona. Such focus relates to the fact that it is one of the European metropolitan regions with highest crime rates in thefts, robberies, burglaries, and intentional homicides. Additionally, data from the Barcelona victimization survey reflects that crime is a pressing issue in the city. Lastly, access to a unique restricted-used administrative dataset provided by the Local Police (*Mossos d'Esquadra*) allowed performing a causal analysis of criminal outcomes in an urban context.

Chapter 2, *"Bolstering community ties as a means of reducing crime"*, studied the effects on crime of a non-traditional policy that bolsters community ties. To do so, I took advantage of the quasi-random nature of a community health policy rolled out in Barcelona from 2008 to 2014, named BSaB. I assessed if the community feature of the policy boosted community ties and reduced crime. Using a staggered difference-in-differences approach and administrative records from the Local Police, I found that this is the case. Concretely, there was a reduction in crime against the person, related to the decrease of intimate crimes. These fell by 25% and only in the short term. Drug crimes also saw a reduction but in the longer term. For outcomes on offense rates, there was a reduction in that of younger individuals. Results also indicated that BSaB increases per capita associations in participating neighborhoods. This chapter evidenced that non-traditional policies against crime work and that less disruptive means of reducing criminal activity in disadvantaged areas can be effective. Even if constructing community ties can be more challenging than deploying traditional policing, this type of alternative policies may work better in several contexts. A better understanding of the interactions between social cohesion and public policy is essential to reduce criminal activity induced by the lack of integration of some citizens facing substandard social and economic conditions.

Chapter 3, *"Sweeping up gangs: The effects of tough-on-crime policies from a network approach"*, analyzed the effects of a tough-on-crime policy against gangs. It explored the impact of police sweeps on the criminal outcomes of individuals arrested in sweeps and those of their peers. To do so, I retrieved the structure of real criminal networks from the Local Police's administrative records. I followed a difference-in-differences (DiD) strategy in the Metropolitan Area of Barcelona, a context in which a drastic change in policy towards gangs took place due to its quick unraveling. Results indicated significant reductions in the criminal activity of those arrested in the sweeps and their known peers. For the former, there was an immediate and sharp drop in crime. This result, alongside average trial and prison times, was consistent with an incapacitation effect. In the case of peers, reductions in criminal activity were shorter, short-termed, and focused on crimes against the person. These outcomes pointed towards a mechanism of loss of the criminal environment. Nevertheless, a counterfactual exercise indicated that sweeps' crime reduction could have been reached by targeting a smaller set of key individuals. In this way, identifying and arresting key players in a gang can help achieve higher crime reductions of policy actions.

Chapter 4, *"Behind closed doors: Crime composition in gang territory"*, examined gangs' territorial influence and crime composition. I identified urban gang presence with granular data and analyzed the existence of tipping points. This was translated into a spatial gang boundary across which I tested for crime differentials. I documented that across the gang boundary, the number of total crimes is not significantly different. However, results indicated a change in crime composition. Results pointed towards a lower share of property crimes and a higher one of personal crimes. There was also a higher share of female victims and male offenders. This change in crime composition carried important welfare implications and highlighted the need for attention to other critical issues in gang areas, as gender violence can be. While tough-on-crime approaches to tackle gangs are still the most used strategy worldwide, this chapter shows how other interventions are needed simultaneously.

Three key lessons arose from this dissertation. First, networks do matter. While some connections incite the decision on crime participation, others dissuade it. On this point, there is also an important distinction on which types of crime networks affect. All chapters document effects on crimes against the person, whereas the impact on property crimes is mixed. In either case, criminal outcomes are highly affected by the individuals' context, surroundings, and personal connections. Second, governments can take advantage of network knowledge to improve crime prevention. Chapter 3 revealed that by adequately identifying, targeting, and deterring the key players of a network, it is possible to achieve broader crime reductions. Also, Chapters 2 and 4 showed how different agents in local communities could influence criminal patterns. Chapter 2 indicated that local associations could be crucial to build close links and prevent crime. Chapter 4 showed that the presence of criminal groups can increase certain crimes and conceal others. So, investing in information that portrays networks might be worthy for policy design. Third, this dissertation evidenced how traditional and non-traditional crime preventive policies are not substitutes. The dissertation presented evidence on how to incorporate both approaches when outlining a crime-fighting strategy. This statement was most evident in Chapter 4. Even in contexts where a tough-on-crime approach might be suited, other less visible issues might need policies based on community approaches. Policy design should incorporate hard, soft, and behavioral paths into a unified strategy, combining and coordinating efforts that tackle crime.

Regarding future research, I here outline three lines that stem from the learning process of this dissertation. First, we need to overcome many data limitations that are still pressing today. Public availability of administrative registries is a must to move forward in understanding the microeconomic determinants of crime. Moreover, datasets from public administration should be able to be linked among them. Such data feature would allow providing a broader understanding of individual circumstances while avoiding biases coming from unobserved factors. Second, further efforts are needed to connect theoretical and empirical analysis. While there are several theoretical models on the effects of social interactions, there are still few and limited applications. This point, closely related to the first one, is an issue to invest in and move forward. Also, we need to allow more flexible and realistic assumptions in models, for example incorporating heterogeneous catching costs for criminals or network rewiring to identify key players. Third, with advanced data availability and modeling, we need to improve the understanding of criminal patterns and drivers in urban settings. As most criminal activity occurs in cities, fine-grained analysis can help us move forward in designing safe cities where social interactions deter crime more than they encourage it.

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