Essays on the Economics of Crime: Determinants of Crime in an Urban Context

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As güelu

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"Mentres escric aquestes paraules lamento sa teva pérdua.

Gràcies pels valors que m'has ensenyat güelu. Per sempre "

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Contents

Chapter 1

Introduction

1.1. Motivation and general background

Legal systems introduce a line between law abiding citizens and criminals by differentiating what is socially accepted from what is not. The position of this line differs across countries and through time, but, in general terms, it can be said that legal systems have been established to reflect the general ideas and beliefs of citizens and the rationality of society. Consider, for instance, the line drawn between criminal liability and insanity in the 19th century, when punishments were severe and included capital punishment. Yet, in a very different vein, the Becker (1968) model of criminal behavior was the first formal study to approach criminal activity from an economic perspective. Specifically, in this model, criminal behavior is conceived as a rational act and concludes that anyone might turn to crime if the incentives are right. People choose which side of the law to stay on depending on the benefits that legal and illegal activities will accrue to them and on the sanctions that the illegal activities may involve. An individual is less likely to commit a crime if their salary is high, the potential sanctions are high or if the rewards of the illegal action are low. This novel vision broke with earlier perspectives that associated criminal behavior with the balance of the mind.

The contribution made by Prof. Gary S. Becker gave rise to a rich strand in the economic literature that sought to provide proof of his theoretical predictions by examining the benefits of illegal activities, employing socio-economic and demographic variables such as income, unemployment rates, education level, inequality, age, race, gender, etc. For instance, Ehrlich (1973) was the first author to attempt this by showing that deterrence variables, such as the probability of apprehension (measured as the number of police officers or the number of arrests) and the punishment (years in prison, economic fine, social sanction) were good predictors of crime. Since the 1980s countless papers have been written seeking to explain criminal behavior by means of unemployment (Freeman, 1991; Grogger, 1998; Buonnano, 2006; Altindag, 2012; Nilsson and Agell, 2014; Speziole, 2014), inequality (Kelly, 2000; Chintrakarn, 2012; Meloni, 2014), income per capita or economic growth (Ehrlich, 1973; Entorf and Spengler, 2000 Buonanno and Montolio, 2008), and education (Usher, 1997; Lochner and Moretti, 2004; Buonanno and Leonida, 2006; Machin *et al.,* 2011; Anderson, 2014; Fella and Gallipoli, 2014).

In the criminological literature, the rational choice theory (Clarke, 1997) takes a similar utilitarian approach and defends, by means of theoretical arguments, that criminal acts are the outcome of a cost-benefit analysis. In contrast, the routine activity theory (Cohen and Felson, 1979) focuses more specifically on the factors determining a crime (not just individual rationality, but also elements associated with the environment) and postulates that the convergence in space and time of a motivated offender, a suitable target and the absence of a capable guardian are the three necessary elements for a crime to occur. The opportunity theory (Cohen *et al*., 1980) subsequently extended the concept of suitable target by identifying four additional dimensions: target attractiveness, target exposure, guardianship and proximity. These four elements, it is claimed, determine the probability of victimization and depend essentially on individual characteristics and casual facts. In this sense, the criminology literature extended the individual utilitarian approach of Becker and Clarke to introduce the elements of the environment that may affect the probability of committing a crime.

In general, theoretical crime models focus on very local events in space and time (basically at the individual level); however, empirical analyses devoted to identifying the determinants of criminal activities have historically focused on highly aggregate data. Most of the studies draw on aggregate data at the regional (Entorf and Spengler, 2000; Buonanno and Montolio, 2008; Bianchi *et al.,* 2012; Montolio and Planells-Struse, 2013), municipal (Akçomak and Well, 2012; Guillamon *et al.,* 2013; Martínez and Cortes-Yactayo, 2015)), or neighborhood level (Damm and Dustman, 2013; Billing, 2013). Using aggregate data for social issues, such as crime, gives rise to certain questions such as the failure to account for the social interactions between agents or the creation of aggregation biases. Crime events are not isolated events, rather they are actions normally taken and influenced by other individuals or even by the specific characteristics of a neighborhood (Wilson and Kelling, 1982). The so-called peer effects would appear to play a vital role in determining crime levels in specific places. For instance, youths (Case and Katz, 1991) and inmates (Bayer *et al*., 2009) have been shown to be especially vulnerable to peer effects in relation to criminal activity. Gang members may see committing a crime as a badge of honor (Wilson and Herrnstein, 1985; Kahan, 1997, Patacchini and Zenou, 2012) and, therefore, when an individual sees a peer committing a crime, in order to stay in the group or to become someone with a certain status, they mimic that behavior. This case has been specifically studied in immigrant ghettos (Patacchini and Zenou, 2008; Patacchini and Zenou, 2012). Peer effects, however, do not necessarily always increase the probability of committing a crime. If networks can increase the chances of getting a job or becoming integrated into the community, peer effects can actually reduce the probability of engaging in criminal activity (Cutler *et al*., 2008). Alternatively, and for the case of immigrants, if the group members are law abiding, social controls are likely to reduce the likelihood of engaging in criminal activities (Glaeser and Sacerdote, 1999).

Using aggregate crime data (at the country or regional level) – the typical practice in most previous studies – does not however capture all these social interactions and their relation with illegal behaviors. This relation is frequently hidden behind the fixed effects used to account for unobserved heterogeneity across countries or regions. Moreover, as Glaeser and Sacerdote (1999) point out, crime levels in urban areas differ considerably from those recorded in rural areas. In this sense, the social interactions that allow, among others, for the learning processes of criminal behavior and for the accessing of larger illegal markets to sell unlawful goods (such as drugs or stolen items) may go some way to explaining why crime is higher in urban areas. Thus, when using regional data, urban and rural settings are likely to be mixed at the same level of analysis resulting in considerable noise in any quantitative analysis. Given the heterogeneity present, only a general view of the impact can be provided in a typical regional analysis of crime and its determinants.

Despite this, a regional level analysis of crime has been the most frequently adopted approach due to the lack of data at the geocoded level. Moral sensitivity to specific crime events as well as the cost of data mining make such data a scarce commodity, available only at the local and geocoded levels in such countries as the USA (Block and Block, 1995; Brendan and Rajiv, 2010) and the UK (Gibbons, 2004). To account for local characteristics, the effect of specific events, as well as for the social interactions among individuals, what is required is a detailed dataset containing information on the exact location as well as the exact time of each crime event. This detail in crime data should yield more precise results concerning the causality of the socio-economic and demographic determinants of crime. Additionally, such data are useful for the specific study of the causes and consequences of crime in a specific area. For instance, detailed geocoded data may be used to study the spatial displacement or diffusion effects of certain police interventions or to identify the optimal areas for patrolling. Unfortunately for researchers, the availability of socio-economic and demographic data at this level (blocks, neighborhoods or districts) is scarce, hindering these types of analysis.

To date, the only available crime dataset for the Spanish case was the yearly province panel published by the Ministry of Internal Affairs. However, privileged access afforded to a unique, non-public geocoded dataset of all crimes recorded in the city of Barcelona (Spain) provided me with the opportunity to analyze the specific determinants of crime in an urban setting. This highly detailed dataset gives a high level of precision for the analysis of the causes of crime in an urban context. This unique dataset, in combination with the theories outlined above, a combination of the economics and criminological literature, provide a plausible theoretical and empirical scenario for explaining crime events and understanding what lies behind criminal behavior. Economically motivated crimes, such as pick pocketing and burglary, are, in general, better explained by socio-economic factors than are personally motivated crimes, which depend much more on specific circumstances, emotions and feelings. In the case of the latter, the social interactions established between individuals tend to play a much more important role.

When reducing the analysis to this disaggregated level, it becomes essential to take into account the characteristics of the specific areas of study as well as such spatial aspects as location, the characteristics of a particular neighborhood or the spatial relationship between neighborhoods. Environmental criminology is the strand of the literature within that of criminology that studies crime from a contextual perspective (Eck and Weisburd, 1995). It focuses on why crime is concentrated in specific places and at specific times, and seeks to explain, by means of theoretical models, why such spatial and temporal concentrations can be found. A related strand in the literature is the analysis of crime based on the development of models of prediction and of policies to tackle this phenomenon, known as Hot Spots (Braga, 2008; Sorg *et al.,* 1999).

1.2. This thesis: crime in an urban context

In this thesis, I draw on these theoretical models from the criminological literature and on the empirical tools from the field of economics to analyze crime from the perspective of economics. Specifically, I focus on the urban context since, as Glaeser and Sacerdote (1999) point out, crime is more of an urban issue. The social interactions that facilitate the learning of criminal behavior (in the case of property related crimes) and that increase the probability of violent crimes, together with the diversity of potential targets and the greater market on which to sell stolen goods, are factors that considerably increase the number of crimes committed.

I use the city of Barcelona, known worldwide for its ability to attract tourists, as my area of study. To the best of my knowledge, no similar crime research has previously been undertaken in this city and, therefore, the results of this thesis should provide interesting outcomes for policy makers. Cities in the same league as Barcelona are frequent hosts to major events, including cultural (concerts, cultural meetings, etc), recreational (world meetings, fun fairs, etc.) and sporting (football matches, horse races, swimming competitions, etc.) occasions almost on a weekly basis. In terms of their impact on criminal behavior, major events of this nature are prone to modify the routine activities of many citizens, thus modifying the criminal behavior of offenders. Large crowds can increase incentives to commit certain types of crime, such as pick pocketing and assaults. Taking advantage of these major events as exogenous shocks that modify peoples' routines, I analyze how such occasions affect crime. Here, I specifically choose football matches as an example of a major event since the city team, Football Club Barcelona, is an obvious magnet for tourists and their games are followed by many citizens.

Before presenting in detail the chapters that make up this thesis, I present a quick overview of the crime figures so as to provide a better understanding of the importance of crime in Barcelona. In 2011 Barcelona accounted for 36.21% of all the crimes committed in the Autonomous Community of Catalonia, while its population represents just 21% of the total population. Distinguishing by type of crime reveals that for minor and major property crimes,[1] these shares are 41 and 35% respectively. This means, property crime rates are relatively higher in urban areas than in other areas, as previously corroborated by Glaeser and Sacerdote (1999).

In terms of the temporal evolution of crime in Barcelona, this figure has risen slightly in recent years from a rate of 115 crimes per 100,000 inhabitants in 2008 to a rate of 117 crimes per 100,000 inhabitants in 2011. During the severest years of economic crisis (2009, 2010), this rate was as high as 127 recorded crimes per 100,000 inhabitants. If we focus on the type of crime, we see that this figure has risen from 124 major property crimes per 100,000 inhabitants in 2008 to 140 in 2011. In the case of minor property crimes, this figure rose from 117 to 129 crimes per 100,000 inhabitants. Interpersonal violent crimes,

[1] Property crimes are the most common, representing almost 85% of all crimes committed in the city of Barcelona.

although lower in absolute terms, also rose from 17 to 19 per 100,000 inhabitants between 2008 and 2011. Among property and violent crimes, there is a variety of crime typologies. For instance, among property crimes, we include the damage caused to the belongings of others, car thefts, thefts from vehicles and pick pocketing; while among violent crimes, we include brawls, sexual offenses and assaults. In this thesis, I perform all the analyses at the lowest level of aggregation in order to avoid aggregation bias (Cherry and List, 2002). In other words, I perform the criminal analysis at the article level of the Spanish Penal Code and do not aggregate crime types of different motivations. The following paragraphs present a brief overview of chapters 2, 3 and 4.

In Chapter 2, entitled "**Should football teams be taxed? Determining crime externalities from football matches**", I begin by demonstrating the economic importance of Football Club Barcelona. I then analyze the effect of Football Club Barcelona matches on crime from a spatial perspective. That is, I first evaluate the effect of the number of spectators on crime (thefts and assaults) by comparing crime rates on match days, both home and away, and days that are very similar in all other characteristics apart from the fact that no match has been played. I analyze two types of crime given that their determinants are likely to be very different: first, I focus on thefts, where the concentration of people in space and time may introduce incentives, or reduce costs, to potential offenders; and, second, I focus on assaults (fights and brawls in the main), whose drivers would appear to be more closely related to hooliganism, i.e., unlawful behavior related to football matches, such as fights, drunken disorder or damage to the belongings/property of others. In the next step, I analyze the impact of a football match on the spatial distribution of crime, by carrying out an Exploratory Spatial Data Analysis (ESDA) of the census tracts around the stadium on football match days and on days free of football. Employing econometric models that account for the positive skewed distribution and the over dispersion of the data (e.g. negative binomial regressions), I analyze how the scheduling of a football match can modify the distribution of crime in the city of Barcelona. In the case of thefts, the results indicate an increase in the number of crimes for the whole city of Barcelona on home match days, especially, in those census tracts that are within a 1-km radius of the stadium. This suggests that despite the increase in the number of police officers deployed around the stadium, pick pockets are attracted to crowds where the rewards are likely to be higher and the probability of being detained lower. These results are confirmed by the placebo test that shows a lower number of crimes are recorded in the census tracts around the stadium when Football Club Barcelona plays away. In the case of assaults, a similar spatial pattern to that described for thefts is found, although the overall impact for the whole city is not significant. This result suggests that there is a marked displacement effect towards the census tracts around the football stadium from other parts of the city. This phenomenon would seem to reflect the hooliganism that is present in and around most football stadiums in Spain. As such, the results obtained in this chapter provide public administrations with the opportunity to raise their revenue levels by taxing the crime externalities generated by football teams.

In Chapter 3, entitled "**How time shapes crime: the displacement effects of football matches in the city of Barcelona**", I purposefully omit the spatial dimension of crime in order to focus on the temporal. I begin by undertaking an analysis of the temporal profile of crime for the city of Barcelona. That is, I carry out a very specific analysis of different types of crime and their unique temporal patterns. I specifically observe temporal crime patterns on a daily, weekly and monthly basis to determine whether they actually follow a clear pattern over time. I then conduct an hourly analysis to examine the impact of a major event, in this case a football match, on different types of crime. The results show that the football matches played by Football Club Barcelona reduce the levels of certain types of crime during the period of the game due to the incapacitation effect, i.e., potential criminals are incapacitated by the fact of their watching the game. Moreover, I find a reduction in those crimes typically reported only by the police, including driving crimes and drug consumption, due to what I identify as a substitution effect, i.e., police officers substitute their duty of reporting crimes for that of safeguarding citizen security. The consequence is an apparent fall in these types of crime, although the reality may be quite different. Finally, the results also show that in the hours leading up to a game and in the hours following the final whistle there appears to be significant increases in certain types of crime such as pick pocketing and violent crimes.

Chapters 2 and 3 give more evidence on the determinants of crime and specifically on crime behavior modifications (as regards both time and place displacements) attributable to major events such as football matches. The results obtained provide police agencies with a better understanding of the way in which criminals shift their decisions regarding the commission of crimes in relation to major events: on the one hand, when criminals decide to commit their crimes on days when a football match is being played; and, on the other, where criminals choose to commit these crimes on match days. Placing these results into the context of public economics, football matches generate negative externalities in the form of higher levels of crime, which serves as a justification for policy makers to find new ways of financing the public sector and compensating the costs of these events. Moreover, and given that tackling crime is one of the main goals of police agencies, Chapters 2 and 3 also shed light on criminal behavior. Specifically, the results reported in these chapters help understand the way in which criminals modify their target preferences (both in terms of time and space) and, therefore, how the police might best deploy police officers in time and space. However, since the early eighties there has been an increasing interest among police officers to ensure that that people not only feel safer, but that they have an enhanced perception of their own safety (Cordner, 2010). Thus, the reduction of the fear of crime has been a major objective of the police given its impact on individuals' well-being. For instance, a robbery not only has an impact on the victim itself, it also affects the individuals that witness the act (and those who subsequently know about it) since they are likely to feel unsafe and to modify their behaviour accordingly. Networking and social interactions can spread this insecurity among individuals consequently affecting individuals' well-being. If the authorities are incapable of ensuring that people perceive their personal integrity as being guaranteed and that they live in a safe environment, public efforts and resources devoted to crime prevention and control may well not be assessed as fulfilling their primary objectives.

In this sense, assessing the determinants of fear of crime and of crime risk perception[2] are crucial for the public sector as they tackle the potential negative effects on individuals' well-being. Community policing is the policy that has been used since the early eighties in an attempt at assessing crime risk perception determinants as well as the potential factors that may reduce crime. It consists of a more human approach to society as the police seek to get closer to the real problems and fears of the citizens. The level of crime risk perception is not only determined by crime or individual characteristics such as gender or age, but also by the characteristics of the neighborhoods. The *broken window* thesis (Wilson and Kelling, 1982) links three important concepts in neighborhoods: disorder, fear and crime. Specifically, this thesis states that the link between the three concepts may start with a minor disorder such as a broken window. If left unchecked, it will generate the perception that no one cares about it. Hence, this minor disorder may generate increasing levels of fear. Levels of distrust among the neighbours consequently rise and they start to

[2] Fear of crime is conceived as the emotional aspect of perception while crime risk perception is more closely related to the cognitive aspect (LaGrange and Ferraro, 1987). In the literature, both have been studied separately although the results regarding the determinants of both feelings are very similar.

behave differently - staying at home more and socializing less with each other. In turn, this leads to a reduction in natural surveillance permitting further disorder and minor crimes.

In sum, crime risk perception is known to be an important determinant of individuals' well-being. Therefore, it is crucial, especially for governments, to understand its determinants and those (public) policies that can reduce it. Among those policies, public resources devoted to police forces emerge as a key instrument not only to tackle criminal activity but also to impact on citizenship crime risk perception. In this framework, the aim of Chapter 4, entitled **"When police patrols matter. The effect of police proximity on citizens' crime risk perception"**, is precisely to analyze the determinants (both individual and neighborhood) of citizens' crime risk perception for the city of Barcelona focusing on the effect of police proximity and taking into account spatial aspects of neighborhood characteristics. We measure, according to the main theoretical theories, how the simplest contact of a police officer with citizens' can affect their level of crime risk perception. In this sense, we analyze how police policies consisting of an approach to citizens, may be effective in terms of reducing peoples' crime risk perception. After controlling for possible problems of endogeneity of police forces and crime risk perception and the potential sorting of individuals across neighborhoods, our results show that crime risk perception is reduced when non-victims (randomly) interact with police forces. Moreover, neighborhood variables, such as proxies for social capital and for the level of incivilities, as well as individual characteristics have an impact on individuals' crime risk perception.

Finally, Chapter 5 presents the overall conclusions of this thesis. It states the main results obtained and concludes with some policy implications as well as some future questions for research.

Although the three main chapters of this thesis differ in their specific objectives and can be read separately, they present the common goal of extending the knowledge of the determinants of crime and criminal behavior in an urban context in order to improve the effectiveness of police agencies in the allocation of police officers across space and time.

1.3. Institutional framework of the thesis: police structure in Spain

The public sector is responsible for determining the line between legality and illegality but also, it is responsible for determining the resources devoted to police agencies, their policies, their way of patrolling and investigating as well as the authority and capabilities they have. These aspects vary enormously across countries and even regions within the same country and, therefore, the analysis of what determines crime and what its relationship with the police is must be carried out separately in each country and region. An important aspect to take into account, and one that differs significantly across countries, is the extent to which police agencies are decentralized. For this reason, in this section, and with the aim of providing an overview of the Spanish police system, I present the main police agencies, their competences and some statistics regarding their presence.

For the case of study, Spain, the police structure is a mixed model that combines both, centralized and decentralized police agencies. Specifically, of the 17 autonomous communities, in 14 the centralized police agencies have a presence, that is, police agencies whose structure and management depend entirely on the Central Government. In Spain we can distinguish between the *Cuerpo Nacional de Policia* (CNP), with more than 70,000 police officers, and the *Guardia Civil* (GC) with over 82,000 officers. Both depend directly on the Ministry of Interior of the Central Government.. The competences of these police agencies are similar, although they differ in the geographical areas in which they operate. While the CNP operates mainly in cities[3] with more than 20,000 inhabitants, the GC operates more in rural areas. In addition to the very specialized centralized police agencies, at the local level (and depending on the city council), we find local police agencies whose main responsibility is to ensure adherence to local laws. Specialist crime prevention and investigation teams in these local police agencies are rare, although some are highly specialized in community policing. The latter seek to reduce citizen insecurity and maintain close contact with the citizens to know their fears and main concerns. These are the police officers that are closest to the citizens and also in constant contact with neighborhood associations as well as local businesses.

In addition to the main police agencies in Spain, we also find the *Port Police,* with authority in the ports of Spain, and the agents of the *Agencia Tributaria,* responsible for investigating money laundering, drug trafficking and tax evasion. This is the only agency that depends on the Ministry of Public Finance. Both agencies play an important qualitative role, although in terms of agents they are not as important as the other police forces.

Importantly for this thesis, apart from these centralized police agencies, local police agencies and the specialized police agencies, three Autonomous Communities in Spain

[3] Ports, airports and borders are patrolled both by the CNP and the GC since they both hold competences in immigration and drugs.

have their own police agency: the Basque Country with the *Ertzainza,* Navarra with the *Policia Foral*, and Catalonia with the *Mossos d'Esquadra.* These police agencies have substituted the CNP and the GC that are present in the rest of the Autonomous Communities. They hold all competences apart from immigration and the issuing of documentation, which continue to be the responsibility of the CNP and the GC.

Decentralization presents several benefits, including innovation and specialization. However, it presents the need to be well-coordinated in terms of the homogeneity of recorded crime data. The failure to homogenize data across the Autonomous Communities that operate autonomous police agencies and those that do not complicates any analyses conducted at this level.

In Chapters 2 and 3, a formal agreement with the *Mossos d'Esquadra* for a crime analysis of the city of Barcelona provided me with a useful geocoded crime dataset that allows a very specific analysis at the local level for the city of Barcelona, and which allows me to overcome the problem present in analyses at other levels. However, for the analysis of feelings and perceptions, such as that conducted in Chapter 4, I need a different type of data. Specifically, I use victimization survey data. This type of data, kindly provided by the Barcelona City Council, has the advantage that it does not suffer from the underreporting issue that can characterize registered data. For instance, many petty crimes are often not reported to the police and so are not captured by official police statistics. Similarly, many crimes such as driving related crimes or drug consumption are not reported unless they have been reported by the police. In this case, victimization surveys can overcome the issue of underreporting and they may include other dimensions of crime, such as perceptions and opinions. I make use of the Barcelona victimization survey to account for the crime risk perception at the neighborhood level. To the best of my knowledge, this victimization survey is the most detailed in Spain being representative at the neighborhood level and being conducted on an annual basis.

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Chapter 2

Should football teams be taxed? Determining crime externalities of football matches

2.1. Introduction

With over 52 million followers on Facebook, 11 million followers on Twitter and a long history of sporting success, Football Club Barcelona (FCB, hereafter) is one of the world's leading football teams. Its current popularity is reflected in an average gate of over 70,000 spectators at its home games. Indeed, the attraction of FCB would appear to represent a sizeable economic benefit for the well-known city and its citizens. For instance, it seems probable that the club's home matches attract a higher number of tourist arrivals and boost levels of consumption in the retail sector with a consequent positive impact on job creation and tax revenues.

However, despite these positive economic effects, a number of negative externalities may affect the city as a result of its being home to such a major team and its hosting of such large events on a regular basis. Above all, the presence of FCB might promote criminal activity. Large crowds are likely to increase the number of potential targets, thus attracting more offenders. Moreover, the increase in the number of social interactions, the high consumption of alcohol combined with the euphoria of a victory or despair of defeat can increase levels of interpersonal violence (see Card and Dahl, 2011 and also Chapter 3 of this thesis). Additionally, celebrations may result in other types of illegal behavior, including vandalism and the assault of police officers.

To guarantee the security of citizens and to prevent crime, large numbers of police officers have to be mobilized on match days. For instance, the Catalan police force (*Mossos d'Esquadra*) estimates that an average of 246 police officers are required to police "high risk" games, such as those between FCB and its historic rival Real Madrid CF. However, this deployment of officers and police resources generates an additional cost and one, moreover, induced by a private activity that has to be borne by the whole of society via general taxation.

In response, various European governments have attempted to levy a tax to cover the negative externalities attributable to large-scale events in the form of higher crime rates. In the UK, for instance, the South Yorkshire Deputy Chief Constable and lead on football policing for the Association of Chief Police Officers (ACPO), Andy Holt, has stated that football clubs should cover the full cost of policing football matches, and not just those incurred within and around a certain distance of the stadiums as is current practice, given that the impact of a match affects a much larger area.[4]

In Spain, where public finances are currently under considerable stress and there is a need to seek alternative sources of revenue, the debate remains ongoing. In 2014, in the city of Barcelona, the Catalan government budgeted a tax to cover extra policing resources for high risk events.[5] The cost of a police officer is estimated at 35 euros per hour, which means policing a "high risk" match costs 54,798 euros; 35,000 of which are to be met by FCB in concept of extra policing costs. The Catalan Home Office estimates that an annual revenue of around 200,000 euros will result from this tax. However, such estimates are not based on the actual impact of a football match on the city's security and this would require an analysis of their full effects on crime counts.

The aim of this Chapter, therefore, is to conduct an in-depth analysis of the impact of FCB matches on different types of crime in an urban context. The use of geocoded data, the approach adopted and the techniques employed make an innovative contribution to the literature. Our results allow us to characterize in full the impact of the football matches of a leading European team on crime in a major European city. Moreover, they provide policymakers with rigorous estimates for the effective introduction of taxes that can reduce the negative externalities associated with private activities.

More specifically, we study the respective impact of FCB's home and away matches on property crime (e.g., theft) and on crime against the person (e.g., assault). Drawing on a panel dataset (containing daily and census tract information), we present a descriptive analysis employing GIS techniques to show that FCB's matches impact crime patterns not just around its stadium, but throughout the city of Barcelona. We also present a spatial confirmatory analysis of the effect of the club's matches on crime around the stadium by analyzing the extent to which the agglomeration of people impacts each type of crime. To

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[4] The ACPO found a statistically significant increase in the number of crimes up to 1 km away from UK football grounds.

[5] See, the Bill for fiscal, administrative and financial measures that accompanies the regional budget for 2014 of the *Generalitat de Catalunya*: http://www15.gencat.net/ecofin_wpres14/pdf/VOL_P_MES.pdf (last accessed, November 2014).

ensure the robustness of our results, we carry out various checks for crime patterns on those days when FCB play away (and when the spatial impacts should not be found).

The rest of the Chapter is structured as follows. Section 2.2 reviews the existing literature that accounts for the potential effects of football on crime. Section 2.3 presents the datasets used and the matching process applied to the data prior to conducting the empirical estimations. Section 2.4 presents the methodology for estimating the impact of football matches on crime and the spatial analysis used. Section 2.5 shows the empirical results from the regression analysis. Section 2.6 presents the descriptive and confirmatory spatial results. Finally, section 2.7 sums up the Chapter and concludes.

2.2. The multiple effects of football on crime: an examination of the existing literature

A major sporting event can have a variety of impacts. In the case of football, studies have focused on the effects of a competition such as the FIFA World Cup on employment, tourism, sales, overnight stays (Allmers and Maennig, 2009; Matheson and Baade, 2004; Hagn and Maennig, 2008) and on psychological aspects, such as individual perceptions about economic prospects, both at a personal and economy-wide level (Dohmen *et al.,* 2006; Süssmuth *et al.,* 2010). Additionally, there is evidence of the effect of football on illegal behaviors. Kurland *et al.* (2013) study the effect of football matches on crime and examine whether football matches act as crime generators or crime attractors.[6]

Marie (2011) describes three main channels through which football matches may affect crime. First, the concentration effect is the most straightforward of the effects to be considered. Simply put, an agglomeration of individuals in a particular place is likely to increase social interactions, which combined with high levels of alcohol intake may lead to interpersonal violence (clashes and fighting)[7] and property crimes (especially, theft and pick pocketing). In accordance with routine activity theory (Cohen and Felson, 1979), for a crime to occur, a suitable target, a motivated offender and the absence of a capable guardian must converge in time and space. A football match increases exponentially the number of potential targets, which in turn attract a certain number of motivated offenders (above all pick pockets given that the rewards should be high), while the agglomeration

[6] See the crime pattern theory (Brantingham and Brantingham, 1993) for a detailed explanation of offense patterns and the dynamics involved; and see Brantingham and Brantingham (1995) for an explanation of their classification of places as crime generators or crime attractors.
[7] Despite the efforts of FCB to eradicate violent behaviour inside the stadium, a violent group of ultra FCB supporters (*Boixos Nois*) continues to gather outside the stadium on match days to “warm up” the atmosphere.

itself reduces the probability of apprehension (anonymity). If these elements all converge, then we would expect to observe an increase in the number of property crimes around a football stadium on match days.

Agglomerations, albeit at a smaller scale, may also occur in other parts of the city (and not only in the vicinity of the stadium), since supporters and football fans often gather in public places to watch the match or to celebrate (lament) a victory (a defeat). Therefore, a rise in thefts might be expected in other areas of the city on a match day. Additionally, when the team is playing away, while an impact around the stadium would not be expected, we might expect to see some effects in those places where matches can be watched (pubs and bars, etc.).

Second, the profiles (gender and age) of the average football fan and potential offender are not dissimilar, which may have a number of implications for crime rates. Specifically, our crime dataset including known offenders in Barcelona between 2007 and 2011 reveals that 79% were male; 76% were under the age of 40; and, 63% were under the age of 35, a profile that is, in general, very similar to that of football fans, as in the case of London, as captured by the FA Premier League Fan Survey 1994-1997. The coincidence of the two profiles might, on the one hand, point toward a potential increase in illegal activities, or, on the other, to a 'self-incapacitation effect', as a share of the population with a similar profile to those presenting a greater propensity to commit illegal activities will always be watching the match, resulting in a fall in the crime rate.[8]

The third effect, also cited in Marie (2011), is that of 'displacement', given the reassignment of police officers to points around the stadium on match days. This represents an opportunity for criminals in areas in which levels of surveillance have been relaxed. The spatial analysis we perform here at the city level provides us with some insights as to whether this effect is evident for the city of Barcelona. Note, however, that if the number of police officers assigned to other areas of the city is not reduced on match days, this effect will not exist.

These three channels may not appear to increase crime when the data is examined on a daily basis; only an hourly analysis can reveal their presence. For instance, Montolio and Planells-Struse (2014) detect the incapacitation effect only during the football match itself,

[8] Self-incapacitation due to attendance of an event by a part of the population with a greater propensity to commit crimes has been examined by Dahl and DellaVigna (2008) for the case of violent blockbuster movies. Here, we expect the incapacitation effect to be manifest during the ninety minutes of the game. However, after the final whistle, crime may increase as a result of both the incapacitation effect being lifted and the outcome of the match (Montolio and Planells-Struse, 2014).

while the same authors report a substitution (displacement) effect with police officers apparently being reassigned from certain activities (driving- and drug-related offenses) to others in which their primary concern is guaranteeing citizen security and maintaining traffic flow.

The study reported in this Chapter – combining regression and spatial analyses – seeks to provide a precise characterization of the spatio-temporal patterns of crime and football in the city of Barcelona.

2.3. Data

2.3.1. Crime data

We use a non-public dataset for the city of Barcelona containing all crimes registered by the autonomous police agency in Catalonia (Spanish region in which Barcelona is located), the *Mossos d'Esquadra*, which is responsible for crime prevention, crime solving and specialized crime investigation in the Catalan region.[9] The dataset holds reports filed by both citizens and the *Mossos d'Esquadra*, as well as by the local police (the *Guardia Urbana*), responsible primarily for urban traffic and upholding municipal laws and ordinances.

The dataset records the time of the crime (when known), the location and the crime type. The dataset, which extends from 1 September 2007 to 31 December 2011,[10] was restricted so as to include only those months that correspond to the official football season (i.e., June, July and August have been removed). Of the remaining 635,065 observations, 98.74% (627,037 observations) were geocoded with a precision of within ten meters.[11]

Illegal activities were classified in accordance with the roughly 190 articles of the Spanish penal code. However, to reduce the number of categories without causing an aggregation bias that might reduce the effectiveness of our estimations (Cherry and List, 2002), we combined some of these articles, paying particular attention not to aggregate

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[9] The *Mossos d'Esquadra* are responsible for virtually all police duties. The Spanish National Police (*Cuerpo Nacional de Policía*) and the military police (*Guardia Civil*) retain a number of administrative responsibilities (e.g., issuing of identity cards and passports) and undertake counter-terrorist and anti-mafia activities.

[10] The original dataset contained a total of 978,218 observations; with 953,257 observations that could be properly geocoded.

[11] The data coordinate type was UTM-31N, based on the European Datum 50 (ED 50) projection, although, for the sake of homogeneity with other layers of polygons, we re-projected the coordinates to ETRS89. The geocoding process was undertaken, in part, by the *Mossos d'Esquadra,* and completed using GIS techniques, with some 40,000 observations being geocoded by hand using Google Maps.

crimes with different offender motivations. For the main property crimes, we used the variable "*Thefts*", i.e., the misappropriation of the belongings of others without resorting to any type of violence, while for the main crimes involving interpersonal violence, we included the variable "*Assaults*", i.e., harmful, offensive contact perhaps resulting in injuries.

After eliminating all observations responding to other crime types, the final data subset comprised 359,711 geocoded observations. We aggregated all the crime data up to the census tract level. The city of Barcelona is made up of ten districts divided into 73 neighborhoods, which are in turn broken down into 1,061 census tracts according to the electoral population.[12] We opted to use this unit of analysis as it is the smallest available and, moreover, it can be directly linked to the districts, which are the primary spatial units employed by the police for their policing and strategy decisions. Additionally, as the census tracts are determined according to the population, we indirectly control for the population at risk in each spatial unit.

2.3.2. Football data

We merged the above crime dataset with that for the football matches played by FCB between 1 September 2007 and 31 December 2011 (again excluding the months of June, July and August).

This data set contains information about the day, time, result, number of spectators and the location of the match (i.e., played either at home or away). Table 2.1 reports the number of matches played and the corresponding attendance figures. The level of attendance was high for home matches with 75% being watched by more than 60,000 spectators and just seven being attended by fewer than 40,000 spectators.[13]

The dataset consists of a total of 125 home and 130 away matches. The majority of matches were played in the Spanish domestic league (169), followed by the King's Cup (32 matches played); however, the European Champions League matches (a total of 50) attracted by far the highest gates. Of the 255matches, ten were played against the historic rival, Real Madrid CF, the majority being Spanish domestic league games.

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[12] We use the census tracts for the 2011 municipal elections. One advantage of this spatial division is its homogeneity, with each containing a minimum of 500 and a maximum of 2,000 citizens.

[13] FC Barcelona's stadium, the Camp Nou, is the fifth football largest stadium in the world with a capacity, at February 2013, of 99,354 spectators.

Table 2.1. FC Barcelona football matches 2007 - 2011.

Attendance	**# of matches**
> 80,000 spectators	36
> 60,000 and < 80,000 spectators	58
> 40,000 and < 60,000 spectators	24
< 40,000 spectators	7
Total number of home matches	125
Total number of away matches	130
Type of match	
Domestic League	169
King's Cup	32
European Champions League	50
Spanish and International Super Cup	4

Note: In this period FC Barcelona played Real Madrid CF, their main rival, ten times (home and away).

2.3.3. Matching process

Given the size of the dataset – comprising 255 days on which a football match was played (home and away), 960 days without a match, and 1,061 census tracts – we opted to undertake a matching process between days on which a game was played with highly similar days on which no match was organized. The main dataset was reduced in order to improve tractability and so as to be able to undertake the empirical estimations.

The matching of 'football days' with 'non-football days' was conducted taking into consideration the high variation in crime rates with time. Montolio and Planells-Struse (2014) show that the time of day, the day of the week and the month of the year, all appear to play a major role in accounting for crime. Weekends are, by far, the time of the week when crime levels are at their highest, while summer months, the first day of the month and bank holidays also record higher rates of crime. In order to capture this variability across time units and to form a dataset in which 'football days' can be compared to 'non-football' days, we employed the following matching process: we matched the days on which a game (home and away) was played (treatment) with a day without football (control) ensuring that these days corresponded in terms of the day of the week, the month and the year and that they corresponded to neither a bank holiday or the first day of a month. After applying these criteria, we were able to match 107 days in the case of home matches and 106 in the case of away matches. For the remaining matches we relaxed the month requirement. Hence, the remaining match days were matched with days that corresponded to the same day of the week in the same year (but not in the same month).[14] In this way, we matched a further 18 days on which home matches were played and a further 24 on which FCB played away.

Thus, we have two datasets: one comprising 125 days on which FCB played at home matched to 125 similar control days on which no football matches were played, and another comprising 130 days on which FCB played away matched to 130 similar control days on which no football matches were played.

To both datasets, we added a number of variables to control for weather conditions. These included rainfall per day, the number of sun hours per day, the average temperature per day, the average daily atmospheric pressure and the average daily wind speed. All these weather factors have been shown to be good explanatory variables for crime (Anderson, 2001; Jacob *et al*., 2004). For instance, rainfall can reduce the potential number of targets in the streets as people prefer to stay at home, while the number of sun hours and higher temperatures can increase this number as people take to the streets and so the potential number of thefts also rises.

Table 2.2 shows the main descriptive statistics for the days with home matches, the days with away matches and for the controls in both subsamples. It is evident that the statistics for the weather related variables are similar in the case of both treatment and control days. This shows that our matching process has been successful in matching ‘football days’ with ‘non-football days’ in terms of similar temperatures, number of sun hours, atmospheric pressure and wind speed. Therefore, our control sample, a priori, includes the same number of individuals on the streets and, hence, the same population at risk.

As for the main dependent variables, the number of thefts is higher on days when FCB were playing both at home and away, although when the match was at home the difference was much greater. In contrast, in the case of assaults, no difference is observed between the number of assaults committed on match days and on control days. As such, we do not expect to find any impact of football matches on the number of assaults, at least, for the city of Barcelona as a whole.

[14] The month fixed effect we introduce captures the heterogeneity across months.

Table 2.2: Descriptive statistics for the whole city of Barcelona.

	Mean		**Std. Deviation**		**Min.**		**Max.**	
Home match days	Match days	Control days	Match days	Control days	Match days	Control days	Match days	Control days
Crime variables								
Thefts	302.048	284.69	59.54	57.09	188	178	485	433
Assaults	13.84	13.54	5.22	5.38	4	3	28	32
Control variables								
Rainfall	1.13	3.36	2.83	10.87	0.00	0.00	14.10	79.80
Sun hours	6.34	6.40	3.67	3.91	0.00	0.00	12.70	13.20
Temperature	13.02	12.95	4.71	5.47	2.70	0.00	25.50	25.50
Pressure	959.40	944.73	86.45	148.31	0.00	0.00	981.35	985.85
Wind Speed	14.81	15.10	5.89	6.54	2.88	3.96	36.00	39.96
Away match days								
Crime variables								
Thefts	298.13	294.18	61.88	54.95	126	182	451	433
Assaults	14.3	14.3	4.922	4.75	3	4	27	25
Control variables								
Rainfall	1.39	3.19	5.55	10.64	0.00	0.00	43.60	79.80
Sun hours	7.31	6.31	3.63	3.72	0.00	0.00	13.30	13.00
Temperature	12.96	13.16	5.30	5.84	0.00	0.00	25.90	25.60
Pressure	960.24	937.92	84.84	167.27	0.00	0.00	982.80	984.55
Wind Speed	14.30	14.32	5.59	5.42	2.88	3.96	36.00	28.08

2.4. Empirical approach: effects of football matches on crime

2.4.1. Regression approach

In order to estimate the overall effect of football matches on crime for the city of Barcelona, we omit, for the time being, the spatial variation of crime. In other words, we use the two datasets presented above with the crime counts by typology and the day of the year. We estimate a model of the following form:

$$Crime_t^m = \beta_1 Match_t + \beta_2 Away\_Match_t + \beta_3 X_t + \gamma + \varphi + \varepsilon_t \qquad (2.1)$$

where t represents the date and m the type of crime (theft or assault). Hence, $Crime^m{}_t$ represents the number of crimes of type m each day t. $Match_t$ is the variable capturing the fact of FCB playing at home or not. This variable takes different forms, including dummies for home match days, number of spectators, and different dummies to account for this level of attendance. Likewise, when FCB play away, we include the variable $Away\_Match_t$ in Eq. (2.1), which takes a value of 1 when FCB play away and 0 otherwise.

X is a vector containing potential predictors of thefts and assaults including averages of rainfall, number of sun hours, temperature, atmospheric pressure and wind speed as presented above. In Eq. (2.1) γ is a vector that contains time fixed effects to capture any potential heterogeneity across days, months or years. Specifically, it contains a day of the year fixed effect to account for specific dates across the year. Additionally, and with the same objective, we include a week of the year fixed effect to account for Easter or the spring break. To account for heterogeneity across months, we introduce a month fixed effect. We also include a day of the week fixed effect to capture the heterogeneity of crime counts across days of the week. In this sense, weekly crime patterns seem to increase from Wednesday to Sunday, with a marked weekend effect. We also include a year fixed effect to reflect the differences in crime across the five years of our data span and a season fixed effect to account for seasonal variations in crime.

Finally, φ in Eq. (2.1) represents a set of variables related to the football match being played. Specifically, it consists of dummy variables for the competitions being played and a dummy variable for special matches, such as those played between FCB and Real Madrid CF. Finally, ε_t represents the error term, which is assumed to be normally distributed with constant variance.

In order to estimate Eq. (2.1), we employ a basic Ordinary Least Squares (OLS) estimation with all the control variables presented above that account for variations in crime over time. We use robust errors to account for any potential problem arising from the errors.

2.4.2. Spatial approach

After estimating the overall effects of football matches on crime, we are interested in analyzing changes in its spatial distribution when FCB play at home and away (treatment) and in comparing these outcomes with ‘non-football days’ (control). To do so, we undertake an Exploratory Spatial Data Analysis (ESDA, hereafter), which allows us to determine the presence of “hot spots” (areas where crime is more spatially concentrated) in the city of Barcelona employing kernel density functions and average nearest-neighbor statistics (Chainey *et al.,* 2008).[15] Additionally, we carry out a confirmatory analysis by means of regressing crime occurrence as a function of a distance to the FCB stadium. More specifically, we carry out the following regression:

$$Crime_{it}^{m} = \sum_{k=300}^{1400} \xi_k dist_{ik} + \sum_{k=300}^{1400} \eta_k dist_{ik} Match_t + \beta_1 Match_t + \beta_2 Away\_match_t + \beta_3 X + \gamma + \varphi + \sigma + \varepsilon_{it} \quad (2.2)$$

where i denotes the census tract, σ denotes a vector containing neighborhood and district fixed effects, and all the other variables and parameters are as in Eq. (2.1) except for two new parameters and variables. The first of these, $\sum_{k=300}^{1400} \xi_k dist_k$, is a set of dummy variables that takes a value of 1 if the centroid of census tract i is within distance k (in meters) of the FCB stadium and 0 otherwise. This set of dummies captures the impact on crime of being within a certain distance of the stadium both on 'football days' and 'non-football days'. The second, $\sum_{k=300}^{1400} \eta_k dist_k Match_t$, represents the interaction term of the previous distance variable and a dummy indicating a match day at the stadium. As such, the parameters η_k capture the effect of being within a certain distance of the stadium when a football match is being held. We expect the number of crimes to rise as we get closer to the stadium, in part, due to the greater number of social interactions between supporters and, in part, due to the concentration effect that attracts offenders to crowded areas around a stadium.

We adopt two approaches to capture the distance decay effect. The first involves examining the way in which crime counts increase within cumulative rings of distance k (where k = 300, 400, ..., 1,400 meters). In other words, we construct cumulative rings that include crime counts in census tracts of increasing distances. In order to estimate this distance effect, we have to regress Eq. (2.2) k times with the k distance dummy, since the upper order rings are likely to be correlated to those of a lower order. The second approach involves estimating the non-cumulative rings. In other words, we focus on the way in which crime counts vary between census tracts at distance k and k-100 (in meters). In both

[15] Using Local Indicators of Spatial Autocorrelation (LISA) would be a very useful tool to identify those census tracts with high/low values of crime surrounded by other census tracts with also high/low values of crime. However, for the case of Barcelona, its city centre distorts the analysis if applying this technique. Focusing only on the surroundings near the FCB stadium reduces the number of spatial units and, hence, the use of LISA technique it is not a plausible solution since it is not recommended for datasets with few number of spatial units (Anselin, 1995).

cases we expect a distance decay pattern, as individuals are likely to be more spread out the further we move away from the stadium. It should be pointed out that the cumulative ring approach is more likely to show the effect of football matches on crime at greater distances since with this approach all rings include the census tracts that lie closest to the stadium, i.e., those that are most likely to show a significant increase in their crime counts.

With the inclusion of this new dimension (the census tracts), the non-trivial number of zeros and the positive skewed distribution of the crime counts, we cannot use OLS since our results could be biased. Moreover, the data present a problem of over-dispersion. In other words, the variance of the crime counts (both thefts and assaults) is larger than their mean. Therefore, we use a negative binomial approach that takes into account all the characteristics that differ from the standard assumptions underlying the OLS estimation. It should be pointed out that the iteration process rarely converged when introducing census tract fixed effects. Consequently, we can only approximate the census tract fixed effects by means of district and neighborhood fixed effects.

2.5. Regression results

We estimate Eq. (2.1) using different definitions for the home matches.[16] We first present the results in Table 2.3 of the impact of an additional 10,000 spectators on the theft and assault counts. The first column represents a simple correlation with no control variables. Column 2 includes all time fixed effects except for the year fixed effects. Column 3 includes also the weather control variables. Finally, in column 4 we include the year fixed effects.

Results in Table 2.3 show that an additional 10,000 spectators increases the number of thefts by around seven; we are able to explain approximately 75% of the variation of thefts across the city of Barcelona. In the case of assaults an increase of 10,000 spectators does not have a significant impact. The average number of assaults (given by the constant) is much lower than the average number of thefts and, also, compared to the theft regressions, the models for assaults are only able to explain, as expected, around 36% of the variance in the number of assaults.

[16] For the sake of homogeneity throughout the Chapter we perform these initial regressions with the dataset containing 'football days' (home and away matches) and their respective controls as presented in section 3.3. Nevertheless, when using the full dataset (containing all available days), we obtain very similar results. The tables are not reported but are available upon request.

Table 2.3: OLS estimations. Effect of number of spectators on theft and assault counts.

VARIABLES	(1) *Thefts*	(2) *Thefts*	(3) *Thefts*	(4) *Thefts*
Spectators/10,000	3.797***	7.818***	6.555***	7.079***
	(0.978)	(2.228)	(2.057)	(2.065)
Constant	279.9***	300.7***	262.4***	233.4***
	(4.986)	(14.87)	(18.67)	(16.42)
R-squared	0.059	0.686	0.735	0.750
	Assaults	***Assaults***	***Assaults***	***Assaults***
Spectators/10,000	0.0867	-0.126	-0.183	-0.213
	(0.0914)	(0.248)	(0.253)	(0.243)
Constant	13.38***	13.37***	11.73***	11.60***
	(0.465)	(1.705)	(2.170)	(2.180)
R-squared	0.004	0.344	0.356	0.365
Observations	250	250	250	250
Climate controls	NO	NO	YES	YES
Time controls	NO	YES	YES	YES
Year fixed effects	NO	NO	NO	YES
Seasonal controls	NO	YES	YES	YES
Derby dummy	NO	YES	YES	YES

Note: Climate controls include: average rainfall, average number of sun hours, average temperature, average pressure and average wind speed. Time controls include: day of the week, day of the year, week of the year, weekend and month. Seasonal controls include dummies for summer (mainly September) and winter. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.4 shows the average effect of a football match being played at home on theft and assault counts. The four columns represent the same estimated model as in Table 2.3 above. The estimated coefficients in column 4 show that, on average, there are 40 thefts more on those days when FCB play at home. In the case of assaults, there is no significant increase in the number of assaults committed in the city of Barcelona.

It might be the case that only the big matches, i.e., those with over 80,000 spectators, affect crime. In our sample, 36 matches can be considered as high risk or "hot" in terms of crime with attendances recorded at over 90% of the stadium's capacity. The variance in the number of spectators might affect the way in which potential offenders perceive their opportunities for committing crimes and their potential rewards. Yet, if police deployment is greater during these "hot" matches, pickpockets may decide that their activities are only worthwhile on match days when police deployment is less intense. In the case of assaults, "hot" football matches may increase the number of potentially violent supporters. In order to account for the effect of big matches, Table 2.5 includes a dummy variable that takes a value of 1 if the home match is played before more than 80,000 spectators.

Table 2.5 shows the impact of big home football matches on theft counts. In column 4, the most complete model, the estimated coefficients identify an increase of almost 23 thefts on such occasions. On days when match attendance does not reach 80,000, the increase is

18 for the whole city of Barcelona. In the case of assaults, the city of Barcelona does not, on average, suffer a significant increase in the number of assaults on big match days.

Table 2.4: OLS estimations. Effect of matches played at home on theft and assault counts.

	(1)	(2)	(3)	(4)
VARIABLES	***Thefts***	***Thefts***	***Thefts***	***Thefts***
Match	17.36**	40.70***	41.53***	40.56***
	(7.378)	(9.348)	(8.258)	(8.564)
Constant	284.7***	289.9***	241.9***	237.8***
	(5.107)	(13.41)	(18.01)	(16.98)
R-squared	0.022	0.669	0.723	0.737
	Assaults	***Assaults***	***Assaults***	***Assaults***
Match	0.304	0.321	0.374	0.406
	(0.671)	(1.057)	(1.072)	(1.065)
Constant	13.54***	12.03***	11.20***	11.47***
	(0.481)	(1.762)	(2.082)	(2.164)
R-squared	0.001	0.343	0.355	0.363
Observations	250	250	250	250
Climate controls	NO	NO	YES	YES
Time controls	NO	YES	YES	YES
Year fixed effects	NO	NO	NO	YES
Seasonal controls	NO	YES	YES	YES
Derby dummy	NO	YES	YES	YES

Note: see Table 2.3.

Table 2.5: OLS estimations. Effect of 'big' home matches on theft and assault counts.

	(1)	(2)	(3)	(4)
VARIABLES	***Thefts***	***Thefts***	***Thefts***	***Thefts***
> 80,000 spectators	43.63***	20.28***	19.59***	22.82***
	(11.41)	(7.364)	(7.096)	(6.823)
Match	4.795	30.19***	19.34**	18.37**
	(7.773)	(8.597)	(7.886)	(7.393)
Constant	284.7***	289.7***	242.0***	236.6***
	(5.117)	(13.29)	(17.64)	(16.01)
R-squared	0.078	0.679	0.733	0.749
	Assaults	***Assaults***	***Assaults***	***Assaults***
> 80,000 spectators	1.902*	1.480	1.465	1.324
	(1.114)	(1.065)	(1.074)	(1.066)
Match	-0.244	-0.445	-0.317	-0.238
	(0.702)	(1.088)	(0.949)	(0.936)
Constant	13.54***	12.01***	11.21***	11.40***
	(0.482)	(1.790)	(2.086)	(2.163)
R-squared	0.014	0.350	0.362	0.368
Observations	250	250	250	250
Climate controls	NO	NO	YES	YES
Time controls	NO	YES	YES	YES
Year fixed effects	NO	NO	NO	YES
Seasonal controls	NO	YES	YES	YES
Derby dummy	NO	YES	YES	YES

Note: See Table 2.3.

So far we have considered the overall impact of home football matches on theft and assault counts. However, as discussed above, away football matches might also increase criminal activity in the city given that people typically gather in the city's pubs and bars to watch the game. This could generate similar crowding effects that might attract pickpockets or result in outbreaks of violence since alcohol is usually consumed while following the match. Table 2.6, however, shows that neither theft nor assault counts are significantly affected by FCB's away matches. Although the average number of thefts is higher on those days when FCB play away, after controlling for weather conditions and time varying variables this increase is not statistically significant. In the case of assaults, we even find a negative effect, although here again it is not significant.

Table 2.6: OLS estimations. Effect of away matches on theft and assault counts.

	(1)	(2)	(3)	(4)
VARIABLES	***Thefts***	***Thefts***	***Thefts***	***Thefts***
Away match	3.946	2.727	8.482	13.05
	(7.259)	(15.24)	(15.94)	(14.29)
Constant	294.2***	341.1***	280.6***	255.0***
	(4.820)	(14.49)	(21.32)	(19.00)
R-squared	0.001	0.715	0.739	0.768
	Assaults	***Assaults***	***Assaults***	***Assaults***
Spectators/10,000	1.069*	-0.740	-0.396	-0.245
	(0.600)	(3.071)	(2.900)	(3.187)
Constant	13.24***	13.62***	12.68***	11.23***
	(0.417)	(2.498)	(2.999)	(2.870)
R-squared	0.012	0.376	0.393	0.410
Observations	260	260	260	260
Climate controls	NO	NO	YES	YES
Time controls	NO	YES	YES	YES
Year fixed effects	NO	NO	NO	YES
Seasonal controls	NO	YES	YES	YES
Derby dummy	NO	YES	YES	YES

Note: see Table 2.3.

2.6. Spatial results

2.6.1. Exploratory Spatial Data Analysis (ESDA)

After analyzing the overall effect of home and away football matches on theft and assault counts, we incorporate the spatial dimension by introducing the 1,061 census tracts of the city of Barcelona. We first present the descriptive statistics of the distribution of crime in the city of Barcelona and we carry out an ESDA analysis to show the main crime patterns on days when FCB play at home, on days when FCB play away and on 'non-football days' (controls).

Columns 1 and 4 in Table 2.7 show the relative increase in theft and assault counts, respectively, in census tracts whose centroid is located at a distance of k meters from the center of the FCB stadium relative to the total increase for the whole city of Barcelona. Specifically, we show the results of the following formula:

$$\frac{\Delta Crime_i^k{}_{Home-control}}{\Delta Crime^{Barcelona}{}_{Home-control}} \tag{2.3}$$

where the numerator in Eq.(2.3) represents the increase in the variable $Crime^k_i$ (either thefts or assaults) in census tract i whose centroid is located within k meters of the center of the football stadium on days with no football (control) and on days when FCB play at home. The denominator simply represents the increase in the number of crimes in the whole of the city of Barcelona. Consequently, if the ratio is greater than 0, then the number of crimes within those census tracts located within a distance of k meters suffers a higher increase than the increase experienced by the city of Barcelona as a whole on the days when FCB play at home.

As can be seen in columns 1 and 4 of Table 2.7, the increase in theft and assault counts in the census tracts located within a certain distance of the stadium represents a sizeable share of the total increase for the whole city on days when there is a home football match. Specifically, in the case of thefts, the increase in census tracts within a radius of up to 1,200 meters represents 43.59% of the total increase. After this threshold, the share decreases, either because the numerator falls or because the denominator rises, or both. From the percentages presented in columns 2 and 3, which represent the share of thefts committed in census tracts located within a certain distance on 'non-football days' (controls) and on days when FCB play at home respectively, it can be seen that the number of thefts in the census tracts whose centroid is within 1,300 meters (or more) of the stadium increases more on the control days than on the days with home football matches. This means that the concentration effect seems to disappear after a certain distance.

In the case of the number of assaults, column 4 shows that the census tracts that are located within 1,100 meters of the stadium account for up to 84.21% of the total increase in the number of assaults across the whole of the city. This increase is not homogenous indicating that the increase in the number of assaults in these census tracts on match days is lower than it is on control days, thus reducing the representation of the total increase in the assault count. Columns 5 and 6 show the share of assaults committed in census tracts located within a certain distance with respect to the total number of assaults in Barcelona on 'non-football days' (controls) and on days when home football matches are played, respectively. Again, the share of assaults committed when FCB are playing at home is higher than the share on 'non-football days' for all distances.

Table 2.7: Relative increase in the number of crimes.

	Thefts			*Assaults*		
	(1) Increase	(2) Control days	(3) Match days	(4) Increase	(5) Control days	(6) Match days
< 300	2.72%	0.05%	0.20%	13.16%	0.00%	0.29%
< 400	15.35%	0.50%	1.35%	31.58%	0.71%	1.39%
< 500	24.38%	0.75%	2.11%	50.00%	1.30%	2.37%
< 600	26.64%	0.83%	2.31%	60.53%	1.30%	2.60%
< 700	29.86%	0.99%	2.65%	55.26%	1.71%	2.89%
< 800	30.97%	1.14%	2.85%	57.89%	1.89%	3.12%
< 900	37.60%	1.70%	3.76%	65.79%	2.42%	3.82%
< 1,000	39.91%	2.07%	4.50%	73.68%	2.60%	4.16%
< 1,100	43.13%	2.54%	5.17%	84.21%	3.01%	4.80%
< 1,200	43.59%	3.03%	5.69%	65.79%	3.90%	5.26%
< 1,300	42.72%	3.44%	6.05%	44.74%	4.61%	5.49%
< 1,400	42.35%	3.84%	6.42%	42.11%	5.02%	5.84%

After analyzing the main statistics and the concentration of thefts and assaults in the census tracts located in the vicinity of the FCB stadium, we are able to depict these results in cartographic form. We show the kernel density estimations in order to identify the places in the city of Barcelona where the risks of being a victim of theft or assault on certain days ('football' and 'non-football') are highest. Kernel density estimations simply provide a smooth estimate of the point process derived by means of a moving window (bandwidth) over the data. In this sense, the objective is to estimate how event levels vary continuously across a study area based on an observed point pattern for a sample of points (Bailey and Gatrell, 1995; Williamson *et al*., 1998). The estimated kernel values represent the predictive risk surface for each type of crime analyzed, in other words, the potential number of events per square km when taking into account potential contagious effects from other areas.

Delimiting the area in which to measure the risk of a certain crime, that is, the radius of the circle centered on each grid cell containing the points that contribute to the kernel density calculation, is known as the bandwidth decision problem. Large bandwidths result in over smoothing, with low density values and, therefore, an over generalized view, while small bandwidths result in maps that are spiky in appearance because of the jumps between spatial units (producing images similar to point patterns). Several rules of thumb have been suggested by Williamson *et al.* (2000) and Bailey *et al.* (1995) based mainly on the k-nearest neighbor mean distances, and dependent on the detail of analysis that the researcher wishes to obtain (city, county, neighborhood, street, parking lot, etc). However, the bandwidth must also be theoretically justified since it reflects the contagious nature of a particular crime across space. For instance, thefts from vehicles may cluster in a specific parking lot because it has no surveillance cameras. It is reasonable to think that thefts from vehicles are likely to occur in the parking lot with the same degree of probability. If the lot extends over 250 meters, then a 250- or 300- meter bandwidth would capture the potential contagious effect. However, choosing a larger bandwidth will have the effect of extending the probability of thefts from vehicles to other areas where no cars are parked. Another example would be domestic violence, which tends to be highly focused on specific households. As such, the bandwidth of the kernel density estimation should be very small. In our case, we use a bandwidth of 300 meters for both thefts and assaults.[17]

In line with our matching process, we first calculate the kernel density functions for thefts and assaults on those days when FCB played at home (K_H) and for their respective controls (K_{CH}). We then compute the difference, K_H - K_{CH}, and plot it on a map. In Figure 2.1, Map 1A shows this difference for thefts and Map 1B for assaults. The areas shaded red present the largest increases in the number of thefts and assaults between days when FCB played at home and days without football (controls) while the areas shaded blue present the largest shifts in the other direction. The unshaded areas present no change in their theft or assault counts.

Map 1A shows that, in the case of thefts, there is an increase mainly in two areas of the city: first, in the city center where people gather in bars and pubs to watch the match and where victories are celebrated; and, second, in the vicinity of the stadium (identified on the map with a green dot). A similar pattern is found in Map 1B for the number of assaults. An increase is observed especially in the city center, but also in areas surrounding the stadium.

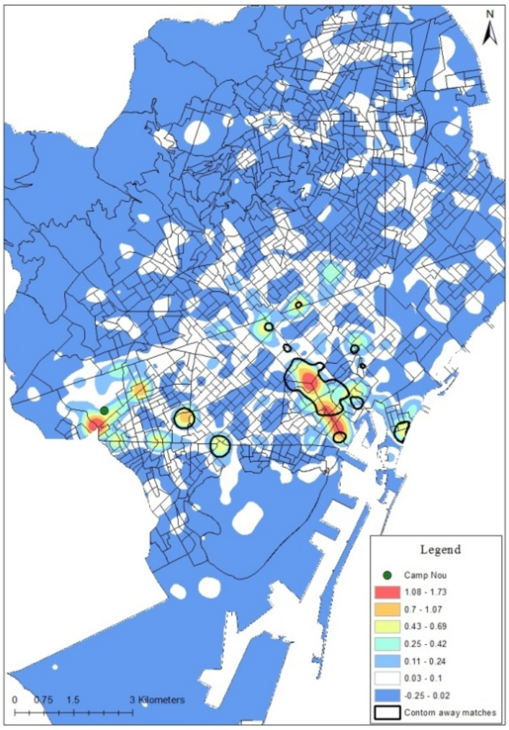
In Figure 2.1 the kernel density functions are the result of the difference between the kernel densities for the number of crimes committed on days when FCB play at home and those for the crimes committed on 'non-football days' (controls). The areas outlined in black on the two maps in Figure 2.1 denote "hot spots" corresponding to differences in densities on days when FCB play away and 'non-football days' (controls). As such, we plot on the same map increases attributable to both home and away matches. It is clear that these respective differences (i.e., home matches vs. controls and away matches vs. controls) do not coincide. On those days when FCB play away, there appear to be increases

[17] Theoretically, the bandwidth for the assaults should be smaller since the contagious effect is lower; however, we opt to use the same bandwidth to make both maps comparable.

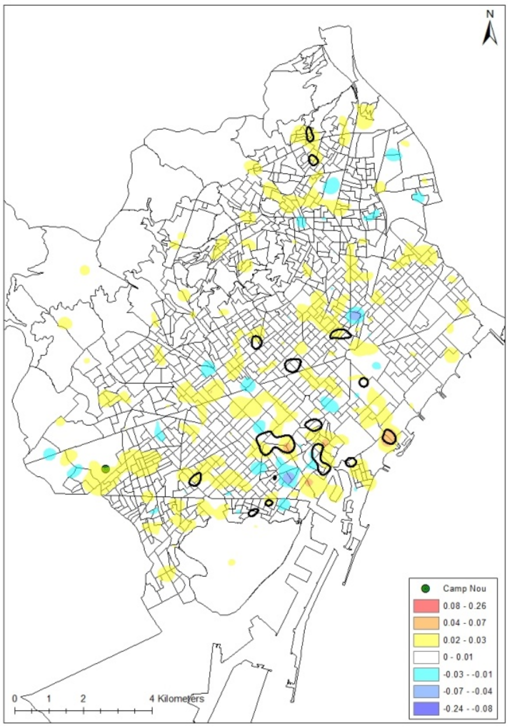
in theft and assault counts both in the center of the city and in certain areas where pubs and bars concentrate.

Figure 2.1: Difference in kernel density values between days when FCB play at home and days with no football (control days).

Map 1A: ***Thefts***.



Map 1B. ***Assaults***.



Note: Quadratic kernel functions. The representation is the density function per square km using natural breaks so as to identify outliers clearly. Bandwidths are set at 300 meters for both thefts assaults. Cell size is set at 20 meters to show as much detail as possible.

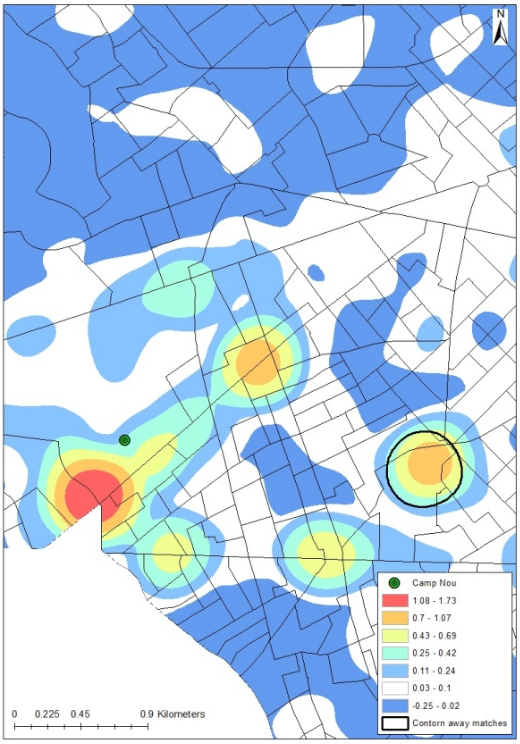
In order to focus our analysis on the vicinity of the FCB stadium, the maps in Figure 2.2 show only the crimes committed within a certain distance of the stadium. In this way we are able to understand more fully the fluctuations in crime counts around the football stadium.[18]

Map 2A shows that the number of thefts increases markedly when FCB play at home. This is particularly evident in the streets en route to the stadium from the main transport facilities. The circles outlined in black indicate the hot spots found when computing the difference in the kernel values when FCB play away and 'non-football days' (controls). Here, again the respective patterns (i.e., home matches vs. controls and away matches vs. controls) do not coincide.

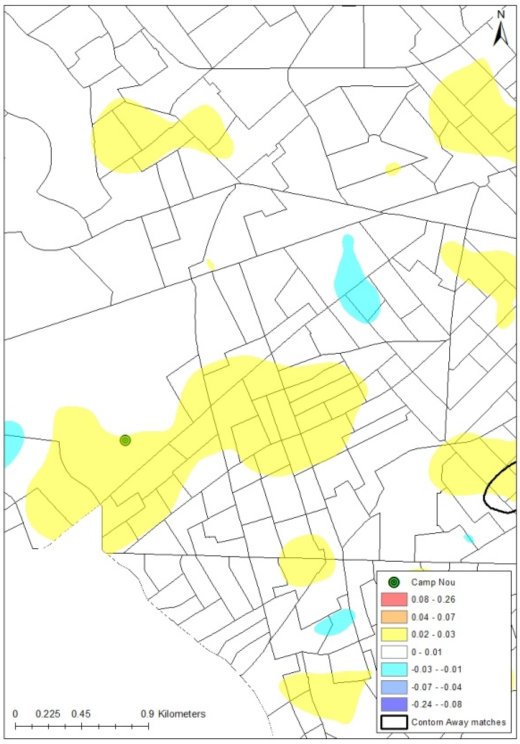
[18] Figure 2.A.1 in the appendix of this Chapter shows exactly the area of the city presented in Figure 2.2.

Figure 2.2: Kernel density functions around FCB stadium for thefts and assaults when the club plays at home, away, and on days without a match.

Map 2A: ***Thefts***.



Map 2B. ***Assaults***.



Note: See Figure 2.1.

Map 2B shows similar results for the case of assaults. Although concentrated in smaller areas, there also appears to be a high concentration of assaults in the vicinity of the stadium.

2.6.2. Confirmatory analysis

In order to confirm the crime concentration patterns around the FCB stadium when FCB play at home, we first estimate the effect of the distance to the stadium on the number of thefts and assaults. These results are presented in Table 2.8 where we also include the square of the distance to account for possible non-linear relationships between crime and distance. Results show that the number of thefts in the census tracts is negatively affected by the distance to the stadium: the greater the distance, the lower the theft count. However, it is worth noticing that the square of the distance presents a coefficient greater than one, indicating a positive impact on the number of thefts. This non-linearity suggests that the effect of the distance on the number of thefts is convex, that is, the greater the distance, the smaller the effect on the number of thefts, with the reduction in this effect being higher.

This reflects the potential presence of the concentration effect. In the case of assaults, Table 2.8 shows no effect of distance on the assault count.

Table 2.8: Distance decay effect. Distance and square distance. Negative binomial.

VARIABLES	***Thefts***	***Assaults***
Distance*Match	0.890***	0.968
	(0.0212)	(0.0605)
Distance^2*Match	1.009***	1.002
	(0.00244)	(0.00592)
Constant	3.223***	3.847***
	(0.0400)	(0.374)
Observations	265,250	265,250
Climate controls	YES	YES
Time controls	YES	YES
Year fixed effects	YES	YES
Seasonal controls	YES	YES
Derby dummy	YES	YES
District fixed effects	YES	YES
Neighborhood fixed effects	YES	YES

Note: see notes to Table 2.3. Each distance is estimated separately so as to avoid any correlation between rings at different distances. Coefficients reported as incidence rate ratios. Standard errors clustered at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Next, we estimate Eq. (2.2) for both thefts and assaults using the cumulative and non-cumulative rings (or buffers); see Tables 2.9 and 2.10 respectively.[19] Table 2.9 shows the results for all home matches (columns 1 and 3) as well as for home matches with an attendance in excess of 80,000 (columns 2 and 4).

In the case of thefts, the results show a clear distance decay pattern as we move away from the stadium – being in a census tract whose centroid is less than 300 meters from the stadium when FCB are at home increases the number of thefts by an average of 260% and by 400% on the day of a big match. This huge increase in pick pocketing during big matches in the same census tract as that of the stadium points to a clear concentration effect. Note that this impact is decreasing as we move away from the stadium.

[19] As explained in Section 2.4.2, each ring represents an increase of 100 meters from the stadium and includes all additional census tracts whose centroid falls within the ring. When using cumulative rings, all census tracts up to the distance ring are included. Figure 2.A.1 in the appendix maps the rings used, while Table 2.A.2 shows the number of census tracts included in each ring.

Table 2.9: Cumulative rings. Negative binomial. Home and 'big' home matches.

VARIABLES	(1) Thefts	(2) Thefts (Big matches)	(3) Assaults	(4) Assaults (Big matches)
<300 m	2.604***	4.000***	5.011***	8.613**
	(0.652)	(1.068)	(2.059)	(7.003)
< 400 m	2.202***	2.684***	1.749**	1.870
	(0.368)	(0.368)	(0.461)	(0.749)
< 500 m	2.502***	2.745***	1.837**	2.247**
	(0.306)	(0.300)	(0.511)	(0.710)
< 600 m	2.534***	2.714***	2.020**	2.582***
	(0.279)	(0.273)	(0.555)	(0.760)
< 700 m	2.555***	2.769***	1.695**	2.309***
	(0.267)	(0.259)	(0.420)	(0.632)
< 800 m	2.339***	2.546***	1.661**	2.455***
	(0.232)	(0.217)	(0.394)	(0.636)
< 900 m	2.257***	2.306***	1.589**	2.414***
	(0.199)	(0.174)	(0.341)	(0.558)
< 1,000 m	2.129***	2.129***	1.619**	1.619**
	(0.144)	(0.144)	(0.333)	(0.333)
< 1,100 m	1.935***	1.982***	1.613**	2.317***
	(0.146)	(0.119)	(0.307)	(0.473)
< 1,200 m	1.812***	1.810***	1.364*	1.993***
	(0.126)	(0.0979)	(0.238)	(0.388)
< 1,300 m	1.752***	1.697***	1.195	1.923***
	(0.116)	(0.0865)	(0.197)	(0.358)
< 1,400 m	1.700***	1.611***	1.166	1.910***
	(0.108)	(0.0778)	(0.185)	(0.342)
Observations	265,250	265,250	265,250	265,250
Climate controls	YES	YES	YES	YES
Time controls	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Seasonal controls	YES	YES	YES	YES
Derby dummy	YES	YES	YES	YES
District fixed effects	YES	YES	YES	YES
Neighborhood fixed effects	YES	YES	YES	YES

Note: see notes to Table 2.3. Each distance is estimated separately so as to avoid any correlation between rings at different distances. Coefficients reported as incidence rate ratios. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The distance decay pattern for assaults appears to be very similar to that observed for thefts. Here again there is a sharp decrease in crimes between census tracts located within 300 meters of the stadium and those located within a radius of 400 meters. The marked increase in assaults in the census tracts closest to the stadium are presumably attributable to the fact that a greater number of social interactions, and possible rivalries between opposing football fans, can lead to clashes and fighting. In the case of big football matches there appears to be a greater impact on crime at all distances computed from the stadium.

Table 2.10 presents our analysis of effects on crime counts at specific distances from the stadium, without taking into account census tracts that lie closer to the football ground. These non-cumulative distance rings show the impact of home football matches in census tracts located 100 meters apart. Our results provide a clearer indication of the distance at which the impact of football on crime disappears. In the case of thefts, distance decay is clear, although not homogeneous as there are specific rings that present higher levels of thefts than rings that are closer to the stadium. This presumably reflects the fact that certain circumstances of an area are likely to increase the number of thefts. For instance, the ring of census tracts located at a distance of between 700 and 800 meters from the stadium presents almost no impact on the number of thefts. This might be because the parking lots in this area are closed and, as spectators cannot park here, there are fewer potential victims in the area. The effect of football matches on the number of thefts seems to disappear in census tracts located at an average distance of 900 meters from the stadium and in those located at 1,100 meters when FCB is playing a big match.

Table 2.10. Non-cumulative rings. Negative binomial. All matches and 'big' matches.

VARIABLES	(1) *Thefts*	(2) *Thefts* (Big matches)	(3) *Assaults*	(4) *Assaults* (Big matches)
<300 m	2.661***	4.141***	5.483***	8.633**
	(0.667)	(1.105)	(2.479)	(7.893)
>300 and < 400 m	2.177***	2.598***	1.554	1.358
	(0.412)	(0.389)	(0.626)	(0.634)
>400 and < 500 m	3.132***	2.936***	1.666	2.824**
	(0.556)	(0.535)	(0.712)	(1.364)
>500 and < 600 m	2.957***	2.553***	2.135***	17.84**
	(0.644)	(0.629)	(1.056)	(20.59)
>600 and < 700 m	2.372***	2.655***	0.701	1.142
	(0.645)	(0.561)	(0.407)	(0.890)
>700 and < 800 m	1.044	1.474*	1.309	4.377*
	(0.337)	(0.312)	(1.000)	(3.431)
>800 and < 900 m	1.993***	1.774***	1.324	2.236
	(0.357)	(0.257)	(0.642)	(1.118)
>900 and < 1,000 m	1.109	1.315**	1.977	0.701
	(0.225)	(0.178)	(1.395)	(0.738)
>1,000 and < 1,100 m	1.229	1.365***	1.542	2.782**
	(0.184)	(0.159)	(0.744)	(1.361)
>1,100 and < 1,200 m	1.178	1.059	0.523	0.546
	(0.182)	(0.127)	(0.233)	(0.406)
>1,200 and < 1,300 m	1.151	0.860	0.324*	1.306
	(0.199)	(0.113)	(0.187)	(0.836)
>1,300 and < 1,400 m	1.102	0.875	0.850	1.729
	(0.216)	(0.116)	(0.470)	(1.143)
Constant	3.088***	3.084***	9.202***	4.039***
	(0.0373)	(0.0373)	(0.740)	(0.376)
Observations	265,250	265,250	265,250	265,250
Climate controls	YES	YES	YES	YES
Time controls	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Seasonal controls	YES	YES	YES	YES
Derby dummy	YES	YES	YES	YES
District fixed effects	NO	YES	NO	YES
Neighborhood fixed effects	NO	YES	NO	YES

Note: see Table 2.9.

The largest increase in the number of assaults during home football matches occurs, as previously found, in census tracts located within 300 meters of the stadium. Indeed, it is probable that the majority of these incidents occur in the same census tract as that in which the stadium is located. The effect seems to disappear in census tracts located 600 meters from the stadium; however, it reappears in census tracts located between 800 and 1,000 meters from the ground.

2.6.3. Placebo test

We conduct a final exercise to verify the robustness of the above results by estimating the following equation:

$$Crime_{it}^{m} = \sum_{k=300}^{1400} \xi_k dist_k + \sum_{k=300}^{1400} \eta_k dist_k Awaymatch_t + \beta_1 Match_t + \beta_2 Away\_match_t + \beta_3 X + \gamma + \varphi + \sigma + \varepsilon_{it} \quad (2.4)$$

where the only difference with respect to Eq. (2.2) is that here we estimate the impact of being in a census tract at a certain distance from the stadium on a day when FCB play away. The results (see Table 2.11) indicate that, in general, when FCB play away the crime counts (both for thefts and assaults) are significantly lower in areas close to the stadium. Note that the only ring that shows an increase in the number of thefts and assaults during away football matches is the one located between 300 and 400 meters from the stadium. This result may be identifying a specific location (concentration of bars or pubs) in which people gather to watch the match

Table 2.11. Placebo test (non-cumulative rings).

Variables	*Thefts*	*Assaults*
<300 m	0.269***	1.70e-08***
	(0.0229)	(1.77e-08)
>300 and < 400 m	1.704***	1.475***
	(0.144)	(0.0448)
>400 and < 500 m	0.924	0.866
	(0.166)	(0.155)
>500 and < 600 m	0.394***	0.545
	(0.135)	(0.474)
>600 and < 700 m	0.361***	0.703***
	(0.0205)	(0.0302)
>700 and < 800 m	0.162***	0.186***
	(0.0368)	(0.111)
>800 and < 900 m	0.927	0.386**
	(0.813)	(0.184)
>900 and < 1,000 m	0.446***	0.600***
	(0.0561)	(0.0995)
>1,000 and < 1,100 m	0.389***	0.528***
	(0.0722)	(0.121)
>1,100 and < 1,200 m	0.575	0.813*
	(0.368)	(0.0982)
>1,200 and < 1,300 m	0.334***	0.824
	(0.0550)	(0.117)
>1,300 and < 1,400 m	0.458***	0.597*
	(0.138)	(0.171)
Observations	275,860	275,860
Climate controls	YES	YES
Time controls	YES	YES
Year fixed effects	YES	YES
Seasonal controls	YES	YES
Derby dummy	YES	YES
District fixed effects	NO	YES
Neighborhood fixed effects	NO	YES

Note: see Table 2.9.

2.7. Conclusions

This Chapter has analyzed the overall effects and the spatial displacement effects of football matches on thefts and assaults in an urban context. Using an OLS regression approach we first estimated the impact on crime across the city of Barcelona of Football Club Barcelona playing at home and away. The results show clear evidence of an increase in thefts when FCB play at home; however, this trend is not present for assaults or when FCB play away.

In order to analyze in depth how large crowds attending football matches can impact criminal behavior, we analyzed crime patterns around the FCB stadium and found that both the number of thefts and assaults increased significantly. This pattern was confirmed using an ESDA and by undertaking a regression analysis. Specifically, we found that the number of thefts increased significantly in census tracts located within a 900-meter radius (1,100 meters on big match days) of the stadium, while the increase recorded in assaults was limited more specifically to areas located in the vicinity of the stadium entrances, that is, in census tracts located within a 600-meter radius (700 meters on big match days) of the stadium.

These results – the overall effects and the spatial crime patterns – point to two different crime generating processes. First, the spatial patterns indicate a clear concentration effect for both types of crime. In the case of thefts, large crowds attract pickpockets that perceive (in terms of the Routine Activity Theory) that their rewards will be higher and their probability of being apprehended lower, despite the increase in police presence around the stadium. The attractiveness of the targets may also drive part of this effect; the presence of spectators carrying cameras and cash, in addition to a large number of inattentive tourists, serve as magnets for pickpockets.

In the case of assaults, the spatial patterns also point to a concentration effect around the stadium when FCB play at home. Indeed, in the census tracts closest to the stadium (and in the census tract in which the stadium is located) the number of assaults increases significantly. However, the absence of any effects for the city as a whole (whether FCB are at playing home or away) suggests a second effect, that of displacement from other areas of the city to the stadium on match days. A possible explanation for this might be the similar profiles shared by football fans and potential offenders.

The results reported in this study, however, do not control for the extra policing provided on match days, as no data are available. Yet, we have been able to show the significant increase in the number of thefts across the city of Barcelona even though there is a greater presence of police officers when FCB play at home.

Thus, in addition to shedding light on the effects of football matches on crime in an urban context, this Chapter may also be used for the effective allocation of police patrols in the city of Barcelona. As the ESDA and kernel density function analyses show, not only does the number of thefts in the vicinity of the stadium increase, there is also a rise in such crimes in the center of the city and in and around large transport hubs, including metro and railway stations. This indicates that additional police officers should be assigned to the area around the stadium and to certain parts of the city, including the city center, since only 46% of the overall increase in the number of thefts, and almost 80% of the overall increase in the number of assaults, take place around the stadium.

The final question we need to address is whether football teams should be taxed. We have presented strong evidence of the increase in certain types of crime throughout the city of Barcelona when football matches are played, above all around the FCB stadium. An increase in illegal activities is recorded in relation to the celebration of a private leisure activity such as football and, hence, additional public resources must be devoted to control for these negative externalities.

While it is true that private institutions already contribute to public budgets via regular tax payments, the extra costs society has to face as a result of their activities need to be taken into consideration. In this regard, we still have much to learn about adapting taxation to the real costs attributable to the impact of football on illegal behavior. For instance, the real costs would have to take into account not only the need for extra police officers on match days around the stadium but also the need for additional policing in other crowed places in the city where, on match days, increases in thefts are recorded. Additionally, the police should not only monitor crowds at the entrance to the stadium, as they do now. As we have shown, the impact of football matches extends over a radius of more than 1 km in the case of thefts and around 500 meters in the case of assaults. In sum, any tax levied should take into account the direct costs of assigning extra police patrols within a radius around the stadium in which football is known to have a significant impact on crime.

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Appendix to Chapter 2

Table 2.A.1. Negative binomial. Control variables.

VARIABLES	***Thefts***	***Assaults***
Derby dummy (FC Barcelona vs Madrid CF)	1.114**	1.155
	(0.0550)	(0.205)
Rainfall	0.998***	0.999
	(0.000615)	(0.00178)
Sun hours	1.006***	1.008*
	(0.00143)	(0.00471)
Temperature	1.006**	1.000
	(0.00291)	(0.00564)
Pressure	1.000	1.000
	(4.06e-05)	(9.04e-05)
Wind speed	0.998***	0.995**
	(0.000341)	(0.00204)
Bank holiday	0.869***	1.113**
	(0.0252)	(0.0509)
Constant	3.195***	4.056***
	(0.813)	(1.146)
Observations	541,110	541,110
Seasonal controls	YES	YES
Domestic League FE	YES	YES
District FE	YES	YES
Neighborhood FE	YES	YES
Day week FE	YES	YES
Day year FE	YES	YES
Week of the year FE	YES	YES
Weekend FE	YES	YES
Month FE	YES	YES
Year FE	YES	YES

Note: Coefficients reported as incidence rate ratios. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.A.2. Buffers from the FCB stadium. Census tracts included in each ring.

Distance from FC Barcelona stadium	# of census tracts
<300 m	2
>300 m and <400 m	4
>400 m and <500 m	6
>500 m and <600 m	4
>600 m and <700 m	4
>700 m and <800 m	7
>800 m and <900 m	9
>900 m and <1,000 m	7
>1,000 m and <1,100 m	10
>1,100 m and <1,200 m	10
>1,200 m and <1,300 m	8
>1,300 m and <1,400 m	7

Figure 2.A.1.

Map 2.A.1.Area shown in maps 2A and 2B

Map 2.A.2. Cumulative rings (buffers) around FCB's stadium

Chapter 3

How time shapes crime. The temporal impacts of football matches on crime

3.1. Introduction

Criminal behavior varies greatly according to the time of day but, while Felson and Poulsen (2003) note that monthly and seasonal cycles of crime are well-known periodicities among criminologists (see, for example, Harries, 1980), the hourly periodicity of crime is under-researched. This lack of research is surprising if we consider that several existing theoretical approaches to the understanding of illegal behavior, including routine activity theory, stress the essential role of hourly activities and their association with crime opportunities (see Felson, 2002). A possible explanation for this absence of formal study of the temporal patterns of crime is because spatial patterns have tended to focus all the research attention. Indeed, the tools developed by geographers have been widely used in the spatial mapping of criminal activity and for the statistical description of spatial processes, leaving the temporal element in a secondary plane.

However, time would seem to play an important role in its own right in defining illegal activities. For instance, time defines when people stumble out of bars, when alcohol or other stupefacients are consumed (concentrating around bar closing times), when drink driving tests are performed by police patrols or when the working day begins and ends. All these events can affect the number of potential offenders, the number of suitable targets and the presence (or otherwise) of police forces and, therefore, in line with routine activity theory (Cohen and Felson, 1979), they have a direct impact on criminal activities.

The impact of time on crime, however, can be *a priori* positive or negative. On the one hand, a positive impact can be expected, given that at certain times of day crime is more likely to occur because of the routines and activities that are being engaged in (work, leisure, etc). On the other hand, activities that are clearly demarcated by time may have a displacement effect and, hence, a negative effect on crime. In this respect, crime displacement may be defined as the relocation of crime from a particular time, place, target, offense, or tactic to another as a result of some activity and/or crime prevention initiative. Spatial displacement is by far the most commonly recognized form, but the other forms are also frequently acknowledged by researchers as they examine the impact of crime prevention policies.

More specifically, the possible forms of displacement are temporal (offenders change the time of day when they commit a crime); spatial (offenders switch from targets in one location to those in another); target (offenders change from one type of target to another); tactical (offenders change the methods used to carry out a crime); and offense (offenders switch from one form of crime to another). Clearly, it is crucial to have a good comprehensive understanding of all of them so that the police forces might define prevention initiatives to tackle criminal activities.

The aim of this Chapter therefore is twofold. On the one hand, and drawing on a unique dataset, we analyze the temporal profile of urban crime in Barcelona (Spain) in an attempt at obtaining further evidence of monthly, weekly and hourly patterns of crime. We undertake an in-depth examination of the temporal nature of crime by determining if there is a temporal displacement of crime attributable to major events in the city of Barcelona, more specifically in relation to the matches played by Football Club Barcelona (FCB, hereafter). The social importance of football in Spanish society makes it an ideal event for determining whether the sport is responsible for a temporal displacement of crime in the city. Football matches, major sporting events that attract a large proportion of the population, provide excellent scenarios for analyzing temporal displacement, given that for certain periods of time (before, during and after the match) the feelings and attitudes of individuals are subject to fluctuation. Such a differentiated time profile is, therefore, optimal for analyzing the potential temporal effects on crime. Moreover, given the media coverage dedicated to football, these effects are not necessarily spatially constrained and, so, football matches are ideal for analyzing temporal displacement effects in criminal activities, and should further our understanding of the relationship between crime and time. The results of this analysis should provide interesting insights into the impact of football on crime, a particularly relevant issue today for governments concerned with the security issues related to major sporting events, among others.[20]

[20] See, for instance, Marie (2010) or the latest episodes of violence that have occurred in and around Spain's football grounds (http://deportes.elpais.com/tag/operacion_neptuno/a/)

The rest of the Chapter is structured as follows. Section 3.2 briefly presents the various temporal patterns presented by crime data by reporting a descriptive analysis of crime on a monthly, weekly and hourly basis. Section 3.3 analyses the potential channels through which football matches may affect criminal activity. Section 3.4 describes the unique dataset on recorded crime for the city of Barcelona and outlines the methodology employed. Section 3.5 presents the main results regarding the temporal effect of football on crime while Section 3.6 presents the results for the case of defeats and violent crimes. Section 3.7 discusses the main results. Finally, section 3.8 concludes.

3.2. Temporal crime patterns: a descriptive analysis for the city of Barcelona

This section analyzes monthly, weekly and hourly crime patterns for the following crime types: property crimes (*Robberies*, *Thefts* and *Criminal damage*), crimes against the person (*Violent crimes* and *Gender violence*) and other crimes (*Against police*, *Driving crimes*, *Drug related crimes*).[21]

Figure 3.1 (panels a to h) gives us a broad temporal picture of the evolution of the sum of offenses, by month, for each type of crime. Several features are worth highlighting. First, all types of crime, with the exception of *Robberies* (which presents an upward trend) and *Gender violence* (which presents a downward trend), are quite stable within the period of study (January 2007 – December 2011). Without seeking to be exhaustive, a priori, the reduction in the number of family related crimes (*Gender violence*) could be related, on the one hand, to the resources devoted by governments (national, regional and local) to tackling this problem in Spanish society[22] and, on the other, to the impact that an economic crisis can have on report rates for this type of crime.

As expected, there seems to be a marked seasonal effect with an increase in *Violent crimes* and, especially, *Thefts* in the summer. This would appear to be associated with the massive arrival of tourists – attractive targets for pickpockets – to the city during these months.[23]

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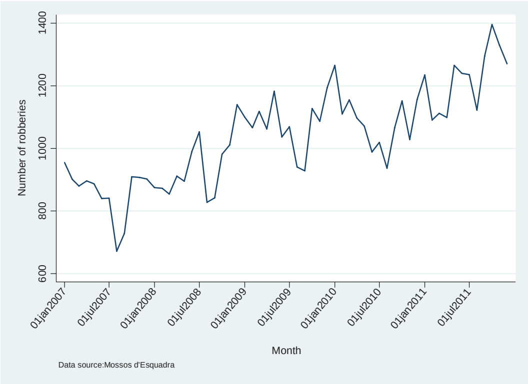
[21] See Section 3.4 for more details on the data used and Table 3.1 for a precise definition of each type of crime used.

[22] Counselling, social housing, rapid police responses to aggressions and faster trials of offenders are some of the policies that have been adopted in recent years in Spain to tackle this problem.

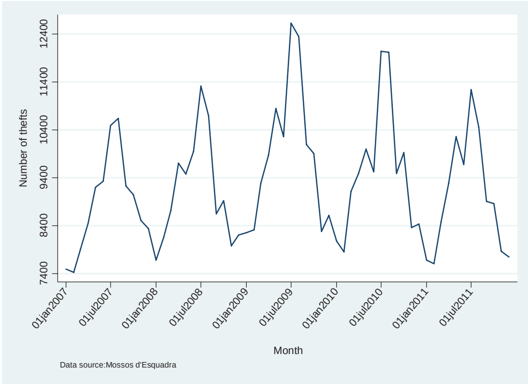
[23] Tourists are known to carry valuable items on their person, including cameras and cell phones. This, together with a low level of surveillance, makes them attractive targets for offenders. See Montolio and Planells-Struse (2013) for an analysis of the impact of tourism on crime for the Spanish case.

Figure 3.1: Monthly crime evolution.

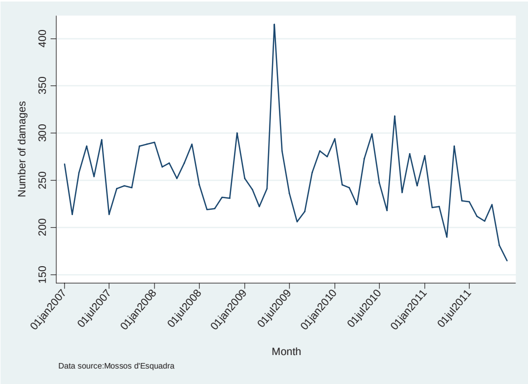
Panel 3.1a: *Robberies*



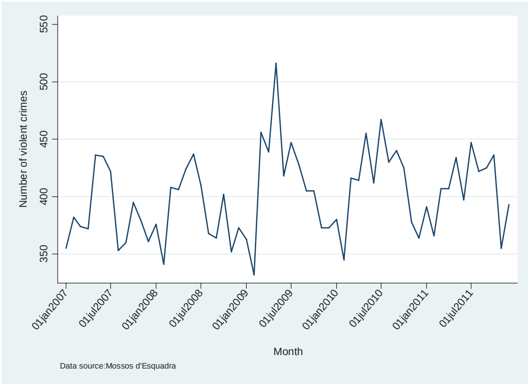
Panel 3.1b: *Thefts*



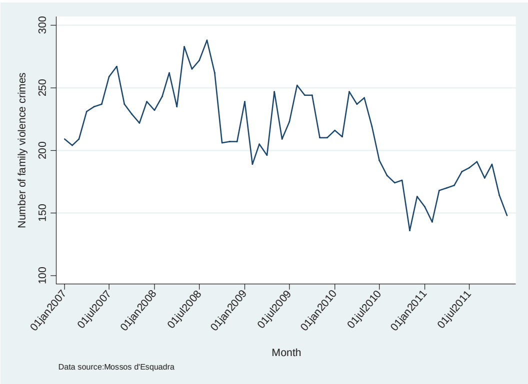
Panel 3.1c: *Criminal damage*



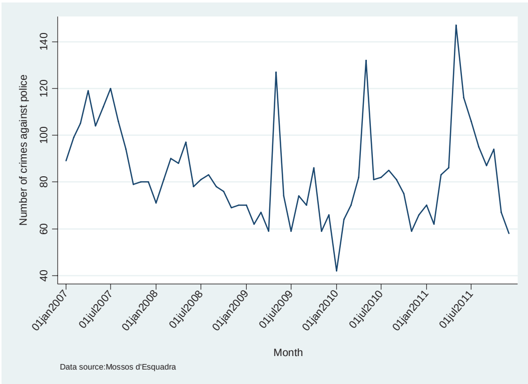
Panel 3.1d: *Violent crimes*



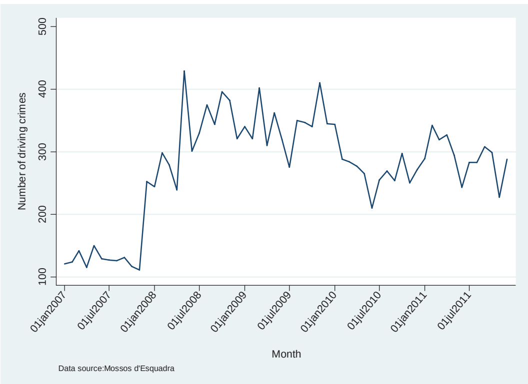
Panel 3.1e: *Gender violence*



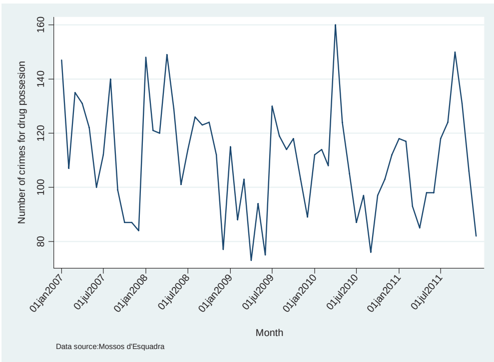
Panel 3.1f: *Against police*



Panel 3.1g: *Driving crimes*



Panel 3.1h: *Drug related crimes*



It should perhaps be pointed out that the sharp rise in *Driving crimes* recorded from the end of the year 2007 reflects the new traffic regulations (*Ley Orgánica* 15/2007) passed on the 30th of November[24], which increased the severity of such crimes and hence the number of offences (see BOE, 2007).

Figure 3.2 (panels a to h) presents the weekly trend for each type of crime. The daily number of crimes of each type has been calculated by taking the average of all daily crime counts for the period of study (2007-2011). For all types of crimes there is a weekend effect with crime rates increasing significantly during the weekend.[25] In general, rates fall from Sunday to Tuesday/Wednesday; thereafter, they begin to rise again reaching a peak on Saturday/Sunday. Note the low level of reports made for drug consumption and trafficking on Sundays (a crime that peaks on Fridays), a pattern that might reflect the incapacitation of drug users by Sunday (i.e., drug consumption is highest on Fridays and Saturdays, with users resting on Sundays before the start of the week).

Finally, Figure 3.3 (panels a to h) shows the hourly patterns of crime. We compute the average number of crimes (by type) for every hour of the day.[26] Various patterns emerge. *Robberies* (panel 3a) and *Thefts* (panel 3.3b) present similar profiles: both peak at 19:00 following an upturn after 15:00 (when people leave work on working days). In both cases, rates are lowest around 9:00, increasing up to 13:00 and falling during lunch time (13:00-15:00). *Criminal damage* committed against the property of others (panel 3.3c) also peaks at 19:00 and is concentrated in the evening hours while during the rest of the day there is little fluctuation in the rate. Panel 3.3e shows the evolution of *Gender violence*, with rates peaking in the late evening (having gradually increased throughout the day) and dropping off at night. *Violent crimes* (panel 3.3d) follows a similar pattern with an increasing rate from the early morning to a peak at around 19.00, but a second peak emerges at around 04:00 in the early morning. This is presumably associated with activities in leisure areas that end up in brawls and fights which, if reported to police, are likely to be catalogued as violent crimes.

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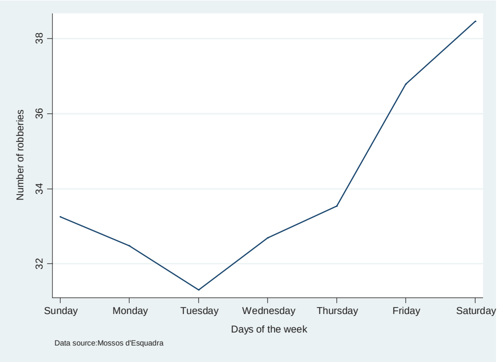
[24] The law actually came into effect on 2nd of December.

[25] The marked weekend effect observed for *Gender violence* has also been reported in Vazquez *et al*. (2005) and Gantz *et al*. (2006).

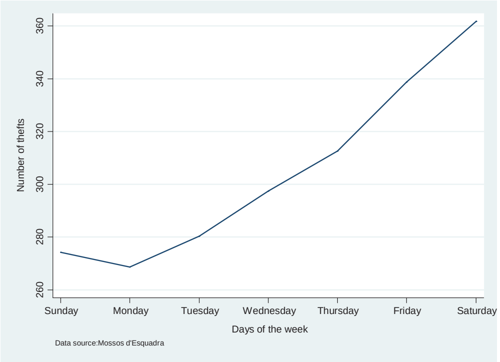
[26] The vertical lines plotted in all the panels of Figure 3.3 denote the typical kick off and final whistle times for FCB football matches (20:00 and 22:00); see footnote 13 for more details. Additionally, and given its utility for the subsequent analysis, Figure 3.3 plots the hourly evolution of crime for days when no matches were played (No game) and for days when FCB played at home (Home game) and when the club played away (Away game).

Figure 3.2: Weekly crime evolution.

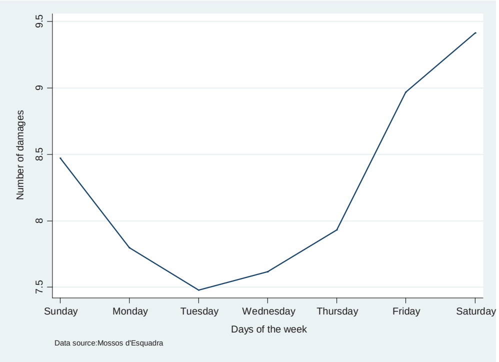
Panel 3.2a: *Robberies*



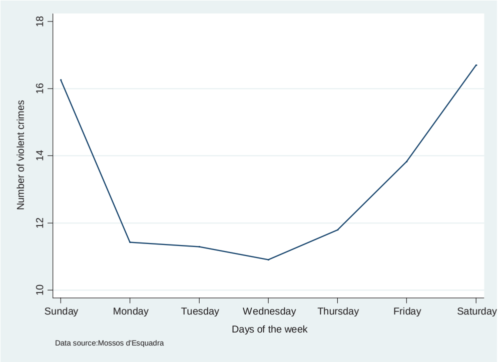
Panel 3.2b: *Thefts*



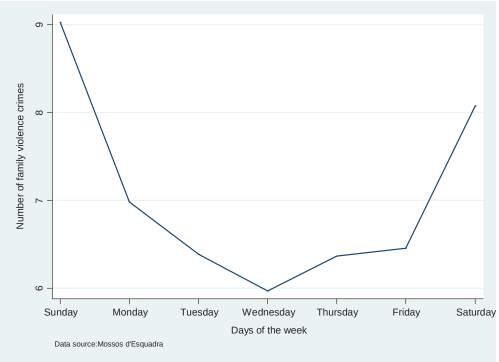
Panel 3.2c: *Criminal damage*



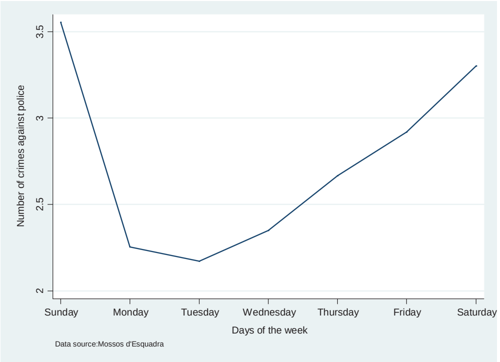
Panel 3.2d: *Violent crimes*



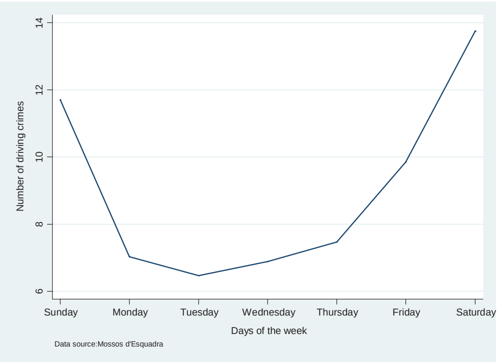
Panel 3.2e: *Gender violence*



Panel 3.2f: *Against police*



Panel 3.2g: *Driving crimes*



Panel 3.2h: *Drug related crimes*

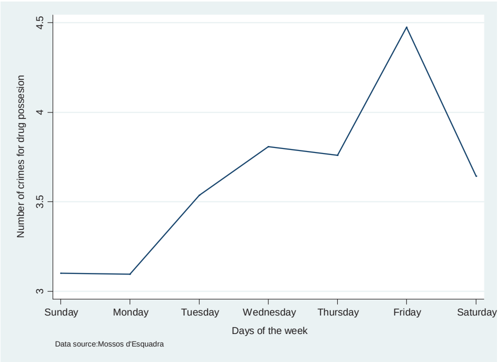
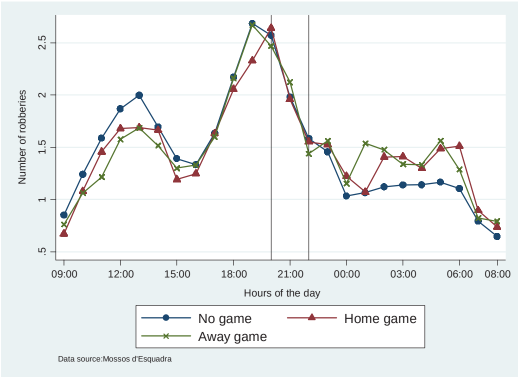
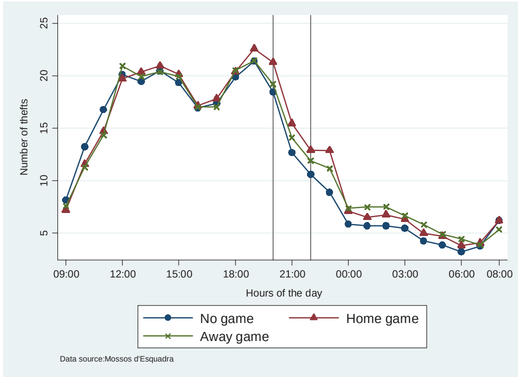


Figure 3.3: Hourly crime evolution.

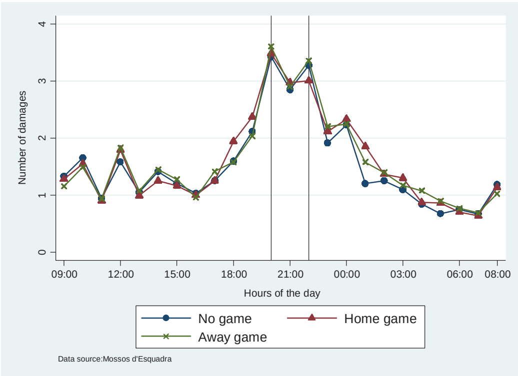
Panel 3.3a: *Robberies*



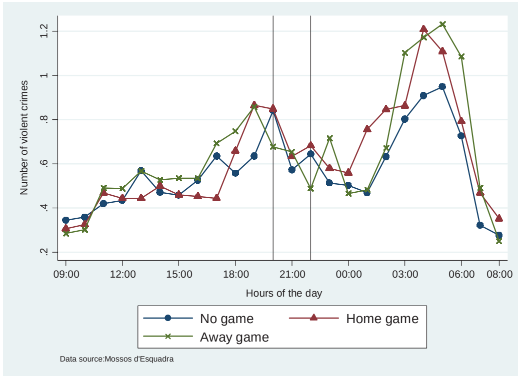
Panel 3.3b: *Thefts*



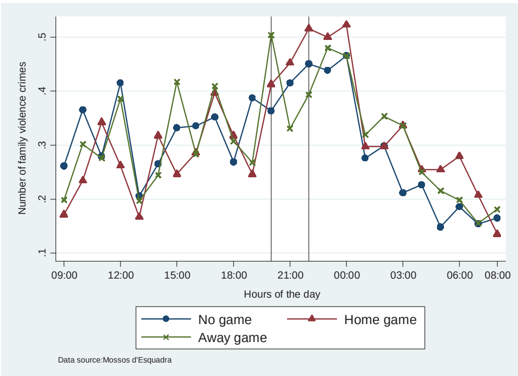
Panel 3.3c: *Criminal damage*



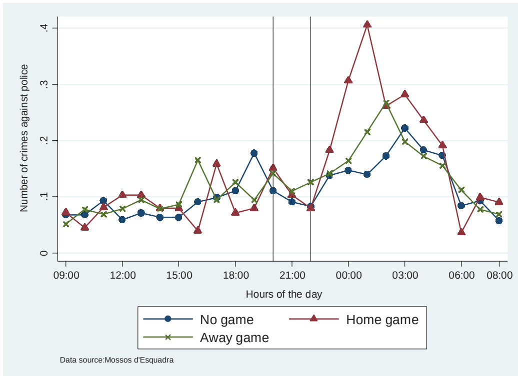
Panel 3.3d: *Violent crimes*



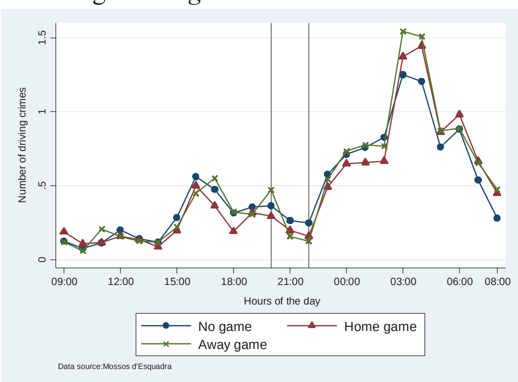
Panel 3.3e: *Gender violence*



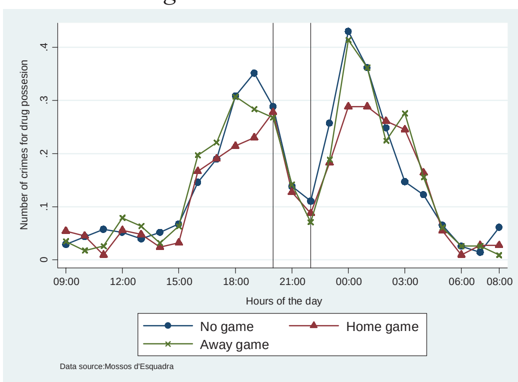
Panel 3.3f: *Against police*



Panel 3.3g: *Driving crimes*



Panel 3.3h: *Drug related crimes*



In the case of the other types of illegal activity, crimes *Against police* (panel 3.3f) peaks at night (00.00 - 03.00), again presumably related with the attempts of police forces to actively control leisure activities, which are likely to result in illegal behavior. This seems to be confirmed by *Driving crimes* (panel 3.3g) and *Drug related crimes* (panel 3.3h), which present very similar time profiles, although the latter presents a second peak between 19:00 and 20:00 (after working hours).

Interestingly, the hourly evolution of the eight typologies of crime analyzed above can be broadly summarized in three time patterns: first, crimes related to leisure activities (crimes *Against police*, *Driving crimes* and *Drug related crimes*), with peaks late at night, low rates during the day-time and rates that increase as the evening progresses; second, crimes against property (*Robberies*, *Thefts* and *Criminal damage*), with low rates at night and a clear peak around 18:00 (related to the time when people are leaving work on weekdays); and, third, crimes involving violence (*Violent crimes* and *Gender violence*), with rates that increase throughout the day, peaking in the evenings. The crime types that might benefit from the hours of darkness (drug related crimes, violent crimes and criminal damage) occur more frequently during the evening, as corroborated by Calandrillo and Buehler (2008).

3.3. Football: time and crime

Having described the temporal profile of crime in the city of Barcelona and having shown that crime varies markedly with time, we now explore whether some activities might displace illegal activities in time. Barcelona is a busy city offering a wide range of cultural and tourist activities (not to mention those organized by the city's neighborhood associations), which can be examined in order to detect the existence of any kind of relationship between the timing of these activities and criminal activity. Barcelona, moreover, has a long tradition in hosting leading sporting events, commencing in 1992 with the Olympic Games and more recently with the organization of numerous World and European Championships, including swimming (2003 and 2013), athletics (2010), basketball (2014) and handball (2013).[27] And, of course, Barcelona, as home to FCB and RCD Espanyol, plays host to football matches on a regular basis.[28]

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[27] Barcelona is also the frequent host of many Spanish Championships in a variety of disciplines.

[28] RCD Espanyol attracts less support than FCB. By way of illustration, RDC Espanyol has 27,000 members (paying an annual fee) and around 70,000 followers on Facebook, while FCB has 169,000 members and

Despite the positive economic effects that hosting a world-wide famous football club undoubtedly has for the city of Barcelona (for a cross-country comparison, see, Sterken, 2006, and Allmers and Maening, 2009**)**, a number of negative externalities arise from its being home to such a major team and its hosting of such large events on a regular basis.[29] The literature dealing with the impact of sport on crime has mainly focused on the spatial patterns of this relationship (see, for instance, Kurland *et al.,* 2013; Rees and Schnepel, 2009; Russell, 2004; Marie, 2010; Breetzke and Cohn, 2013; Breetzke and Carl, 2009), while only a few studies have focused on the possible temporal displacement effects of such events (Card and Dahl, 2011; Doleac and Sanders, 2012; Kirk, 2008; Sachs and Chu, 2000). As such, this Chapter, rather than addressing the so-called crime pattern theory (Eck *et al*., 2007), which states that certain specific places (such as football stadiums) are rich in suitable targets and attract potential offenders, focuses on the temporal displacement effects of football matches.

In order to provide an initial, visual evaluation of the potential temporal displacement effect of FCB matches on crime, in Figure 3.3 we depict the hourly crime evolution in Barcelona on days when FCB played at home and away as well as on days when FCB were not involved in a game.[30] In general, the hourly patterns of crime on the three types of day are fairly similar; however, closer inspection reveals some interesting features.

In general, home match days and away match days do not differ considerably from other non football days except in the time band following the final whistle. In the case of *Robberies, Thefts, Violent crimes, Gender violence,* and crimes *Against police* officers there is an increase in the number of illegal activities in the hours after the football (both for home and away games). The same is true for *Driving crimes*, but in this case five to six hours after the match has finished. For *Criminal damage*, there are no apparent differences across the different types of day analyzed, while there is a lower level of *Drug related crimes* in the hours following home matches.

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more than 45 million followers on Facebook. Moreover, although originally with its home ground in Barcelona, RCD Espanyol moved to the neighbouring city of Cornellà-El Prat in September 2009. Therefore, for the purposes of this study we focus only on the temporal impact FCB matches have on criminal behaviour in the city of Barcelona.

[29] Given that FCB typically gets to the final rounds of most of the competitions that it enters means that in some periods of the season, the club is playing almost every three days (taking into account both home and away matches).

[30] Note that FCB matches kick off at different times, depending on the match and on the competition. For instance Champions League matches always kick-off at 20:45 (CET), however, Domestic League matches may vary, the average starting time being 20:20 (and the mode 20:35). In Figure 3.3, therefore, the additional vertical lines correspond to a 20:00 starting time and 22:00 final whistle.

Certain characteristics of the days under analysis provide us with plausible explanations for the crime patterns observed. For instance, police deployment when FCB are playing at home to guarantee the protection of those going to the stadium or congregating in recreational areas to watch the match may be responsible for the marked increase observed in crimes *Against police* officers on home match days (given the greater interaction between fans and police officers), a decrease in *Drug related crimes* as the police are concerned with other security issues, and also the time profile of *Driving crimes* with traffic checkpoints being set up after matches.

Fluctuations in supporters' emotions following a defeat or victory may account in part for the sharp increase in *Violent crimes*, the rate of which also increases in the hours prior to a match. The same post-match pattern is observed for *Robberies* and, albeit to a lesser extent, for *Thefts*, which in the case of the city of Barcelona are limited mainly to pick pocketing. Incidents of *Gender violence* also seem to rise on match days, but the graphical evidence here is less conclusive.

Clearly the preceding has been an attempt at providing a descriptive approximation of the evolution of crime over time, and the possible effects that a major sporting event can have on illegal behavior. In the next section, we address the issue by means of formal estimations taking into account other possible determinants of the differences observed (day of the week, type of match, weather conditions, etc.) in crime patterns across football and non-football days.

3.4. Data and empirical methodology

3.4.1. Crime data

In this section we formally describe our unique data (used in the previous sections to describe the time patterns of crime). We use a non-public dataset for the city of Barcelona containing all registered crimes obtained from the autonomous police agency in Catalonia (Spanish region in which Barcelona is located), the *Mossos d'Esquadra*, which is responsible for crime prevention, crime solving and specialized crime investigation in the Catalan region.[31] The dataset contains reports made both by citizens and police officers.

[31] The *Mossos d'Esquadra* are responsible for virtually all police duties. The Spanish National Police (*Cuerpo Nacional de Policía*) and the military police (*Guardia Civil*) retain a number of administrative

Additionally, the dataset contains information on all the crimes registered by Barcelona's local police (the *Guardia Urbana*), responsible primarily for urban traffic and upholding municipal laws and ordinances.

The crime dataset records the time of the crime (when known) and the exact location. The dataset spans from 2007 to 2011 and is classified according to the more than 190 articles making up the Spanish penal code.[32] In order to reduce the number of categories without creating an aggregation bias (Cherry and List, 2002) that could reduce the effectiveness of our estimations, we combined some of these articles according to the type of crime, paying particular attention not to aggregate crimes with different offender motivations (for example, crimes against the person and crimes against property). Table 3.1 specifies the type of crime included in each category.

Table 3.1: Crime classification.

Type	**Description**
Property Crimes	
Robberies	Misappropriation of the belongings of others against their will with the use of violence.
Thefts	Misappropriation of the belongings of others against their will without the use of any violence.
Criminal damage	Minor/serious damage to the belongings/property of others.
Crimes against the Person	
Violent crimes	Physical injuries to other individuals. Mass fights and brawls.
Gender violence	Abuse in the home. Physical and psychological violence in the home.
Other Crimes	
Against police	Misconduct, intimidation, resistance, use of force and aggressions against police officers.
Driving crimes	Dangerous driving. Driving with no license. Driving under the influence of alcohol or drugs (considered a serious crime when alcohol tests are above a certain threshold). Endanger lives of other drivers.
Drug related crimes	Drug consumption in public areas and drug trafficking. The amount of drugs determines the classification.

responsibilities (e.g., issuing of identity cards and passports) and undertake counter-terrorist and anti-mafia activities.

[32] The *Mossos d'Esquadra* were fully deployed in the city of Barcelona in 2006.

For the main property crimes, we include *Robberies*, i.e., the use of violence in the misappropriation of the belongings of others, as opposed to *Thefts*, which do not involve any violence. Among property crimes, we also include *Criminal damage* which accounts for any type of damage caused to the belongings of others. Aggregated categories of property crime often include this type of crime but the motivation that may lead an offender to commit a theft or criminal damage are clearly different.

Among violent, interpersonal crimes we include the category *Gender violence*, which refers to crimes committed against a family member, and *Violent crime*s, which includes the inflicting of injuries of any type against another person or persons. This category also includes fights that break out among crowds in places of leisure (such as night clubs or discos) or at major events (such as football matches).

Finally, we create a separate category (Other crimes) to account for special types of crime normally reported by police officers and not by citizens. Broadly speaking, this means that if the police are not concerned with these crimes, they tend to go unreported and so are not accounted for in the registered crime data. In this category we include crimes *Against police*, i.e., misconduct (normally reported by the police themselves), such as, disobeying police orders or injuring a police officer; *Driving crimes*, i.e., driving under the influence of drugs or alcohol or traffic violations that endanger the lives of others; and, finally, *Drug related crimes*, i.e., crimes related to drug trafficking and/or consumption.

Table 3.2 shows the main descriptive statistics of the crime types used in this study. It is evident that property crimes are much more common than other types of crime. The most common offence committed in the city of Barcelona is that of *Thefts*, primarily pick pocketing, with a daily average of 306.79 recorded instances (nearly ten times greater than *Robberies* and *Criminal damage*). Fewer crimes against the person are recorded, although the figures for *Gender violence* are worrying given their implications. Finally, *Driving crimes* are the most common crime type among those directly recorded by police officers.

In order to control the size of our analysis, and given that our focus is on the temporality of crime, we have opted not to include crimes such as *Burglary* (illegal entry into a building for the purposes of committing an offence) and *Car theft*. Note that all the crime types included in Table 3.1 are characterized by the fact that the timing of the offence can be quite accurately determined, either because they directly involve victims and offenders or because they are reported by police officers. In contrast, just when exactly a *Burglary* or a *Car theft* occurred is usually unknown, and has to be approximated by police officers (or victims) when filing the complaint. Moreover, police officers usually state a time window for when the crime is likely to have occurred. Therefore, so as not to distort the main aim of the study – namely, the time analysis of crime and the possible (hourly) displacement effect of football matches, we do not include these crimes.

Table 3.2: Average number of crimes by different time dimensions.

Type	Hour	Day	Month	Year
Property Crimes				
Robberies	1.46 (1.43)	34.96 (8.73)	1,064.39 (144.44)	11,069.6 (4,430.41)
Thefts	12.80 (8.58)	306.79 (61.57)	9,339.25 (1,273.94)	97,128.2 (34,918.44)
Criminal damage	1.50 (1.55)	35.96 (9.84)	1,094.69 (128.42)	11,384.8 (4,329.19)
Crimes against the Person				
Violent crimes	0.55 (0.81)	13.21 (4.80)	402.25 (36.90)	4,183.4 (1,507.29)
Gender violence	0.29 (0.56)	6.95 (3.16)	211.48 (37.31)	2,199.4 (787.54)
Other Crimes				
Against police	0.11 (0.41)	2.63 (2.63)	79.96 (19.18)	831.6 (288.21)
Driving crimes	0.41 (0.75)	9.75 (5.23)	296.85 (65.55)	3,087.2 (1,425.48)
Drug related crimes	0.15 (0.41)	3.56 (2.09)	108.40 (20.18)	1,127.4 (438.09)

3.4.2. Football data

We merge the above hourly crime dataset with the dataset containing all the football matches played by FCB between the 25th of September 2007 and the 31st of December 2011. The latter contains information regarding the day, the exact time of the match, the rival, the match result, the number of spectators and whether it was played at home or away match. Table 3.3 summarizes the number of matches by level of attendance and by type of match. It shows that the level of attendance was high for home matches, with 70% attracting more than 60,000 spectators to the stadium and just seven presenting an attendance of less than 40,000 spectators.

Table 3.3: FCB football matches 2007-2011.

Attendance	**# of matches in the sample**
> 80,000 spectators	36
> 60,000 and < 80,000 spectators	58
> 40,000 and < 60,000 spectators	24
< 40,000 spectators	7
Total home matches	125
Away matches	130
Type of match	
Spanish Domestic League	169
Spanish King's Cup	32
European Champions League	50
Spanish and International Super Cups	4

Note: In this period FCB played Real Madrid CF, its main rival, ten times (home and away).

Our dataset contains a total of 125 home and 130 away matches. Most of the matches were played in the Spanish domestic league (169). The Spanish King's Cup is the second most important domestic competition (32 matches played); however, the European Champions League is the competition that attracts by far the most spectators (50 matches played). Table 3.4 completes the description of the datasets used in this Chapter presenting the main types of crimes by match day type (no match, home match and away match).

Table 3.4: Daily average number of reported crimes by typology and by type of match played.

Crime type	**No Match**	**Home Match**	**Away Match**
Property Crimes			
Robberies	34.95	36.29	35.68
Thefts	288.02	310.96	303.68
Criminal damage	8.15	8.27	9.19
Crimes Against the Person			
Violent crimes	12.71	14.03	14.55
Gender violence	6.78	7.30	7.32
Other Crimes			
Against police	2.53	2.64	2.98
Driving crimes	9.43	10.61	11.95
Drug related crimes	3.62	3.15	3.58

3.4.3. Empirical methodology

The evidence presented above seems to indicate a clear crime time profile and that a major event, such as a football match, can influence criminal behavior, especially after the event. In order to study the temporal behavior of crime and potentially distinct patterns on match days, we use a panel approach comprising two time dimensions: time of day and days. Thus, we compare the same times on different days while controlling for any potential source of heterogeneity across days, weeks, months and years. The empirical model used is the following:

$$Crime^{k}_{d,h} = Match^{t}_{d,h}\sum_{l=-7}^{7}\delta_{d,h+l} + \beta X_{d} + \gamma_{y} + \gamma_{m} + \gamma_{w} + \sum_{c=1}^{3}\gamma^{c}_{d} + \gamma_{h} + \varepsilon_{d,h} \qquad (3.1)$$

where *k* denotes the type of crime, *d* denotes the day in our time span running from the 25th September 2007 to 31st December 2011 and *h* is the time of day from 00:00 to 23:00. *t* denotes the type of match played (home or away);[33] thus, the variable $Match^{t}_{d,h}$ can be transformed into $Home_{d,h}$ and $Away_{d,h}$, which are dummy variables taking a value of 1 if it is a time when there is a home or an away match being played, respectively, and 0 otherwise.[34] The subscript *l* denotes the lag and lead effects of home and away matches. We analyze a period of up to seven hours before and after the match, assuming this to be a reasonable time period to observe the displacement effect of football on crime rates.

In Eq. (3.1) X_d represents a vector of control variables that can affect (recorded) crime, such as weather variables (average rainfall, average number of sun hours, average temperature, average pressure, average wind speed).[35] The weather has long been recognized to be an important factor influencing crime dynamics. For instance, higher temperatures can explain, through a psychological effect, higher levels of violent crimes (Anderson, 2001; Harries *et al.,* 1980; Jacob *et al*., 2004). Rain has also been shown to be a determinant in explaining lower levels of violent crime, perhaps due to the lack of social interactions among individuals (people are more likely to stay at home and not go out) or due to the lack of potential targets. We also include a dummy variable accounting for the

[33] We retain only those months corresponding to the football season in the sample; that is, we discard the summer months from the beginning of June to the end of August. Recall, the summer months are characterized by high seasonal crime records.
[34] We assume a match has a two-hour duration (90 minutes plus stoppage time).
[35] Weather variables present daily variation.

lunar phase (indicating the presence of the full moon) since some police agencies have reported experiencing higher levels of violent crime when there is a full moon.[36] This set of control variables is completed by a dummy variable that indicates if a particular day is a bank holiday; summer and winter seasonal dummies, dummies for days (home and away) with special matches such as the big derby between historic rivals FCB and Real Madrid CF which is considered, by the police, as a potentially dangerous match, and dummies to control for the type of competition (Spanish Domestic League, European Champions League, Spanish King's Cup, Spanish Super Cup and International Super Cup) since this may determine the typology of person interested in (and following) the match.

In order to account for unobserved heterogeneity across time, days, weeks and years in our data span, we include a full set of time fixed effects. First, we include an hour of the day fixed effect (γ_h) since, as shown in Figure 3.3, those hours with the greatest movement of workers (early morning or after work) are more likely to coincide with the peak times for pick pocketing.[37] By including hour of the day fixed effects, we capture this unobservable time characteristic and ensure our estimations of the effect of football matches on crime are unbiased. Second, we include three types of dummies related to different days (γ_d^c); (*i*) day of the week fixed effects to account for the heterogeneity of crime across days. As shown in Figure 3.2, there is a clear weekend effect (maybe due to higher outdoor/leisure mobility of individuals or to higher alcohol and drug consumption). By including these specific day of the week fixed effects we can capture these weekend effects as well as other specific day effects, such as, (*ii*) day of the month fixed effects, which account for days with specific monthly characteristics (for instance, pay day in the lasts days of a month); and (*iii*) day of the year fixed effects, which control for special days such as Christmas Day, New Year's Eve, local holidays (*fiestas*) or any other special day.

Third, we also include week of the year (γ_w), month of the year (γ_m) and annual fixed effects (γ_y). Finally, we draw on monthly and yearly trends to account for potential trends (e.g., thefts increase from the beginning of the year to the end of August) or for different levels of popularity expressed for FCB (e.g., the club may be more popular one year because it won a major title the previous season or because it bought a world-class player).

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[36] See "Crackdown on lunar-fuelled crime". BBC News. 5 June 2007 at http://news.bbc.co.uk/2/hi/uk_news/england/kent/6723911.stm (last accessed 14 March 2014).
[37] All the temporal fixed effects and trends included in the regressions have been based on the descriptive temporal crime analysis carried out in the previous section.

As we employ hourly data, the crime count in our dataset is positively skewed with a large presence of zeros. Taking logs would result in a considerable increase in the number of missing values, which could bias our estimations. In order to deal with data of this type, we follow Marie (2010) and Dahl and DellaVigna (2009) and use a negative binomial approach. Such estimations constitute a generalization of the Poisson model but allow for the over dispersion of data, in other words, they allow for the variance of the outcome to differ from the mean.

3.5. Main results

In this section we present the results of estimating Eq. (3.1), that is, the temporal effect of football on crime. The columns of each table of results present the different crime types considered. All the regressions include the full set of controls previously presented. Note that given that we estimate a negative binomial model, the coefficients reported are the incidence rate ratios that represent the increase or decrease in percentage of the number of counts of each crime type.

Table 3.5 shows the results of the impact of FCB playing at home on crime, focusing on the time when the games are played (recall, we consider a game to have a duration of two hours (20:00 – 22:00). The first row represents the impact of an increase of 10,000 spectators on the different types of crime. For the case of *Robberies*, the coefficient presents a decrease in the expected number of *Robberies* of 2.6% (1-0.974) during the football match for each 10,000 additional spectators in the stadium. Similarly, the following rows analyze the effect of different matches depending on attendance. In general, it seems that football matches only have a significant impact on crime (for the duration of the game), in the case of those attended by over 80,000 spectators. These matches are typically important games for FCB. During such matches, there is a decrease in the number of *Robberies* in the city, and there is some weak evidence of a reduction in crimes *Against police*, the number of *Driving crimes* and *Violent crimes* during the two hours of the game. This lack of significant results for crime during the time of the match (or even the reductions in some crime types) might point to an incapacitation effect on offenders, as found by Dahl and DellaVigna (2009) in relation to violent movies.[38]

[38] Note that in our case, *a priori*, there is a similar profile of football supporters and that of (potential) offenders: basically young males.

Table 3.5: FCB home matches attendance and crime in the city at time of the match.

	(1) *Robberies*	(2) *Thefts*	(3) *Criminal damage*	(4) *Violent crimes*	(5) *Gender Violence*	(6) *Against Police*	(7) *Driving crimes*	(8) *Drugs*
Stadium attendance	**0.974****	1.013	1.007	0.999	0.981	0.963	0.959	1.017
	(0.0102)	(0.00955)	(0.00995)	(0.0219)	(0.0207)	(0.0494)	(0.0258)	(0.659)
>80,000	**0.802****	1.023	1.023	**0.743***	0.959	**0.496***	**0.624***	0.727
	(0.0827)	(0.0406)	(0.0688)	**(0.117)**	(0.189)	**(0.208)**	**(0.176)**	(0.236)
>60,000	0.930	0.986	1.009	0.929	0.780	0.878	0.783	0.707
	(0.0691)	(0.0356)	(0.0658)	(0.115)	(0.124)	(0.260)	(0.159)	(0.159)
>40,000	**0.781***	**0.908***	0.961	1.137	0.999	0.443	0.745	0.462
	(0.112)	**(0.0475)**	(0.0970)	(0.187)	(0.257)	(0.307)	(0.222)	(0.227)
>20,000	1.014	0.964	1.045	1.045	1.004	1.689	0.999	0.602
	(0.241)	(0.0955)	(0.172)	(0.382)	(0.258)	(1.225)	(0.645)	(0.391)
Observations	29,123	29,123	29,123	29,123	29,123	29,123	29,123	29,123
Climate controls	YES	YES	YES	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES	YES	YES	YES
Seasonal controls	YES	YES	YES	YES	YES	YES	YES	YES
Monthly trends	YES	YES	YES	YES	YES	YES	YES	YES
Yearly trends	YES	YES	YES	YES	YES	YES	YES	YES
Lunar phase	YES	YES	YES	YES	YES	YES	YES	YES
Holiday dummy	YES	YES	YES	YES	YES	YES	YES	YES
Derby dummy	YES	YES	YES	YES	YES	YES	YES	YES
Type of competition	YES	YES	YES	YES	YES	YES	YES	YES

Note: Attendance is expressed in 10,000. >80,000, for instance, is a dummy that takes the value of 1 for matches with an attendance above the specified threshold. The estimations for each level of attendance are performed separately. Climate controls include: average rainfall, average number of sun hours, average temperature, average pressure and average wind speed. Time controls include: hour of the day, day of the week, day of the month, day of the year, week of the year, month and year. Seasonal controls include dummies for summer (mainly September) and winter. Type of competition includes dummies for: Spanish Domestic League, European Champions League, Spanish King's Cup and Super Cups (both Spanish and International). Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The detailed results for the vector of control variables (X_d) for the above estimation are reported in Table 3.6. In general, some climate variables are related to crime behavior. For instance, longer days in terms of sun hours, warmer days in terms of temperature, calm days in terms of wind speed, and non-rainy days, are related to higher crime rates (especially property crimes).

We examine in greater depth the temporal profile of crime and the way in which football can shape it in Table 3.7 by presenting the detailed results of crime in the hours leading up to and following FCB home matches. On the one hand, in the pre-match hours there seems to be fewer *Driving crimes* and *Drug related crimes*. In the case of interpersonal *Violent crimes* there also seems to be a reduction in the crime rate, but at a much earlier point in the day (between four and five hours before the match). In the case of *Thefts* (primarily pick pocketing), in the hour immediately prior to the match, the number of thefts increases by around 15%. Less robust is the increase (10%) found for *Criminal damage* one hour prior to kick-off.

Table 3.6: Control variables.

	(1) *Robberies*	(2) *Thefts*	(3) *Criminal damage*	(4) *Violent crimes*	(5) *Gender Violence*	(6) *Against Police*	(7) *Driving crimes*	(8) *Drugs*
Rainfall	**0.998****	**0.998*****	**1.002****	**0.996****	0.999	0.999	**0.996****	0.996
	(0.00093)	**(0.0004)**	**(0.00094)**	**(0.0015)**	(0.0020)	(0.0034)	**(0.0019)**	(0.0029)
Sun hours	**1.004****	**1.006*****	**1.006*****	**1.006****	0.993	1.009	1.000	0.997
	(0.00195)	**(0.0009)**	**(0.00190)**	**(0.0031)**	(0.0040)	(0.0072)	(0.0036)	(0.0056)
Temperature	**1.009*****	**1.008*****	0.999	**1.012*****	**1.015*****	1.001	**1.023*****	**1.021*****
	(0.00236)	**(0.0012)**	(0.00226)	**(0.0038)**	**(0.0052)**	(0.0083)	**(0.0045)**	**(0.0072)**
Pressure	**1.000****	**1.000****	1.000	1.000	1.000	1.000	1.000	1.000
	(0.0000)	**(0.0000)**	(0.00005)	(0.00008)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Wind speed	**0.998****	**0.999***	0.998*	1.000	1.000	0.996	**0.997***	**0.993****
	(0.001)	**(0.0005)**	(0.0010)	(0.0017)	(0.0023)	(0.0038)	**(0.0020)**	**(0.0031)**
Summer dummy	**0.524****	0.863	1.061	1.480	1.914	1.111	0.720	2.108
	(0.142)	(0.112)	(0.241)	(0.679)	(0.874)	(1.256)	(0.361)	(1.387)
Winter dummy	1.357	0.996	0.903	**3.206*****	0.450	0.680	0.634	0.539
	(0.383)	(0.123)	(0.256)	**(1.306)**	(0.298)	(0.622)	(0.393)	(0.437)
Lunar phase	0.996	1.020	1.038	1.021	1.087	0.927	1.045	0.985
	(0.0335)	(0.0168)	(0.0342)	(0.0543)	(0.0746)	(0.111)	(0.0656)	(0.0974)
Holiday dummy	0.993	0.981	**0.953***	1.038	0.952	1.183	0.962	1.136
	(0.0289)	(0.0147)	**(0.0267)**	(0.0470)	(0.0573)	(0.127)	(0.0497)	(0.0986)
Derby dummy	0.868	1.045	1.063	**1.910****	1.447	2.356	0.704	0.753
	(0.243)	(0.114)	(0.133)	**(0.540)**	(0.423)	(1.603)	(0.436)	(0.701)
King´s Cup	0.815	1.103	1.023	0.709	0.890	0.420	1.048	0.178*
	(0.116)	(0.0825)	(0.142)	(0.210)	(0.302)	(0.440)	(0.381)	(0.181)
Champions League	1.070	1.015	**1.215****	0.893	0.827	1.162	0.950	0.743
	(0.127)	(0.0405)	**(0.104)**	(0.196)	(0.231)	(0.458)	(0.320)	(0.248)
Domestic League	**0.845*****	**0.907*****	0.937	**0.819****	**0.763***	1.032	**0.680****	0.750
	(0.0517)	**(0.0269)**	(0.0498)	**(0.0800)**	**(0.108)**	(0.259)	**(0.124)**	(0.136)
Super Cups	1.044	0.927	0.822	1.082	**1.6e-08*****	2.977	**1.6e-08*****	1.889
	(0.360)	(0.215)	(0.226)	(0.332)	**(8.37e-09)**	(3.099)	**(9.52e-09)**	(1.308)
Observations	29,123	29,123	29,123	29,123	29,123	29,123	29,123	29,123
Hour of the day	YES	YES	YES	YES	YES	YES	YES	YES
Day of the week	YES	YES	YES	YES	YES	YES	YES	YES
Day of the month	YES	YES	YES	YES	YES	YES	YES	YES
Day of the year	YES	YES	YES	YES	YES	YES	YES	YES
Week of the year	YES	YES	YES	YES	YES	YES	YES	YES
Month of the year	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.7: Hours prior to and after FCB home matches.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robberies	*Thefts*	*Criminal damage*	*Violent crimes*	*Gender violence*	*Against police*	*Driving crimes*	*Drugs*
T - 7	0.916	0.966	1.045	**0.763***	0.936	1.020	0.933	0.655
	(0.0811)	(0.0288)	(0.0729)	**(0.120)**	(0.164)	(0.306)	(0.197)	(0.289)
T - 6	**0.826****	**0.944****	0.977	0.827	0.901	0.941	0.810	0.634
	(0.0702)	**(0.0247)**	(0.0835)	(0.112)	(0.167)	(0.271)	(0.168)	(0.207)
T - 5	0.892	**0.919*****	0.908	**0.770***	0.787	0.824	0.844	0.679
	(0.0759)	**(0.0264)**	(0.0801)	**(0.115)**	(0.155)	(0.238)	(0.124)	(0.175)
T - 4	0.929	0.983	0.922	**0.668*****	0.808	0.954	**0.737***	**0.692***
	(0.0732)	(0.0272)	(0.0830)	**(0.0814)**	(0.154)	(0.271)	**(0.115)**	**(0.151)**
T - 3	0.896	0.966	0.963	0.898	1.090	0.607	**0.587*****	**0.678****
	(0.0655)	(0.0257)	(0.0656)	(0.112)	(0.167)	(0.186)	**(0.112)**	**(0.134)**
T - 2	0.948	1.014	1.101	0.954	0.945	**0.561***	**0.618*****	**0.728***
	(0.0626)	(0.0308)	(0.0696)	(0.0988)	(0.151)	**(0.190)**	**(0.113)**	**(0.132)**
T - 1	0.928	**1.154*****	**1.107***	0.989	0.917	0.865	**0.715***	**0.533****
	(0.0602)	**(0.0328)**	**(0.0670)**	(0.101)	(0.155)	(0.216)	**(0.137)**	**(0.136)**
T + 1	1.052	**1.429*****	0.963	**0.789***	0.959	1.062	0.880	**0.673***
	(0.0797)	**(0.0619)**	(0.0585)	**(0.103)**	(0.189)	(0.309)	(0.124)	**(0.153)**
T + 2	1.086	**1.325*****	**1.148****	0.964	0.780	1.245	0.920	1.047
	(0.0955)	**(0.0760)**	**(0.0760)**	(0.117)	(0.124)	(0.366)	(0.118)	(0.182)
T + 3	1.102	**1.252*****	**1.311*****	**1.262***	0.999	**2.002****	0.928	0.745
	(0.106)	**(0.0778)**	**(0.113)**	**(0.155)**	(0.257)	**(0.575)**	(0.117)	(0.205)
T + 4	1.149	**1.203*****	**1.238****	**1.251***	1.004	**1.892****	1.051	1.059
	(0.100)	**(0.0849)**	**(0.131)**	**(0.166)**	(0.138)	**(0.523)**	(0.116)	(0.205)
T + 5	**1.347*****	**1.235*****	1.091	1.175	1.016	1.368	0.911	0.933
	(0.121)	**(0.0937)**	(0.139)	(0.149)	(0.136)	(0.322)	(0.0941)	(0.213)
T + 6	**1.429*****	**1.331*****	1.113	1.018	1.088	1.347	1.082	0.696
	(0.133)	**(0.105)**	(0.119)	(0.114)	(0.169)	(0.288)	(0.0956)	(0.238)
T + 7	**1.332*****	**1.261*****	0.893	1.150	1.039	0.770	0.946	0.882
	(0.128)	**(0.102)**	(0.107)	(0.120)	(0.166)	(0.214)	(0.102)	(0.328)
Observations	29,123	29,123	29,123	29,123	29,123	29,123	29,123	29,123
Climate controls	YES	YES	YES	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES	YES	YES	YES
Seasonal controls	YES	YES	YES	YES	YES	YES	YES	YES
Monthly trends	YES	YES	YES	YES	YES	YES	YES	YES
Yearly trends	YES	YES	YES	YES	YES	YES	YES	YES
Lunar phase	YES	YES	YES	YES	YES	YES	YES	YES
Holiday dummy	YES	YES	YES	YES	YES	YES	YES	YES
Derby dummy	YES	YES	YES	YES	YES	YES	YES	YES
Type of competition	YES	YES	YES	YES	YES	YES	YES	YES

Note: Climate controls include: average rainfall, average number of sun hours, average temperature, average pressure and average wind speed. Time controls include: hour of the day, day of the week, day of the month, day of the year, week of the year, month and year. Seasonal controls include dummies for summer (mainly September) and winter. Type of competition includes dummies for: Spanish Domestic League, European Champions League, Spanish King's Cup and Super Cups (both Spanish and International). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In the hours following the match there seems to be a marked increase in crime. This result is, as expected, very strong and robust for *Thefts*. Victory celebrations bring supporters out on to the streets making them targets for thieves. The number of *Thefts* peaks just one hour after the match, but the impact of the event remains significant throughout the night (up to seven hours after the match). Likewise, an increase in the number of *Robberies* (thefts involve some sort of violence) is recorded, especially five hours after the final whistle, along with more instances of *Criminal damage*, *Violent crimes* and crimes *Against police* between three and four hours after the match. These results are related to post-match activities that include victory celebrations and/or going out after the match.

Tables 3.8 and 3.9 show the results for away matches, given that a city with a major team will have a large number of supporters that are liable to modify criminal patterns, even when the team plays away.

Table 3.8: FCB away matches and crime in the city during the game.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robberies	*Thefts*	*Criminal damage*	*Violent crimes*	*Gender violence*	*Against police*	*Driving crimes*	*Drugs*
Away match	0.934	**0.951****	0.991	0.989	**0.784***	**1.507***	**0.797***	**0.533*****
	(0.0727)	**(0.0241)**	(0.0451)	(0.0891)	**(0.106)**	**(0.321)**	**(0.109)**	**(0.0956)**
Observations	29,123	29,123	29,123	29,123	29,123	29,123	29,123	29,123
Climate controls	YES	YES	YES	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES	YES	YES	YES
Seasonal controls	YES	YES	YES	YES	YES	YES	YES	YES
Monthly trends	YES	YES	YES	YES	YES	YES	YES	YES
Yearly trends	YES	YES	YES	YES	YES	YES	YES	YES
Lunar phase	YES	YES	YES	YES	YES	YES	YES	YES
Holiday dummy	YES	YES	YES	YES	YES	YES	YES	YES
Derby dummy	YES	YES	YES	YES	YES	YES	YES	YES
Type of competition	YES	YES	YES	YES	YES	YES	YES	YES

Note: see notes to Table 3.7.

Table 3.8 shows a significant reduction in *Drug related crimes* and *Thefts* and a reduction (albeit less strong in terms of statistical significance) of *Gender Violence* and *Driving crimes*. Again, these results could be driven by an incapacitation effect during the match.[39] Table 3.8 also shows a slightly significant increase in the number of recorded crimes *Against police*: the coefficient seems to be positive and significant at the 10% level

[39] Note that in Table 3.5 we include attendance at home games. If we perform a similar regression as that presented in Table 3.8 but with a dummy variable indicating home match we also find a reduction in the crime committed in the city during the hours of the game.

indicating an increase in the number of crimes of 50.7%. This result might be attributed to the celebrations of the football fans who meet in bars or at specific locations in the city.[40]

Table 3.9. Hours prior to and after FCB away matches.

	(1) Robberies	(2) Thefts	(3) Criminal damage	(4) Violent crimes	(5) Gender Violence	(6) Against Police	(7) Driving crimes	(8) Drugs
T - 7	0.899	**0.912*** **	1.040	0.916	1.264	1.145	0.835	0.874
	(0.0664)	**(0.0232)**	(0.0826)	(0.118)	(0.195)	(0.335)	(0.185)	(0.372)
T - 6	**0.765*** **	**0.898*** **	0.964	0.922	**0.670** **	1.134	0.686	0.858
	(0.0635)	**(0.0249)**	(0.0831)	(0.112)	**(0.132)**	(0.306)	(0.204)	(0.274)
T - 5	0.925	**0.922*** **	0.956	0.886	0.988	1.387	0.946	0.922
	(0.0684)	**(0.0262)**	(0.0842)	(0.110)	(0.180)	(0.349)	(0.132)	(0.180)
T - 4	0.903	**0.936*** **	1.024	**0.789***	1.228	0.892	0.640	0.799
	(0.0675)	**(0.0240)**	(0.0875)	**(0.0969)**	(0.190)	(0.287)	(0.223)	(0.164)
T - 3	0.936	**0.924*** **	**0.866** **	0.953	0.955	0.683	0.973	0.910
	(0.0608)	**(0.0276)**	**(0.0614)**	(0.100)	(0.158)	(0.200)	(0.137)	(0.161)
T - 2	0.999	**0.909*** **	0.932	1.023	1.049	1.303	0.818	0.777
	(0.0646)	**(0.0228)**	(0.0645)	(0.120)	(0.146)	(0.374)	(0.129)	(0.145)
T - 1	**0.873** **	**0.917*** **	1.034	**0.794***	0.965	0.662	**0.719***	0.759
	(0.0592)	**(0.0289)**	(0.0644)	**(0.0949)**	(0.157)	(0.199)	**(0.141)**	(0.135)
T + 1	0.934	0.951	1.062	1.008	1.092	0.784	0.900	0.890
	(0.0727)	(0.0433)	(0.0706)	(0.121)	(0.144)	(0.230)	(0.134)	(0.168)
T + 2	**1.164***	**1.152*** **	**1.173** **	0.970	0.866	0.831	0.972	0.905
	(0.0937)	**(0.0591)**	**(0.0826)**	(0.118)	(0.114)	(0.202)	(0.128)	(0.167)
T + 3	**1.220** **	**1.165** **	**1.183** **	0.870	1.145	1.451	0.983	1.250
	(0.103)	**(0.0753)**	**(0.0861)**	(0.111)	(0.165)	(0.358)	(0.105)	(0.195)
T + 4	1.110	**1.232*** **	0.974	1.143	1.274	1.447	**1.191***	1.299
	(0.101)	**(0.0755)**	(0.0864)	(0.140)	(0.199)	(0.347)	**(0.110)**	(0.240)
T + 5	1.099	**1.218*** **	**1.246*** **	1.022	1.025	1.261	1.022	0.710
	(0.123)	**(0.0841)**	**(0.100)**	(0.124)	(0.187)	(0.290)	(0.106)	(0.194)
T + 6	1.165	**1.340*** **	**1.193***	**1.264** **	1.285	0.866	1.013	**1.683** **
	(0.116)	**(0.0949)**	**(0.120)**	**(0.144)**	(0.246)	(0.199)	(0.106)	**(0.359)**
T + 7	1.165	**1.339*** **	**1.192***	**1.264** **	1.284	0.866	1.013	**1.682** **
	(0.116)	**(0.0948)**	**(0.120)**	**(0.144)**	(0.245)	(0.199)	(0.106)	**(0.358)**
Observations	29,123	29,123	29,123	29,123	29,123	29,123	29,123	29,123
Climate controls	YES	YES	YES	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES	YES	YES	YES
Seasonal controls	YES	YES	YES	YES	YES	YES	YES	YES
Monthly trends	YES	YES	YES	YES	YES	YES	YES	YES
Yearly trends	YES	YES	YES	YES	YES	YES	YES	YES
Lunar phase	YES	YES	YES	YES	YES	YES	YES	YES
Holiday dummy	YES	YES	YES	YES	YES	YES	YES	YES
Derby dummy	YES	YES	YES	YES	YES	YES	YES	YES
Type of competition	YES	YES	YES	YES	YES	YES	YES	YES

Note: see notes to Table 3.7.

[40] Barcelona football fans traditionally meet at the *Canaletes* fountain in the city center to celebrate their victories.

Table 3.9 presents the time profile of crime in the hours leading up to and following FCB away matches. In this case the results seem quite clear: *Thefts* fall prior to the game and increase after it (at an increasing rate whereas after home games the rate appears to decrease with time). Some weak evidence of a lower level of crime prior to the game can also be observed for *Robberies*, *Violent crimes*, and *Driving crimes*. In common with home games, in the hours following the match, people typically go to bars and meet with friends to celebrate or to console themselves in defeat. This can create large crowds that attract pick pockets, increase *Criminal damage* (including urban furniture) or, by increasing the level of social interaction, lead to higher levels of interpersonal violence.

In sum, the results obtained for the temporal impact of away matches on crime broadly confirm the patterns observed for home matches. The differences observed can be attributed to the spatial dimension, which has purposefully been omitted from the present analysis. Clearly, the high spatial concentration of individuals when FCB play at home is likely to be the driver for some of the results obtained during home matches and not during away matches, such as the increase in crimes *Against police* observed during home games.

3.6. Further results

Note, that all the results obtained up to this point seem to indicate that football matches do not have any effect on *Gender violence*. However, and as reported by Card and Dahl (2011), what seems to spark family violence (and violence in general) are defeats. Indeed, in such instances the authors find a direct relationship between these emotional cues and crime,[41] which suggests this type of crime may occur after a football match. Here, our results (see Table 3.10) point to the presence of this temporal displacement effect, indicating that it is a relevant crime type to analyze from a temporal perspective. Indeed our results show a positive and significant effect of defeats on *Gender violence*. Thus, from between two and four hours after a defeat, there appears to be an effect on violent behavior in a family related environment, with such crimes rising by up to 150%. A similar result was reported by Card and Dahl (2011) for the case of the NFL in North America. In the case of non-family *Violent crimes*, there does not appear to be a consistent increase, though five hours after a defeat an increase in the number of violent crimes is noted.

[41] Our sample includes 25 defeats and 56 draws in total. Of these, 15 defeats and 38 draws occurred in away matches.

Table 3.10: Psychological effects of an FCB defeat.

	Violent crimes	Gender violence
T + 1	0.658	0.932
	(0.296)	(0.464)
T + 2	0.813	**1.565***
	(0.416)	**(0.411)**
T + 3	0.827	1.045
	(0.380)	(0.405)
T + 4	1.104	**1.673****
	(0.565)	**(0.439)**
T + 5	1.353	0.826
	(0.552)	(0.369)
T + 6	**3.050*****	1.057
	(1.004)	(0.297)
T + 7	1.418	1.069
	(0.711)	0.932
Observations	29,123	29,123
Climate controls	YES	YES
Time controls	YES	YES
Seasonal controls	YES	YES
Monthly trends	YES	YES
Yearly trends	YES	YES
Lunar phase	YES	YES
Holiday dummy	YES	YES
Derby dummy	YES	YES
Domestic dummy	YES	YES

Note: see notes to Table 3.7.

3.7. Discussion

The results reported above regarding the temporal displacement effect of football matches on crime rates require a fuller discussion. As already mentioned, the results associated with home matches can be explained if we take into account the spatial dimension. For instance, the fact that the number of *Thefts* increases an hour before the match would seem to indicate that offenders take advantage of the agglomeration of supporters entering (or congregating near) the stadium. Although a proper spatial analysis needs to be conducted to confirm that this increase in *Thefts* is due to the agglomeration of football fans, the fact that a similar increase does not occur before away matches provides partial confirmation.

The results obtained in the hours leading up to a home match can be accounted for in terms of a substitution effect. That is, since large numbers of police officers are deployed in order to safeguard citizen security around the stadium, less attention is given to other criminal activities (for instance, drug consumption, dangerous driving or alcohol consumption) and so crime reports fall (especially since these crimes are reported by the authorities themselves). In the case of *Drug related crimes* this effect also appears to last for an hour after the game. These results again are confirmed by the apparent effect of away matches, which as expected present no impact on these types of crime, given the absence of any substitution effect.

Importantly, therefore, our estimates, after controlling for a wide range of possible temporal determinants, indicate that certain crime types increase after FCB football matches. Some of these increases can be attributed to victory celebrations or the commencement of weekend leisure activities after watching the game, accompanied by consumption of alcohol. This is the case of *Robberies*, *Criminal damage*, and *Violent crimes*, regardless of whether FCB have played at home or away (albeit in different time spans), indicating that this impact can be attributed, in general, to the euphoria occasioned by football. Logically, crimes *Against the police* only increase after home matches, attributable to agglomerations and problems of euphoric crowds clashing with police officers in the vicinity of the stadium.

3.8. Conclusions

This Chapter has presented the first detailed temporal analysis of crime in an urban context, with a particular focus on the hourly displacement of crime patterns attributable to the scheduling of a major sporting event (i.e., FC Barcelona's football matches). In short, we have analyzed the principal effects of these games on crime before, during and after the match.

First, as expected, the results reveal a clear time pattern for criminal activities. Although different patterns are found according to the specific type of crime under analysis, we can report a number of stylized facts. Crimes most closely associated with leisure activities (e.g., crimes *Against police*, *Driving crimes* and *Drug related crimes*) peak late at night, presenting low rates during the day-time which increase as the evening progresses. Crimes against property (*Robberies*, *Thefts* and *Criminal damage*) peak after 18:00 (associated with people coming out of work on weekdays), but fall again as the night progresses. Crimes involving violence (*Violent crimes* and *Gender violence*) gradually increase throughout the day and peak in the evenings. Additionally, we find evidence of a week-end effect for all crimes, while some types of crime present a marked seasonal pattern, especially those most closely associated with tourism (*Violent crimes* and *Thefts*).

Second, our results point to the temporal impact of football matches on crime rates. Thus, we find a fall in some types of crime in the hours before an FCB football match is played and an increase in some types of crime afterwards. The reduction in crime prior to a match would appear to be capturing the incapacitation effect of potential offenders, whereas the post-match increase appears to depend on the type of crime. Thus, increases in *Thefts*, *Robberies* and *Criminal damage* occur regardless of whether FCB have played at home or away, indicating that offenders are taking advantage of victory celebrations or the initiation of post-match leisure activities. Other significant increases appear to be related to the spatial distribution of individuals in association with the match that has just been played; thus, for instance, the increase in crimes *Against police* reported after home games but not after away matches appears to point to the impact of spatial concentration on crime.

Our study identifies an interesting impact that is likely to be related to the possible substitution effect experienced by some types of crime and which reflects the specific deployment of police resources during a football match. In general, during major events, such as FCB matches, police officers inevitably switch their attention away from fighting certain types of crime in favor of safeguarding citizen security in and around the event. For example, police check points or random checkpoints are not manned with the subsequent fall in the number of reports of drunk driving, drug consumption or drug smuggling.

In general, football matches do not appear to have any impact on rates of *Gender violence*; however, an increase is noted when the sample is restricted to those games in which FCB were defeated, and so we obtain some evidence of a link between sports results and violence in the family.

The results reported herein provide new, broader evidence on the crime patterns produced on football match days, pointing to the temporal displacement effects that football matches may have on crime. As such, it is our belief that these results can be useful in determining the temporal deployment of police officers on match days as well as in understanding the way in which offenders behave according to the characteristics of a match day. Further research needs to be focused on spatial analyses, which should illustrate how the crimes are spatially distributed across the city and how football matches can alter these crime patterns. Similarly, closer collaboration with police agencies should improve the data available for researchers, since a knowledge of the actual allocation of police officers and their deployment during a match is essential for identifying crime displacement and concentration effects.

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Chapter 4

When police patrols matter. The effect of police proximity on citizens' crime risk perception.

4.1. Introduction

Crime is a major concern for both individuals and governments in many countries. Its negative effects on people's well-being as well as its direct economic and social costs justify devoting large quantities of public resources to its prevention and control.

From an individual standpoint, crime affects the well-being of those that directly suffer criminal activity and, more generally, of all citizens through the insecurity it creates.[42] At an aggregate level, governments dedicate a sizeable share of public resources to crime prevention and control. A wide range of policies are employed to reduce criminal attitudes and here police forces are the main tool used. Proximity or community policing is frequently the strategy adopted to reduce insecurity.[43] In the US, the Community Oriented Policing Services (COPS) Office[44] recognizes that people need not only to be safe, but to feel safe. As Cordner (2010) points out, "*treating both of these issues [to be safe and to feel safe] as two parts of a greater whole is a critical aspect of community policing*".

In this Chapter we estimate the main individual and neighbourhood determinants of citizen insecurity in the City of Barcelona (Spain)[45] by using a multilevel ordered logit

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[42] Citizen insecurity is a common concern. For instance, in Latin America and the Caribbean, one of the regions with the highest homicide rates in the world, feelings of insecurity in the region are widespread (see Latinobarometro, 2009:77) and studies from the Inter-American Development Bank show that around 60% of the population report not feeling safe in their neighbourhoods. In a European country such as Spain, with much lower crime rates, the Centre of Sociological Research reported that citizen insecurity, between 2006 and 2008, was among the three main concerns of almost one in every five Spaniards (note that, in this case, citizen insecurity does not include concerns about terrorism).

[43] Proximity units comprise police officers that work in the community with citizens. The officers, who typically patrol on motorbike or on foot, are therefore more visible and are able to establish contact with citizens, associations and neighbours in order to learn about their main problems and needs on matters of security.

[44] http://www.cops.usdoj.gov/ (last accessed October 2014).

[45] The City of Barcelona is a large, highly populated, modern, tourist city where petty crime rates are on the increase. Newspapers tend to focus increasingly on the impact of pick-pocketing and burglaries on crime risk perception; see for instance La Vanguardia (2012);

model and a unique individual victimization survey for the period 2008 - 2010. By drawing on such a rich dataset for an urban setting[46] we are able to address various issues, including a number of new questions, regarding crime risk perception and so contribute substantially to the existing literature. First, we report new evidence about individual and neighbourhood determinants of perceived insecurity (measured as crime risk perception). Second, we examine the effect of police proximity on people's crime risk perception, controlling for the spatial effects of citizen evaluation of police performance as well as other neighbourhood characteristics. Third, we are able to overcome two important identification problems; on the one hand the likely problem of endogeneity between police proximity and the individual level of insecurity by means of exogenous source of interaction between these two variables, and on the other hand the likely problem of the endogenous sorting of individuals across neighbourhoods by means of a subsample of the surveyed individuals.

Our main finding is that the simple fact of being stopped by a police officer (in a traffic control) to be a signal of police proximity lowers the level of crime risk perception, albeit only for those individuals that had not recently suffered victimization. Hence, we find a positive causal relation between police forces and individual security feelings. These results add to the empirical literature concerned with understanding the impact of the police on crime (Corman and Mocan, 2000; Di Tella and Schargrodsky, 2004; Draca *et al.*, 2010; Evans and Owens, 2007; Klick and Tabarrok, 2005; Levitt, 2002; McCrary, 2002) and on citizens' insecurity (Della-Giustina and Silverman, 2001; Ferguson and Mindel, 2006; Groff *et al.*, 2013; Moore and Trojanowicz, 1988; Pate *et al.* 1987; Trojanowicz, 1982). This literature had not produced clear cut results in part due to the difficulty and methodological challenges faced when trying to establish causal relations between these variables.[47] A shortcoming we rectify here.

Moreover, the need still exists to obtain a better understanding of the determinants of individual crime risk perception, especially as to how individual and neighbourhood

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http://www.lavanguardia.com/sucesos/20121129/54355929103/consecuencias-psicologicas-robos-domicilios.html (last accessed October 2014).

[46] Note that the literature on crime acknowledges that the urban setting is the optimal environment in which to analyze the determinants and impact of criminal behaviour. For instance, cities present higher crime rates than rural areas and, moreover, in urban settings social interactions (crucial nowadays to our understanding of criminal behaviour) are more prevalent (Glaeser and Sacerdote, 1999).

[47] For instance, as police resources may be allocated geographically according to the level of criminal activity across an area, results would tend to indicate that a greater number of police officers increase criminal activity, unless police intervention is random and exogenous.

characteristics interact in shaping people's insecurity. Such an analysis should help in the design of preventive public policies that can be effective in reducing crime risk perception. There is also a need to evaluate the impact of police on reducing crime risk perception as this should provide essential insights as to the effectiveness of public resources devoted to security issues, at least as regards those aimed at increasing individual well-being and, hence, the overall well-being of society.

In short, in the light of the existing literature, given the importance of the analysis of the determinants of crime risk perception, and the debate on the effectiveness of police measures to reduce this perception, here we focus on the individual and neighbourhood determinants of crime risk perception paying special attention to the impact of police proximity. This analysis is novel not only for Spain but also for the European case, and serves to contrast the results obtained here with those in the broader literature focused mainly on the US case.[48]

The remainder of the Chapter is organised as follows. Section 4.2 describes the data and the institutional setting. Section 4.3 presents our empirical approach and the potential estimation problems. Section 4.4 presents the results obtained. Finally, section 4.5 summarizes the main conclusions of the study.

4.2. Data description and institutional details

4.2.1 The city of Barcelona

Barcelona is one of Spain's largest cities with a population in 2011 of over 1.5 million inhabitants. It lies in the Autonomous Community of Catalonia, on the north-east coast of Spain, and is one of the country's leading tourist destinations and a magnet of economic activity. This modern, open, international city is organized in 38 neighbourhoods and 10

[48] In particular, quantitative studies linking crime, crime risk perception and police forces are scarce for the European case. The British case has been examined drawing on the well-known British Crime Survey (Gray *et al.* 2008). Other studies include one conducted for Greece by Tseloni and Zarafonitou (2008), while for Spain the only analysis relating fear of crime and police interventions is that undertaken by Medina (2003) who shows that the so-called Belloch Plan (named after the head of the Spanish Home Office, the socialist Juan Alberto Belloch (1994-1996), involved increasing the number of police officers in Spain's main cities in 1995 in order to increase public safety, reduce the fear of crime and cut the response time to emergency calls) did not have any impact on people's fear of crime but it did have an effect on people's perception of the police.

districts, over which four police forces have jurisdiction.[49] Spain's process of decentralization granted Catalonia its own police force, the *Mossos d'Esquadra*, which plays the leading role in the region's security. In addition, Barcelona operates a local police force, the *Guardia Urbana*, which is also responsible for security at the city level. The main Spanish State police forces, the *Cuerpo Nacional de Policia* and the *Guardia Civil*, have retained some competences in Barcelona following the deployment of the autonomous police in 2005, including administrative duties (issuing of ID/passports and immigration documentation) and the fight against terrorism and other specific crimes (drug trafficking, organized crime, etc.). Here, we examine the impact of both the local and the regional police forces (*Guardia Urbana* and *Mossos d'Esquadra*) on crime risk perception given that they are known to be the closest to the citizens.[50]

4.2.2 Individual survey data

We use individual level data from the Barcelona public security survey, a victimization survey carried out annually by the City Council.[51] The survey was first carried out in 1984 and it consists of between 4,500 and 6,000 phone interviews conducted each year with Barcelona residents across the 38 neighbourhoods. The survey explores victimization experiences and gathers information about the respondents' socio-economic and personal characteristics. Importantly, its sampling methods are representative at the neighbourhood level. The survey is divided in three parts: the first collects the respondents' personal information; the second enquires about the possible victimization of individuals and gathers detailed information about criminal acts they have suffered; the third (which is carried out with just 50% of those surveyed) records opinions about the police forces and safety issues.

In this study, we use data for the years 2008, 2009 and 2010,[52] giving a total number of, after removing missing values, 11,608 individuals.[53] The survey is not conceived as a

[49] A fifth police force, the "Harbour Police", does operate but it only has jurisdiction over the traffic within the city's harbour and, as such, has no impact on common crime typologies such as property crimes or crimes against the person.

[50] In the case of Catalonia one of the main goals of the regional police (*Mossos d'Esquadra*) is to reduce citizen insecurity and, so, many police officers patrol the streets not only to prevent crime but also to make citizens feel safer.

[51] Table 4.1 presents the basic descriptive statistics of the variables described in this section and used in the empirical estimations.

[52] We choose this sample period as the data for earlier years presented problems of homogeneity for the time span of the main variables of interest, which could affect the interpretation of our results.

panel since respondents change from one year to the next. Therefore, in order to take advantage of all the data available, we construct a pooled cross-sectional database for the three years of study including all the variables of interest.

Table 4.1: Descriptive statistics.

Individual/Neighbourhood variables	Obs.	Mean	Standard Dev.	Min.	Max.
crime_risk_perception	11,608	1.68	0.98	0	4
police_call	11,608	0.22	0.41	0	1
police_stop	11,608	0.14	0.35	0	1
age	11,608	46.19	17.85	16	95
gender	11,608	0.51	0.50	0	1
victim_property	11,608	0.35	0.48	0	1
victim_person	11,608	0.06	0.24	0	1
foreign_born	11,608	0.09	0.28	0	1
education	11,608	4.14	1.47	1	9
N_crime_rate	11,608	0.38	0.13	0.19	0.89
N_incivilities	11,608	5.79	0.63	3.96	6.79
N_male_immigrant	11,608	3.46	1.89	1.71	10.73
N_youth_male	11,608	9.67	1.41	7.33	17.29
N_average_income	11,608	3.01	0.07	2.64	3.17
N_education	11,608	3.95	0.46	3.09	4.83
N_election_partc	11,608	51.87	5.49	32.87	60.91
N_police_perception	11,608	5.68	0.19	5.34	6.29

Dependent variable

Our main dependent variable, "*crime_risk_perception*" is based on the following survey question: "*Assess from 0 to 4 the level of insecurity in your neighbourhood where 0 means very unsafe and 4 means very safe*".[54] This measure of insecurity can be considered as being close to the concept of crime risk perception as it assesses the cognitive component of perception more than it does its emotional component. Therefore, henceforth we refer to our dependent variable as individual crime risk perception. Note to facilitate the interpretation of the empirical results we reverse the valuation of the response (with 0 being very secure and 4 very insecure). According to Map 1 in Figure 4.1a some neighbourhoods present a high number of respondents with high levels of crime risk

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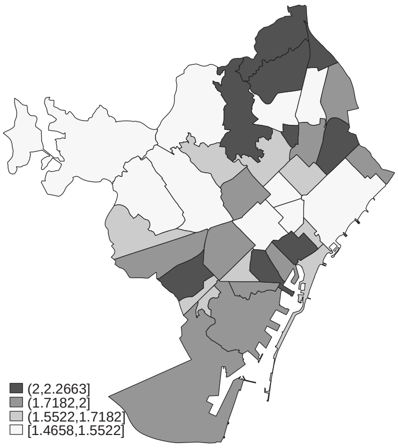
[53] Missing values represent around 2,000 observations; however, this does not constitute a risk of sample selection bias given that the deleted individuals do not systematically present a tendency not to respond to a certain type of question.

[54] From the outset it is essential we clarify what we understand by the main concept addressed in this study, namely, citizen insecurity. Insecurity, in the broad and interdisciplinary literature dealing with it, is given a wide range of interpretations, but typically two related concepts are distinguished: fear of crime and crime risk perception. LaGrange and Ferraro (1987) suggest that the former can be conceived as the emotional or affective component of perception, while the latter is the cognitive component of perception. However, as further suggested by LaGrange *et al*. (1992) perceived risk mediates the effect on emotionally generated fear. In other words, the greater the individual's crime risk perception, the greater is their fear of crime. This is confirmed by Wilcox and Land (1996) who report considerable alignments between these two concepts.

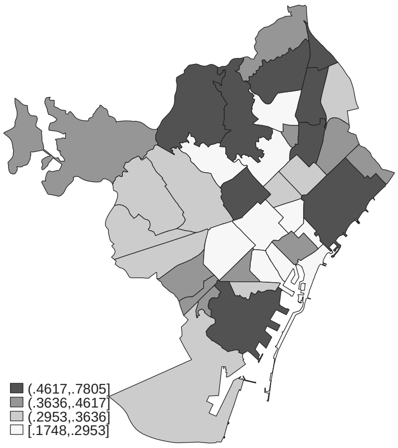
perception especially in the north-east and south-west of the city, corresponding to neighbourhoods that present specific socio-economic characteristics, as we see below.

Figure 4.1a: Maps for main variables of interest across the 38 Barcelona neighbourhoods

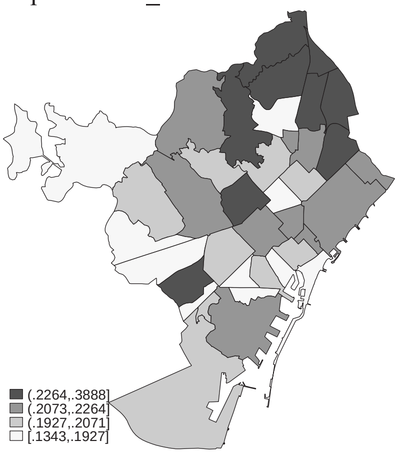
Map 1: Crime risk perception



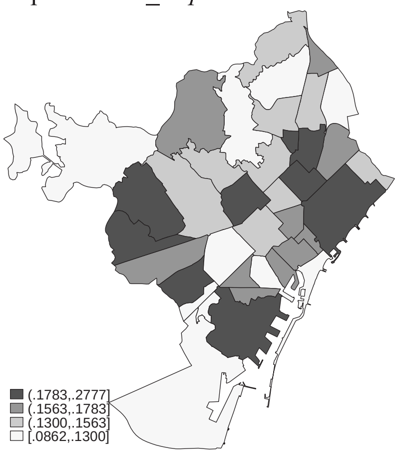
Map 2: Distribution of victimization index



Map 3: *Police_call*



Map 4: *Police_stop*



Individual exposure to police forces

The survey offers two possible approximations for our variable of interest, that is, a measure of police proximity. These two variables are "*police_call*" and "*police_stop*". The first variable is a dichotomous variable taking a value of 1 if there has been contact between the individual and the police either by telephone (a request for help, a complaint or a request for information) or in person (reporting crimes to the police) and 0 otherwise. Note, however, that this variable can suffer from reverse causality given that an individual's level of risk perception can determine their propensity to contact the police. To overcome this problem, we employ an exogenous (to the individual crime risk perception) variable that is indicative of police proximity. In this case, "*police_stop*" is also a dichotomous variable taking a value of 1 if someone has been stopped by a police officer and 0 otherwise. In our survey, we select those individuals that have been stopped because of an alcohol/drug test when driving or in routine traffic controls (documentation). We consider this variable as exogenous because police stops citizens independently of their individual crime risk perception, while the location of police officers when stopping individuals for car/documentation controls is also exogenous to the neighbourhood crime level. By using this variable our estimations of police-citizen contact can be seen as being causal and not as being driven by reverse causality issues.[55]

We believe that the interaction with police forces, in the form being pulled over in a car control, can psychologically affect the individual crime risk perception even if the control is performed in a place different from the individual's usual residence. In this sense, police stops are not perceived by individuals as relevant regarding the characteristics of where they are performed (many of them change location to increase effectiveness and are set randomly). Individuals in general perceive car controls as police at work more than as a proxy for the level of crime in the place where the control is set.

In our sample 21.2% of the respondents reported having had contact with the police ("*police_call*") and 16.24% had been stopped ("*police_stop*"). Maps 3 and 4 (in Figure 4.1a) present the distribution of these variables across the neighbourhoods. As expected the spatial distribution of the "*police_call*" variable resembles closely the distribution of the victimization index (see Map 2 in Figure 4.1a) and this should also determine a higher presence of police officers in these neighbourhoods. Note, however, that given its nature, the spatial distribution of the "*police_stop*" variable does not appear to be related to the victimization index. Therefore, we employ this "exogeneity" to identify the impact of police contact on crime risk perception.

The expected results of the impact of citizen-police contact on individual crime risk perception could, in principle, be either positive or negative. A negative impact (a positive sign in our multilevel ordered logit model) would imply that someone that has been stopped by the police is more likely to report lower levels of crime risk perception than someone who has not (a greater sense of protection). By contrast, a positive impact might also occur if an individual's crime risk perception is increased after their being stopped (a greater sense of danger). Indeed, Braga (2001) and Hinkle and Weisburd (2008) report that

[55] See section 4.3.1 for more details on the exogeneity of the variable "*police_stop*" with respect to the individual crime risk perception.

those living in neighbourhoods where police crackdowns are frequent, despite the reduction in crime, may suffer an increase in their levels of crime risk perception.

Other individual explanatory variables

Moreover, we include several variables that may affect people's crime risk perception. First, we account for an individual's physical and social vulnerability by including a dummy variable ("*gender*") that takes a value of 1 if the individual is a woman and 0 otherwise. We also include the age of the individual ("*age*") since, like women (Ferraro, 1996), the elderly are also expected to present less physical strength and competence (Clemente and Kleiman, 1977) and, hence, a higher crime risk perception.[56]

The literature has also identified a strong relationship between crime risk perception and prior direct or indirect (knowing a victim) victimization (Ho and McKean, 2004; Mesch, 2001; Rountree and Land, 1996; Skogan, 1986; Tseloni and Zarafonitou, 2008). This relationship has been found to be both positive and negative. In the former case, being victimized eliminates people's belief of their being invulnerable to negative events and of their living in a substantially benevolent and meaningful world (Janoff-Bulman, 1989). In the latter case, Hill *et al.* (1985) and McGarrell *et al.* (1997) report that previous victimization might lead some individuals to believe that they are at greater risk of future victimization, but those who have experienced prior victimization might also avoid certain areas or people they deem dangerous, thereby reducing their perceived vulnerability and fear. An alternative explanation is that individuals who were previously victimized may consider that the odds of their suffering another crime are now quite low. As such, they might present lower levels of crime risk perception.

In our empirical model we include the variables "*victim_property*" and "*victim_person*" to account for prior victimization related to crimes against property or crimes involving interpersonal violence, albeit with a number of restrictions. First, the variables account solely for direct victimization, since no questions are asked about relatives/friends' victimization and, second, the survey enquires solely about victimization experiences during the previous year. It should be pointed out that prior victimization may not be correlated with crime risk perception if unobservable characteristics of individuals are not taken into account (Maris and Ortega, 2013). However, as the authors point out,

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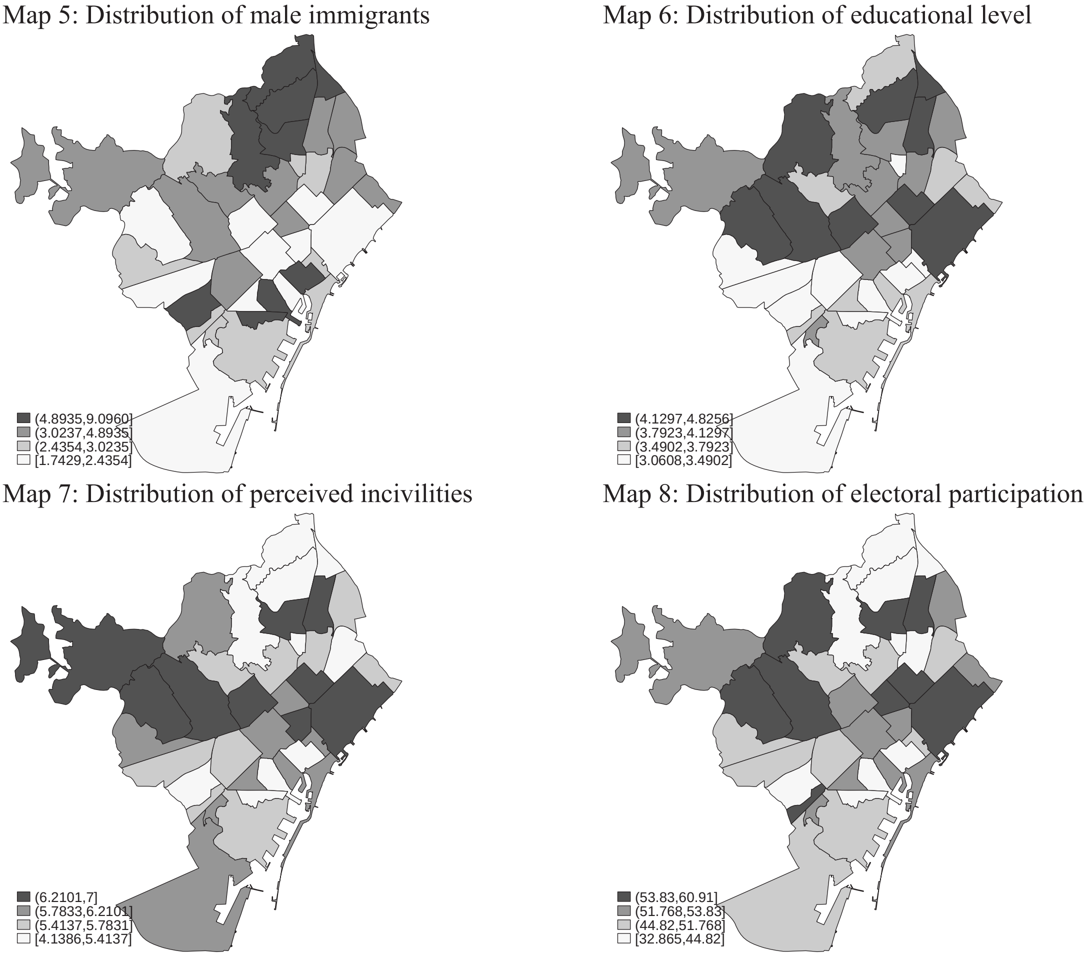
[56] Rountree and Land (1996) showed that this result may be reversed if instead of crime risk perception a study uses the emotional fear of crime as its dependent variable.

using pooled cross sections can overcome this issue. Map 2 (in Figure 4.1a) plots the overall victimization index and shows that the spatial distribution does not necessarily coincide with that of crime risk perception.

We include the variable "*foreign_born*" which takes a value of 1 if the individual is foreign born and 0 otherwise. By adding this variable we seek to account for the effect of immigration on crime risk perception (Map 5 in Figure 4.1b presents the distribution of male immigrants across the 38 Barcelona neighbourhoods). Foreign born individuals may present a different level of crime risk perception if, for instance, in their countries of origin crime and violence are more common events or even if such events are perceived differently from a social perspective.

Figure 4.1b: Maps for main variables of interest across the 38 Barcelona neighbourhoods (cont)



We also include the individual level of education. The variable "*education*", plotted in Map 6 in Figure 4.1b, may influence the levels of crime and, therefore, the levels of crime risk perception. By including this variable we measure both the income level of each individual (given the correlation between income and education) and, also, the general level of knowledge that individuals possess. It seems reasonable to assume that the more educated perceive reality clearer as their sources of information tend to be broader. Similarly, they tend to socialize more (Lochner and Moretti, 2004) and read the press more frequently, which suggest that information concerning the reality of their neighbourhood is likely to be obtained almost instantly and in a clear fashion. This variable ranges from 1 if individuals have received fewer than five years of education (primary school completed) up to 9 if they have a university degree.

4.2.3 Neighbourhood data and variables[57]

As discussed above, we also conduct our estimates taking into account neighbourhood characteristics as possible determinants of crime risk perception in a multilevel framework. Our neighbourhood data are taken from the official statistics published by the Barcelona City Council. Given that we use data for three years at the individual level, we need to homogenize the yearly neighbourhood data. We do this simply by taking the average of each variable for each neighbourhood over the three-year period of study. By doing this, we cancel out any yearly fluctuations (white noise) in the neighbourhood variables (Hoogue *et al*., 2011) and we overcome the panel data structure drawbacks that multilevel models have. Hence, we implicitly assume a certain stability in the neighbourhoods' characteristics.

In the case of data being unavailable from the Barcelona City Council's Statistics Department, we draw on information from the survey clustered at the neighbourhood level. We include the victimization index of each neighbourhood "*N_crime_rate*" to account for the effect of the total neighbourhood victimization crime rate on individual crime risk perception (Roundtree and Land, 1996). Moreover, the "*broken window*" thesis claims that incivilities or minor disorders are likely to influence a chain of events that will affect crime risk perception.[58] To test this, we include the level of perceived incivilities at the

[57] To distinguish these from individual variables, we refer to the neighbourhood variables as "*N_namevariable*".

[58] The "broken window" thesis (Wilson and Kelling, 1982) holds that personal and neighbourhood characteristics can account for the fear of crime and even for crime itself. The thesis draws links between three important neighbourhood concepts, namely, disorder, fear and crime. Thus, a minor disorder such as a broken window, if left unchecked, will generate the perception that no one cares about it, generating increasing levels of fear. Levels of distrust among the neighbours rise and they start to behave differently -

neighbourhood level calculated as the average of the perceived incivilities for all the individuals belonging to a certain neighbourhood, "*N_incivilities*", in order to approximate these minor disorders. This variable is defined from 0, many incivilities perceived in the neighbourhood, to 10, no incivilities perceived (see Map 7 in Figure 4.1b).

The neighbourhood composition may also affect people's crime risk perception since those living in neighbourhoods with a large influx of immigrant population may perceive this as "an invasion" by different racial and ethnic groups (Skogan, 1995). If the local population are prejudiced towards immigrants and hold them responsible for increased crime rates,[59] seeing immigrants around the neighbourhood might be interpreted as a sign of their being at a greater risk of falling victim to crime. For this reason, we include the variable "*N_male_immigrant*", defined as the proportion of male immigrants in each neighbourhood. Similarly, we also control for the number of male youths "*N_youth_male*" since, as Buonanno and Montolio (2009) point out for the Spanish case, young people are more likely to engage in criminal activities. Socio-economic status is also one of the main determinants of crime risk perception (Wyant, 2008) and, here, we employ the average income "*N_average_income*" of individuals in each neighbourhood to obtain an approximation of this status.

Following Lochner and Moretti (2004), who find that education increases opportunities of obtaining legitimate rents from the legal labour market, which implies that education may negatively affect both property and violent crime and, consequently, lead to an overall reduction in the crime risk perception, we introduce the average level of education in the neighbourhood "*N_education*".

We also consider a proxy for the level of social capital in the neighbourhood since community values, relationships between individuals and involvement in public affairs may create a sense of community trust and union. We include an approximation of the neighbourhood level of social capital, "*N_election_partc*", which is the voter turnout at the 2006 local elections (see Map 8 in Figure 4.1b). In this regard, social capital is seen as an increasing function of participation in civic life, and voter turnout has been used broadly as an approximation of social capital since it is hypothesized to capture civic involvement and participation in community decision making. Again, the larger this share, the greater the

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staying at home more and socializing less with each other. In turn, this leads to a reduction in natural surveillance permitting further disorder and minor crimes.

[59] The 2008 European Social Survey revealed that almost 40% of Spanish citizens surveyed agreed or strongly agreed that "immigrants make the country a worse place to live in".

implication of individuals in public affairs and, therefore, we would expect a negative effect on crime risk perception.

Finally, we also control for the average perception of the tasks performed by the police as revealed by the individuals surveyed in each neighbourhood. As shown by Asadullah and Chaudhury (2012), the institutional quality may influence the citizens' well-being. This variable, "*N_police_perception*", takes a value from 0 (highly unfavourable view of police forces) to 10 (the highest assessment of their work). A priori, we expect that the better the outcomes of police officers in solving neighbourhood crime, the higher the assessment given by individuals and therefore, the lower the level of crime risk perception.

4.3. Empirical strategy

4.3.1 Endogeneity issues of crime risk perception and police contact

Our empirical approach is parsimonious and we begin by running a multilevel cumulative logit model (see Appendix A for technical details) in which individual and neighbourhood level control variables are introduced.[60] Our variables of interest can then be added. First, we include the "*police_call*" variable which, as explained, is potentially endogenous, that is, its estimated coefficient may be biased because individuals who present a higher crime risk perception are more likely to contact the police when they witness something suspicious. For instance, someone with a high crime risk perception that sees a group of youths in the park at night may call the police because she believes they are likely to cause trouble (get into fights, consume drugs, vandalise public facilities, etc.). As such, police contact may reflect a positive impact on crime risk perception.

Therefore, the key concern in our estimates is that we address the causal effects of policing on individual crime risk perception properly. We deal with this endogeneity issue by using the alternative measure of police contact, the "*police_stop*" variable, which takes into account citizen-police contact when the former are stopped by the police. As previously explained this is, a priori, an exogenous measure since police traffic controls typically stop citizens "at random". Clearly, however, there are individual stereotypes that the police tend to pull over more frequently. Drivers of red cars, youths, and late-hour and weekend drivers are more likely to be stopped. However, while this is true for drug- and

[60] As a robustness test regarding the empirical model estimated, we provide in the Appendix B the (main) results using an ordered logit model (instead of our multilevel strategy) with neighbourhood and year fixed effects. In general, we qualitatively obtain the same results as those presented in the following sections.

drink-driving tests, there are also generic police car controls for documentation that, in principle, may stop any citizen independently of their age, appearance or vehicle type. In any case, it is not the case that the declared individual's "*crime_risk_perception*" can affect the probability of being stopped because it is declared afterwards any possible contact with the police.

As discussed in Cornaglia *et al*. (2014), an important issue to account for is the distinction between victims and non-victims, since previous victimization experiences may bias the relation between the "*police_stop*" variable and an individual's crime risk perception. More precisely, we expect police encounters to have a different effect on victims and non-victims given their previous experience. Here, victims are likely to have had recent contact with the police (during the previous year) and so it might be that coming into contact with the police again reminds them of their victimization experience, hence distorting the impact of police contact on crime risk perception. By contrast, for non-victims the effect of "exogenous" police encounters should, in principle, not be biased by previous experiences involving crime and, quite likely, the police.

4.3.2 Controlling for spatial issues and endogenous sorting of individuals

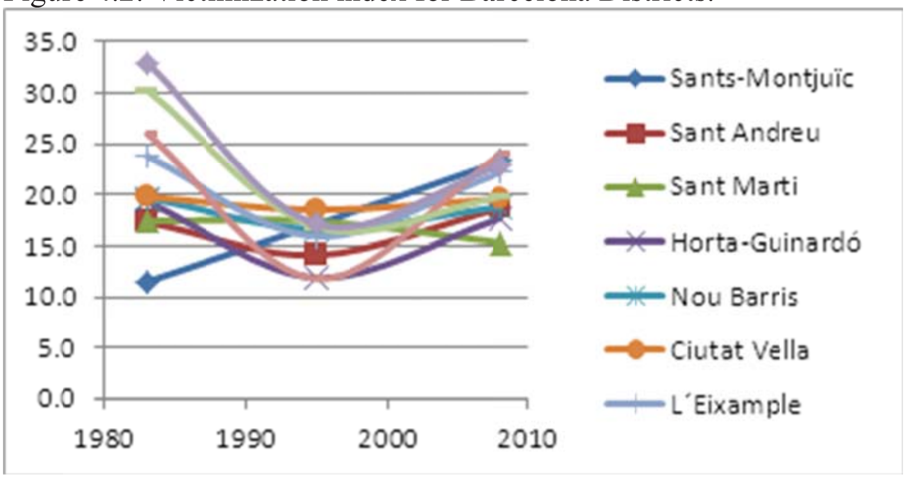
A further aspect to be taken into account when working in urban settings is spatial dependence. Individuals do not make their choices independently; their decisions and perceptions are also the consequences of their social environment (including their neighbours, friends or ethnic groups). These peer influences have given rise in the literature to the theory of social interactions (Akerlof, 1997). Since our dependent variable measures opinions expressed by individuals, responses are likely to be influenced not just by neighbourhood characteristics, but also by the characteristics of surrounding neighbourhoods, with the expectation that closer neighbourhoods are more likely to exercise an influence.

To address this important issue we include spatial lags for the dependent variable as well as for "*N_crime_rate*", "*N_incivilities*" and "*N_police_perception*" using a binary distance based matrix of 500 and 1,000 meters threshold (see Anselin, 1988). We consider that these variables will not only affect citizens' crime risk perception in a given neighbourhood, but given the distance (Barcelona occupies a municipal area of 101.4 km^2) and the high level of mobility between neighbourhoods (for reasons of work or leisure), they could also affect the crime risk perception of individuals in adjacent neighbourhoods.

Finally, a possible sorting problem of individuals across neighbourhoods, i.e. people with higher levels of crime risk perception tending to live in areas with lower levels of crime or with certain specific characteristics, should not have any impact on our main variable of interest ("*police_stop*") given its exogenous nature. However, it could have an impact on the estimated effect of the main neighbourhood explanatory variables. For instance, in the case of the "*N_crime_rate*" if we obtain a negative effect on crime risk perception, this correlation could be simply driven by the presence of unobservable factors and/or by an endogenous sorting of individuals into areas depending on, precisely, the crime rates. If this issue is not dealt with, the estimated results could be biased and, thus, lead to misleading conclusions.

In order to deal with the possible sorting problem, we restrict our sample to those surveyed individuals who have been living in the same neighbourhood for five years (or more). The intuition of this empirical strategy is that these individuals would have had to choose where to live several years ago, taking into account the characteristics of each neighbourhood (victimization indexes, number of immigrants, etc.) at that time. These characteristics may well have changed over the years and, consequently, people may be sorted according to the characteristics of the past but not to the characteristics of the years of the study. Figure 4.2 presents the evolution of the victimization index for the ten districts of Barcelona for 1983, 1995 and 2009. It can be seen, for instance, that the aggregate evolution of the victimization index has changed considerably over the years, which supports our strategy.[61]

Figure 4.2: Victimization index for Barcelona Districts.



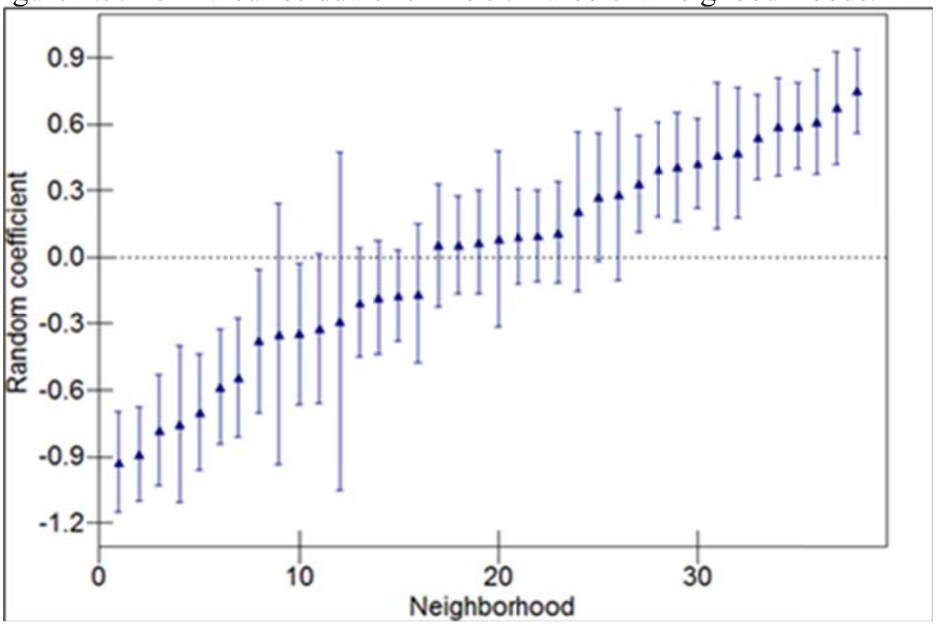
[61] Unfortunately, we do not have neighbourhood data of the victimization index for such a long period.

4.4. Empirical results and discussion

Tables 2 to 6 present the results for all the approaches adopted in the present study. To interpret the coefficients obtained when estimating our multilevel ordered logit model, and given the ordering of our dependent variable, note that a negative estimated sign for a given variable corresponds to a decrease in the probability of being in a lower part of the distribution of the crime risk perception and, hence, to a negative impact of that variable on the individual's crime risk perception (an increase in insecurity).

Before explaining the results in detail, it is worth determining the percentage of the variance of the individual crime risk perception that is due to neighbourhood characteristics. The results show that approximately 6.71% of the variance in the individual crime risk perception is due to neighbourhood characteristics. This seems to be lower than results in other studies including Taylor (1997) who reported a figure of 11% and Wyant (2008) who reported 12%.[62] Figure 4.3 confirms the need to account for the differences across neighbourhoods since several neighbourhoods are statistically different from the mean.

Figure 4.3: Estimated residuals for the 38 Barcelona neighbourhoods.



[62] However, when we use the data for just a single year, the variance is similar to that reported in these other studies.

4.4.1. Police effects on individual crime risk perception

Table 4.2 presents the results for the estimation of the determinants of the individual crime risk perception. In relation to our main variables of interest capturing police proximity to citizens, the results when using the "*police_call*" variable (column 1) present the expected negative sign, indicating that direct contact with the police decreases the probability of individuals reporting a lower level of crime risk perception (i.e., greater insecurity after contact with the police). However, as pointed out above, this variable suffers problems of endogeneity as it is quite likely that those that are most prone to feelings of insecurity will present a higher propensity to contact the police. The negative sign obtained for this variable seems to reflect this hypothesis.

Column 2 in Table 4.2 presents the results when using the alternative variable for police proximity, "*police_stop*", which captures the fact of being exogenously stopped by a police officer. Here, recall, we are confident that the estimated coefficients do not suffer the same bias as suffered by the "*police_call*" variable. The results are not statistically significant when we consider the effect to be the same for victims and non-victims; however, as shown above, the exclusion restriction (required for our empirical strategy to work) does not hold for the non-victims.

Therefore, in Table 4.3 we perform the estimations again, but now we distinguish between these two groups and we relax the proportional odds assumption, that is, up to this juncture we have assumed that the effect of the "*police_stop*" variable is the same across different types of respondents. However, the effect of contact with the police could differ across individuals depending on their crime risk perception: someone who is more fearful, in general, may be positively affected by contact with the police. By contrast, someone who does not perceive any risk of crime may not be affected by having contact with the police. By allowing the effect of the "*police_stop*" variable to vary across the intercepts we can capture these differences.

Table 4.2: Multilevel estimations for crime risk perception with "*police_call*" and "*police_stop*".

VARIABLES	(1) *Police_call*	(2) *Police_stop*
α_0	-12.72***	-13.09***
	(1.888)	(1.934)
α_1	-9.905***	-10.29***
	(1.887)	(1.933)
α_2	-8.221***	-8.613***
	(1.886)	(1.933)
α_3	-6.885***	-7.283***
	(1.886)	(1.932)
Individual level variables		
police_call	-0.403***	
	(0.0427)	
police_stop		-0.0295
		(0.0518)
gender	-0.257***	-0.263***
	(0.0350)	(0.0354)
age	-0.00714***	-0.00654***
	(0.00104)	(0.00105)
victim_property	-0.721***	-0.748***
	(0.0383)	(0.0384)
victim_person	-0.469***	-0.537***
	(0.0725)	(0.0721)
foreign_born	0.891***	0.877***
	(0.0652)	(0.0652)
education	0.0831***	0.0762***
	(0.0130)	(0.0130)
Neighbourhood level variables		
N_crime_rate	-0.340*	-0.346*
	(0.189)	(0.190)
N_incivilities	0.606***	0.599***
	(0.151)	(0.155)
N_education	-0.228	-0.225
	(0.166)	(0.170)
N_youth_male	0.0160	0.0191
	(0.0424)	(0.0435)
N_male_immigrant	0.0735	0.0687
	(0.0472)	(0.0483)
N_average_income	0.776*	0.812*
	(0.439)	(0.450)
N_police_perception	0.395*	0.427*
	(0.239)	(0.245)
N_election_partc	0.0538***	0.0547***
	(0.0194)	(0.0198)
η_{jk}	0.0308***	0.0334***
	(0.0106)	(0.0113)
Observations	11,602	11,602
Number of groups	38	38

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The intercepts (α_k) represent the log-odds of being in each category or lower.

Table 4.3: Multilevel estimations for crime risk perception with *police_stop*.

VARIABLES	*Non-Victims subsample*	*Victims subsample*
α_0	-12.84***	-12.01***
	(1.664)	(2.791)
*police_stop_*0	-0.302*	-0.227
	(0.156)	(0.181)
α_1	-9.991***	-9.434***
	(1.662)	(2.790)
*police_stop_*1	0.132	-0.216***
	(0.0844)	(0.0823)
α_2	-8.161***	-7.993***
	(1.660)	(2.788)
*police_stop_*2	0.481***	-0.0505
	(0.149)	(0.0889)
α_3	-6.824***	-6.649**
	(1.660)	(2.788)
*police_stop_*3	0.512*	-0.0773
	(0.270)	(0.130)
Individual level variables		
gender	-0.229***	-0.321***
	(0.0455)	(0.0569)
age	-0.00450***	-0.0101***
	(0.00129)	(0.00182)
victim_property		-0.525***
		(0.141)
victim_person		-0.443***
		(0.0949)
foreign_born	0.991***	0.699***
	(0.0866)	(0.100)
education	0.0950***	0.0436**
	(0.0165)	(0.0216)
Neighbourhood level variables		
N_crime_rate	-1.020***	-0.146
	(0.298)	(0.224)
N_incivilities	0.792***	0.330
	(0.138)	(0.230)
N_education	-0.100	-0.137
	(0.161)	(0.244)
N_youth_male	0.0265	-0.0223
	(0.0377)	(0.0628)
N_male_immigrant	0.0869*	0.0589
	(0.0453)	(0.0711)
N_average_income	0.791*	0.437
	(0.418)	(0.649)
N_police_perception	0.251	0.690*
	(0.222)	(0.357)
N_election_partc	0.0365**	0.0649**
	(0.0181)	(0.0282)
η_{jk}	0.0217***	0.0670***
	(0.00714)	(0.0241)
Observations	7,255	4,340
Number of groups	38	38

Note: see Table 4.2.

The results show that coming into contact with the police is more likely to affect those that present a high crime risk perception and who have not been victims in the previous year. In general, contact with the police reduces citizens' insecurity. As expected, for the subsample of victims this effect seems to be non-significant for almost all levels of crime risk perception, but when it is significant (for low levels of crime risk perception) it presents the opposite sign to that shown by non-victims; in other words, the crime risk perception of victims with low perception levels when being pulled over by the police tends to increase. As explained above, this would seem to be related to their recent experience with the police resulting from an earlier episode of victimization.

To fully interpret the results, it should be stressed the fact that individuals are stopped by the police in controls possibly located in other neighbourhoods or outside the city. As such, the channel via which the fact of being pulled over affects individuals' crime risk perception is likely to be psychological, since individuals are asked about their crime risk perception in their neighbourhood of residence. The fact that being stopped in a different neighbourhood affects individuals' (non-victims) crime risk perception suggests that individuals do not take into account where they have been stopped. Simply coming into contact with police officers gives non-victims a certain degree of security in their place of usual residence, even though this contact might have taken place in other locations.

The predicted probabilities of reporting a lower category of crime risk perception (feelings of greater security) for someone who has been pulled over by the police are shown in Table 4.4. The overall conclusion is that non-victims who have been randomly stopped by police officers have a lower crime risk perception (lower insecurity), especially when their level of crime risk perception is high. However, there is also evidence that for individuals with low levels of crime risk perception random contact with the police may increase their perception of insecurity.

Table 4.4: Predicted probabilities (non-victims).

	Police_stop = 0	*Police_stop* = 1
Predicted probability of reporting crime risk perception = 0	0.068	0.052
Predicted probability of reporting crime risk perception = 1 or lower	0.557	0.589
Predicted probability of reporting crime risk perception = 2 or lower	0.886	0.926
Predicted probability of reporting crime risk perception = 3 or lower	0.967	0.979

Note: All the variables have been fixed at their means or in the case of binary data at their proportions.

Finally, the joint estimation of the individual level equation jointly with the neighbourhood intercept (both the fixed and the random part) shows, as expected, that the effect of being stopped by the police does not vary significantly across neighbourhoods. This result, indeed, reinforces the exogeneity assumption of our main independent variable.

4.4.2. Individual and neighbourhood determinants of insecurity

Note that the obtained results for the individual and the neighbourhood variables are very similar in Table 4.2 and Table 4.3 (and across the various columns presented). More precisely, the approximation to the physical and social vulnerability of individuals' "*age*" and "*gender*" present a negative and statistically significant coefficient, implying that the elderly and women have a higher crime risk perception: more specifically, women ("*gender*" = 1) and the elderly are more likely to be in a higher category of crime risk perception. Moreover, the variables reflecting prior victimization against the person "*victim_person*" and against property "*victim_property*" reflect a negative estimate sign meaning that people who have suffered recent prior victimization (in the preceding year) are more likely to report a higher crime risk perception. Here our results are in line with those reported previously in the literature (see, for instance, Quann and Hung, 2002). Being a victim of a property crime has a greater effect on an individual's crime risk perception than being the victim of a crime against the person. This result is somewhat unexpected as we expected those who had directly suffered a crime against the person (for instance, an assault) to be more likely to feel insecure. However, the results seem to be driven by the fact that the majority of property crimes suffered in Barcelona involve muggings or larceny, which differ from a burglary where the victims tend not to see the criminals.

The results for the "*foreign_born*" variable present a positive sign, indicating that immigrants' crime risk perception is lower than that of residents. This result may be explained by the fact that foreign-born individuals (especially from developing countries) are used to (even worse) criminal environments in their countries of origin and, therefore, in relative terms, living in Barcelona might be perceived as being safer for them. This result contradicts findings reported by Skogan and Maxfield (1981) who found that racial and ethnic minorities tend to be more fearful. This difference might be due to the fact that in our study the racial issue is not explicitly taken into account (as we control for country of origin rather than race).

The "*education*" variable presents a positive and significant sign indicating that more educated people have a higher probability of being among the lower values of the crime risk perception variable, that is, less perception of insecurity. This seems to show that the social interactions of more highly educated citizens decrease their crime risk perception. Additionally, more educated people tend to be better informed and, consequently, understand the reality of their neighbourhoods more accurately.

As for the neighbourhood determinants of crime risk perception, our results seem to indicate that two of the variables are statistically significant, while the rest generally present the expected sign. Several results draw our attention. First, "*N_incivilities*" shows a positive estimated coefficient with crime risk perception,[63] indicating that the higher the citizens' assessment of incivilities in the neighbourhood, the lower the probability of their reporting a lower level of crime risk perception; or, in quantitative terms, on average, a one-point increase in the assessment of incivilities in the neighbourhood increases the probability of being in a higher category of the crime risk perception distribution by 0.60 (from results in Table 4.3). This effect is strongly significant serving to demonstrate that "fear in the urban environment is above all a fear of social disorder" (Hunter, 1978) and lending support to the "*broken window*" theory. Second, as expected, the "*N_crime_rate*" variable has a positive effect on crime risk perception. Thus, citizens living in neighbourhoods with higher crime rates are less likely to report a lower category of crime risk perception (greater insecurity). Third, the variable capturing each neighbourhood's social capital, approximated by "*N_election_partc*", also presents a positive and significant effect on crime risk perception. This suggests that the higher the political participation (i.e., a proxy of the levels of trust and civic involvement in community decision making) the higher the probability of citizens' reporting a lower level of crime risk perception.

4.4.3 Robustness checks

Spatial patterns

Table 4.5 presents the results for the multilevel ordered logit model when taking into account the spatial effects of some of the variables of interest.[64] The prefix W reflects the spatial lag of the variable that follows it. The two columns present different matrix

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[63] Recall that "*N_incivilities*" ranges between 0 (many incivilities perceived) and 10 (no incivilities perceived).

[64] Despite showing only the results for the spatial lagged variables, we introduce in the equation all variables.

definitions. When using binary distance based matrix of 500 metres threshold (first column) the results show positive and significant impact of all variables from neighbouring areas on individual crime risk perception (the weakest result is obtained for *W_police_perception*).

Table 4.5: Estimations for crime risk perception with spatial lags (whole sample).

	W= Binary distance based matrix of 500m threshold	*W*= Binary distance based matrix of 1,000 m threshold.
W_crime_risk_perception	0.0442**	0.0295*
	(0.0215)	(0.0151)
W_incivilities	0.0136**	0.0101**
	(0.00692)	(0.00495)
W_police_perception	0.0120*	0.00959*
	(0.00674)	(0.00502)
W_crime_rate	0.293***	0.134*
	(0.113)	(0.0702)
Individual variables	YES	YES
Neighbourhood variables	YES	YES
Observations	11,605	11,605
Number of groups	38	38

Note: Robust Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The individual and neighbourhood variables present the same sign and statistical significance as those reported in previous tables.

Column 2 of Table 4.5 uses a binary distance based matrix of 1,000 metres threshold showing consistent results, although with lower statistical significance as expected. The results show that, first, the higher the crime risk perception in contiguous neighbourhoods (greater insecurity), the higher the probability of a lower crime risk perception (greater security) being reported. Second, the perception of a greater number of incivilities in other neighbourhoods increases the level of crime risk perception (greater insecurity). This is logical if we realise that incivilities are directly perceived by individuals (unlike a neighbourhood's crime rate or a neighbourhood's crime risk perception), given that they can take the form of broken windows, dirty streets or abandoned cars in the street. Third, the spatial lag of "*N_police_perception*" shows the expected positive sign indicating that the higher the valuation of police forces in contiguous neighbourhoods, the greater the probability of a lower category of crime risk perception being reported. Fourth, the higher the crime rate in the contiguous neighbourhoods, the greater the probability of a lower level of crime risk perception (more security) being reported. This result can be explained by the fact that individual perceptions are expressed in relative terms. Thus, if individuals know that crime rates are higher in other neighbourhoods, they may think that their own neighbourhood is more secure.

Endogenous sorting

Table 6 presents the results for the restricted sample constructed to avoid possible problems of sorting of individuals into certain neighbourhoods. The sample comprises those citizens living in the same place for five years or more. Note that there are fewer observations in this sample because the question regarding length of residence was posed to just 50% of the individuals surveyed. Having fewer observations reduces the power of our estimations; however, we performed these estimations as it is the only way to deal with the potential endogeneity arising from the neighbourhood variables and the sorting of individuals in these neighbourhoods. Consequently, these results should be interpreted with some caution given that the individual observations may not be fully representative at the neighbourhood level and, as before, we further distinguish individuals between victims and non-victims.

Interestingly, our main variable of interest, "*police_stop*", presents the same effect as before. Citizens that have not recently suffered victimization and who present a high crime risk perception are positively affected (reduced crime risk perception) by the fact of their having been stopped by the police. Likewise, at the individual level, the variables seem to present the same signs with the exception of "*age*" which is no longer significant. Indeed, the individual variables should not change (sign and significance), since by restricting the sample only the neighbourhood variables should be affected. However, the minor variations in the results for the individual variables may, we believe, be driven by the reduction in the number of observations in the demanding multilevel estimations.

In the case of neighbourhood variables, when using the whole restricted sample, the neighbourhood crime rate index still does not affect citizens' crime risk perception, although it does present the expected sign. However, when using the non-victims subsample, the effect is similar to that described above. Moreover, note that incivilities are still positive and significant at the 1% level. We obtain the same result for the variable capturing the average assessment of the police but our proxy for the level of social capital ("*N_election_part*") is no longer significant.

4.5. Conclusions

This study has analyzed the main individual and neighbourhood determinants of crime risk perception paying particular attention to the role of police proximity in the level of insecurity expressed by citizens. In order to account for the hierarchical structure of the data (at both individual and neighbourhood levels) and given the ordering of our dependent variable capturing an individual's crime risk perception, we used an ordered multilevel logit model. This model has enabled us to account for the differences both within and across neighbourhoods and to obtain robust estimations.

The results show that individual characteristics such as being old, being a woman, being a native resident, having suffered victimization and being poorly educated increase the reported level of crime risk perception. In the case of neighbourhood characteristics, the level of perceived incivilities and the level of social capital (measured by means of voter turnout) seem to affect crime risk perception in the expected way – that is, the lower the assessment of the neighbourhood (i.e. the greater the number of incivilities), the higher the level of crime risk perception. In the same line, increased voter turnout as a measure of social capital seems to reduce the level of crime risk perception. Both variables, together with the assessment of police institutions, are spatially correlated with the level of crime risk perception. This means that crime risk perception is not only affected by the level of social capital, the number of incivilities and the citizens' assessment of the police in a given neighbourhood, but also by the levels of these variables in the contiguous neighbourhoods.

We have tackled the potential issue of individual sorting across neighbourhoods by using a subsample consisting of those individuals that had lived for more than five years in the neighbourhood. The results seem to be unchanged for the majority of the variables used, confirming the results obtained.

As for our main variable of interest, i.e., police proximity (having first controlled for the potential endogeneity derived from the fact that individuals with higher crime risk perception are more prone to contact the police), we found the simple fact of being exogenously stopped by a police officer to be a signal of police proximity that lowers the level of crime risk perception, albeit only for those individuals that had not recently suffered victimization. This result differs across different levels of crime risk perception. More insecure individuals (those reporting higher levels of crime risk perception) are more positively affected by contact with the police. Indeed, we find no evidence that contact with the police affects the level of crime risk perception (insecurity) in the case of those non-victims that present the lowest level of crime risk perception (fearless).

In the case of citizens that have suffered prior episodes of victimization, we find some evidence of their being negatively affected by contact with the police (feelings of greater insecurity). It might be that victims, when coming into contact with the police again, are reminded of their previous victimization experience and, hence, feel more insecure.

These results have a number of important policy implications especially as regards security, since they serve to reinforce the call for the police to play a greater socializing role – in other words, patrolling the streets preventing crime should not be the sole role of community police officers. Stopping citizens and interacting with them can have an important impact on levels of security, making citizens feel safer. It could therefore be interesting if police officers were to enhance their socializing skills so as to learn how to get closer to citizens and to handle situations with the aim of making people feel safer.

Finally, the socializing role of police forces should be taken into account when estimating their output since the sole consideration of crime clear-up rates could be misleading. Public expenditure on policing should be seen as an investment in deterring crime as well as an investment in individual, and overall, well-being since, as we have shown in this study, individual benefits can be gained from police proximity.

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Appendix A to Chapter 4 (Multilevel Ordered Logit Model)

In order to explain the main individual and neighbourhood determinants of individual crime risk perception and the impact of police proximity on this perception, and as we measure crime risk perception on a scale from 0 (no crime risk perception at all) to 4 (maximum level of crime risk perception) as our dependent variable, we need to use a link function. This link function may be either logit or probit; however, here, for simplicity's sake, we opt for the logit function.[65] The dependent variable can take up to five values and, hence, the probability of each response is denoted by:

$$\Pr(y = k) = \pi_k \text{ where } \sum_{k=1}^{4} \pi_k = 1 \text{ for } k = 0,1,2....4 \quad (4.A.1)$$

where y represents our dependent variable (crime risk perception) and π_k is the probability of response k. As the data is ordered, we can define the cumulative response probabilities that reflect the ordering of the values of y. We define γ_k the cumulative probability of being in category k or lower as:

$$\gamma_k = \Pr(y \leq k) = \pi_1 + \pi_2 + ... + \pi_k \,. \quad (4.A.2)$$

Suppose we have m control variables, then the cumulative logit model (or ordered logit model) for individual i is defined as:

$$\log\left(\frac{\Pr(y_{ij} \leq k}{\Pr(y_{ij} > k)}\right) = \text{logit}(\gamma_{kij}) = \alpha_k + \sum_m \beta_m X_{mi} \,, \quad (4.A.3)$$

where α_k refers to a threshold parameter or intercept in each category of the dependent variable. As individuals are clustered into neighbourhoods (denoted by j), they may follow a certain distribution within each neighbourhood, which needs to be taken into account by using a multilevel approach. The use of multilevel models is justified mainly on statistical grounds. If observations are clustered into categories and ordinary least squares (OLS) is used, the estimations will be unbiased but inefficient since the variances of errors could be underestimated leading to incorrect inferences. A potential way of dealing with clustered data would be to introduce dummy variables that account for the cluster specific effect. However, it is not possible to observe cluster specific errors or the effects due to observed and unobserved group characteristics. In a multilevel (*random effects*) model, the effects of both types of variables can be estimated separately and the residual variance is partitioned

[65] The two functions are similar and the results do not vary considerably when using the probit model. In the case of the logit specification taking exponentials of the estimated coefficients gives the odd ratios and they are, therefore, easily interpretable.

into a between-group component (variability across groups) and within-group component (variability across individuals). Therefore, estimations will have the correct standard errors as well as providing estimates of the between-group and within-group variances.

The estimation is performed by maximum likelihood (ML), implying some OLS starting values are given and, then, adopting an iterative procedure, the likelihood function converges to the efficient, unbiased values. If both the coefficients and the random effects are included in the likelihood function, we use a full maximum likelihood (FML) procedure. Alternatively, if only the random effects are included, we use a restricted maximum likelihood (RML) procedure. The former presents certain advantages over RML, including the fact that it provides for easier computations as well as the possibility of testing differences between two nested models that differ only in the fixed part. Here we present the general multilevel logit ordered model to be estimated:

$$\log\left(\frac{\Pr(y_{ij} \le k}{\Pr(y_{ij} > k)}\right) = \text{logit}(\gamma_{kij}) = \alpha_k + \beta_{0jk} + \sum_m \beta_{mjk} X_{mij} \tag{4.A.4}$$

$$\beta_{0jk} = \gamma_{0k} + \sum_l \beta_{mlk} Z_{lj} + \eta_{jk} \tag{4.A.5}$$

$$\beta_{mj} = \gamma_m + \varepsilon_{jm} \tag{4.A.6}$$

The above model presents three equations. Eq. (A.4) represents level 1 or the individual level with threshold parameters of the single level logit model. However, this model differs from Eq. (A.3) in two respects. First, β_{0jk} is the intercept (see Eq. A.5) and represents level 2, which varies across neighbourhoods and comprises a fixed part $\gamma_{0k} + \sum_l \beta_{mlk} Z_{lj}$ where the latter are the l explanatory variables of neighbourhood j, and a random part $\eta_{jk} \sim \mathrm{N}(0, \sigma^2{}_{\mathrm{u0}})$. Second, Eq. (A.6) is the random and fixed part for the coefficient m of neighbourhood j. It also comprises the fixed part γ_m, and the random part $\varepsilon_{jm} \sim \mathrm{N}(0, \sigma^2{}_{\mathrm{um}})$. The coefficients present the subscript k because the impact of the random intercept or the variables may be different for the four categories of crime risk perception (proportional odds assumption). We test if this assumption holds by means of a Wald test.

Since we are using an ordered multilevel logit model the coefficients are interpreted as the effect of a 1-unit change in the independent variable on the log-odds of being in a lower category of the dependent variable as opposed to being in a higher category (Rabe-Hesketh and Skrondal, 2008). Taking exponentials of each estimated coefficient yields the multiplicative effect of a 1-unit increase in the independent variable on the odds of being in a lower category of crime risk perception holding constant the group effect. Alternatively, if we apply $exp(\beta+\alpha_k)/[1+exp(\beta+\alpha_k)]$ to the coefficients, we would obtain the predicted probabilities. As for the cut-offs or interceptions, each α_k (if taking exponentials) represents the predicted probability of being in category "*k*" or lower (holding constant the group effect) and, because of the ordering of the dependent variable, it increases with the response variable.

Appendix B to Chapter 4 (Ordered Logit Model).

Table 4.B.1: Ordered logit estimation for crime risk perception.

VARIABLES	*Non-Victims subsample* (1)	*Victims subsample* (2)
α_0	6.881***	8.130***
	(1.356)	(1.894)
police_stop_0	0.331**	0.245
	(0.152)	(0.279)
α_1	4.008***	5.530***
	(1.358)	(1.863)
police_stop_1	-0.106	0.210**
	(0.0741)	(0.104)
α_2	4.008***	4.068**
	(1.358)	(1.860)
police_stop_2	-0.430***	0.0244
	(0.154)	(0.104)
α_3	0.240	1.924
	(1.351)	(1.878)
police_stop_3	-0.565*	0.0847
	(0.315)	(0.265)
Individual level variables		
gender	0.236***	0.317**
	(0.0483)	(0.125)
age	0.00468**	0.0104***
	(0.00229)	(0.00376)
victim_property		0.588**
		(0.240)
victim_person		0.462***
		(0.160)
foreign_born	-0.990***	-0.763***
	(0.134)	(0.176)
education	-0.0959***	-0.0516
	(0.0269)	(0.0409)
Neighbourhood level variables		
N_crime_rate	0.907***	0.173
	(0.343)	(0.321)
N_incivilities	-0.370***	0.0134
	(0.136)	(0.0346)
N_youth_male	-0.0152**	0.00342
	(0.00726)	(0.00907)
N_male_immigrant	-0.0529**	-0.613***
	(0.0209)	(0.157)
N_average_income	-0.0427	0.440
	(0.241)	(0.507)
N_police_perception	-0.158	-0.0765
	(0.127)	(0.198)
N_election_partc	-0.0147	-0.0755***
	(0.0257)	(0.0225)
Observations	7,270	4,341
Time fixed effects	YES	YES
Neighbourhood fixed effects	YES	YES

Note: Robust standard errors clustered at neighbourhood level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *N_education* has been automatically dropped since its inclusion causes a collinearity problem.

Chapter 5

Concluding remarks and future research

This thesis comprises three novel essays on the economics of crime, more precisely on the determinants of crime in an urban context. Specifically, given the availability and homogeneity of the data used, I have focused the analysis on the city of Barcelona. Chapters 2 and 3 focus on the effects of football matches on crime in this city. They analyze how large football matches can impact criminal behavior by shifting the location in which certain types of crime are committed, or by shifting the time of day when crimes are committed. Chapter 4 analyzes another important dimension of crime, individuals' crime risk perceptions. In this concluding chapter, I present the main findings of each study as well as the policy implications that may be derived from the results. Moreover, I discuss the potential channels via which the present research topic might be extended.

Routine activity theory (Cohen and Felson, 1979) states that the convergence in space and time of a motivated offender; a capable guardian and a suitable target are necessary conditions for the occurrence of a crime. In Chapter 2, I first present the overall effects of home and away football matches on the number of thefts and assaults throughout the city of Barcelona using a panel series dataset. The results show that thefts increase throughout Barcelona when Football Club Barcelona plays at home, but not when they play away, indicating that the agglomeration of people in space and time increases the incentives of pick pockets. In the case of assaults, neither home nor away matches seem to impact the number of assaults committed. On carrying out the spatial analysis, I find that there is a marked concentration effect. This means that in the census tracts located around the stadium both the number of thefts and the number of assaults increase significantly. In the case of thefts, this concentration effect is explained by the agglomeration of people in space and time, which increases the number of available targets and, therefore, increases the net benefits of pick pocketing. In the case of assaults, this concentration effect is, in part, translated into what is known as hooliganism (i.e., the unlawful behavior of football fans).

The spatial results show that the distance decay effect is not constant (as some census tracts located further away from the stadium present a higher number of thefts or assaults), but that it is present. Thefts are significantly higher in those census tracts whose centroid lies within 1,100 meters of the stadium. In the case of assaults, this distance is 800 meters. The combination of overall effects as well as the spatial concentration effects shows that football matches create an environment that results in a spike in the number of thefts. The increase in thefts around the stadium accounts for 46% of the total increase in thefts throughout the city of Barcelona on match days, although this means that other areas, such as metro/bus stations and bars, are also significantly affected in terms of the number of thefts committed on match days. In the case of assaults, the overall number does not rise significantly across the city, but the number is higher in the vicinity of the stadium. This evidence suggests that violent offenders shift their area of operation from other parts of the city to the areas surrounding the stadium. The similarity of the profile of the offenders, on the one hand, and that of football fans, on the other, could explain this result.

The results obtained in this chapter have some important implications for urban security issues and public policies. First, given the overall increase in the number of thefts in the whole city of Barcelona – that is, given the presence of a negative externality induced by a private leisure activity, the public sector could levy taxes to compensate the negative externality induced by football matches. Moreover, and given the actual debate concerning the violent behavior associated with sports events (hooliganism), the results point to the possible role played by the rivalry between football fans of opposing teams, which together with the use (or abuse) of certain substances (alcohol and drugs) may account for the increase in the number of violent assaults around the stadium. An additional fee on top of the entrance price, that is, a small sum paid as a tax on each ticket sold, or levying a tax directly on football teams, could be effective policies to internalize the costs of the negative externalities created by football matches.

Despite the appealing results obtained in Chapter 2, we should remain aware of its potential limitations as well as of channels via which the spatial effects of football matches on crime might be researched further. First, in Chapter 2, no extra police officers are accounted for. This means that, owing to a lack of data (although it is readily verifiable that extra police officers are deployed on match days), it is not possible to know where these extra forces are located around the stadium (specific locations). The present analysis could therefore be extended by taking these two aspects into account: on the one hand, the exact numbers of extra policing on match days; and, on the other, the exact location of these patrols around the stadium. The addition of this information would enable us to analyze the optimal allocation of police officers around the stadium. Chapter 2 might also usefully be extended by analyzing whether locations with bars and other recreational facilities are responsible for the rest of the increase in the number of thefts. In the vicinity of the stadium, I account for 46% of the total increase in the city of Barcelona. Further, other types of crime should be analyzed even though they are less important in quantitative terms. Their impact on citizens' well-being may be more psychological than physical (for instance, criminal damage of public facilities or damage to banks and stores).

Chapter 3 also focuses on the effect of football matches on crime, highlighting the role of time (an issue widely neglected in the recent literature) on criminal behavior. In this chapter the analysis is carried out at the hourly level and for several types of crime, including thefts, assaults, robberies, criminal damage, driving crimes, gender violence and other violent crimes, drug related crimes and crimes against the police. In a descriptive analysis, we first analyze how these types of crime behave on an hourly, daily and monthly basis. This descriptive analysis shows that crime varies according to the hour of the day, the day of the week and the month of the year. The dynamics of people on the streets seem to explain, in part, these crime behavior variations since peak times are correlated with peoples' routines when going to work, home or school. Moreover, the regression analysis shows that the rates of some types of crime increase significantly in the hours leading up to and following a match, but during the hours of the football match itself the incapacitation effect seems to be confirmed. Given the similarity of the profile of the football fan and the offender, the rates of some types of crime are lower during the match. It should be pointed out, however, that the rates of some types of crime, such as driving offences and drug smuggling and consumption, are lower during pre- and post-match hours because of what I have called a substitution effect. In other words, police officers substitute their role of pursuing crimes and reporting them for that of safeguarding citizen security. Thus, while such crimes might be being committed anyway, they are not being reported and, therefore, do not appear in the statistics. These results contribute enormously to the literature of the effect of football matches on crime (Marie, 2010). Chapter 3 also finds empirical evidence of increases in violent behavior and gender violence after defeats in football matches. The psychological effects of a defeat increase this type of crime, which are likely to occur in households and not in the vicinity of the stadium. As such, gender violence is not spatially but rather temporally determined, making it a perfect case study for the analysis of possible temporal displacement effects observed in criminal activities. Chapter 3 allows us to estimate these temporal displacement patterns in time.

Finally, Chapter 4 focuses on an alternative dimension of crime, that is, crime risk perception. The public sector must tackle crime, but also the perception (fear) that individuals have of it. In this chapter, I perform an analysis of the determinants of crime risk perception focusing on individual and neighborhood determinants. The results show that individual characteristics, such as being old, female, a prior victim of a crime or having a low level of education, are negatively correlated with the level of crime risk perception. In the case of neighborhood determinants of crime risk perception, I find that the level of incivilities, higher crimes rates or a low level of social capital are negatively correlated with the level of crime risk perception. These results seem to be similar for victims and non-victims. Finally, my main finding in Chapter 4 is that the interaction with a police officer may decrease the level of crime risk perception, at least, for non-victims with a profile of a high level of crime risk perception. This result holds no matter the specification we regress and it is also robust to the regression methodology.

The results of this chapter have several policy implications. First, police performance must not only be evaluated in terms of crime reports but also in terms of police interventions. Contact with the police is shown to have considerable benefits for citizens in the form of a reduction in the level of crime risk perception. Second, community policing is highly desirable for the public administration since it can save money in the mid and long terms. High levels of crime risk perception are shown to have negative effects on people's well-being, for instance, high crime risk perception may be translated into high public health spending (Cornalia *et al*., 2014; Dustmann and Fasani, 2014) and, therefore, police actions aimed at establishing contact with citizens may reduce the level of crime risk perception and, hence, future public spending on health. However, as shown by the neighborhood determinants of crime risk perception, the actions taken by public administrations should not end with the increase in community policing. Governments need to undertake actions aimed at reducing neighborhood incivilities.

Chapter 4 presents robust results although the analysis could be improved if panel data were available. Analyzing the same individuals over time would allow the unobserved heterogeneity present in our estimations to be overcome. Also, a consideration of different time periods would allow the construction of a difference-in-difference estimator to account for the average treatment effect when being pulled over by a police officer.

To summarize, the results obtained in this thesis provide a better understanding both of criminal behavior and of the fear it generates among citizens, above all in the presence of a major event in an urban environment. On the basis of the results reported here, police agencies may provide better police deployment in space and time during football matches and thus take into account shifts in criminal behavior during such events. The results obtained in Chapters 2 and 3 are probably not fully exportable to other cities, given that urban structures as well as the specific characteristics of a society may change across countries and even regions. Because of the idiosyncratic nature of local characteristics, it is important to encourage the training of crime analysts, that is, experts in data management and analysis who can analyze crime patters in order to allocate police officers more effectively in time and space. Furthermore, these analysts would increase institutional transparency and make police agencies more efficient.

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