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

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Abstract: 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 polices, 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 set up, the aim of this paper is to analyze the determinants (both individual and neighborhood) of citizens' crime risk perception for the City of Barcelona (Spain) by means of a multilevel ordered logit model focusing on the effect of police proximity and taking into account spatial aspects of neighborhood characteristics. The results, once controlling for possible problems of endogeneity of police forces and crime risk perception and sorting of individuals across neighborhoods, reflect that crime risk perception is reduced when individuals (randomly) interact with polices forces, and that spatially lagged 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.

Key words: Crime risk perception, police forces, multilevel ordered logit model
J.E.L. codes: C21, H50, K42.

1. Introduction

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

From a microeconomic standpoint, crime affects individual well being of those that directly suffer a criminal activity and, more generally, of all citizens through the insecurity it causes. For instance, a robbery will not only affect the victim, but also the individuals spotting the act (and those who have been told about it) since they will likely feel unsafe and possibly modify their behavior. If authorities are not capable of making people perceive that their personal integrity is guaranteed and that they live in a safe place, public efforts and resources devoted to crime prevention and control may not be assessed as fulfilling its primary objectives. For instance, in Spain, from 2006 to 2008, the Center of Sociological

Research (CIS) reported that citizen insecurity was within the three main concerns for almost one in every five Spaniards.[1]

From an individual point of view insecurity can cause both direct and indirect effects. First, insecurity can cause depression and increases in levels of anxiety (Perkins and Taylor, 1996). Recently, using data from the British Household survey panel, Dustmann and Fasani (2012) show that property crimes (not violent) may lead to higher levels of anxiety and distress and an important loss on confidence.[2] Moreover, insecurity may also lead to changes in daily routines and behavior such as higher levels of distrust (Conklin, 1975), lower outdoor physical activity (Ross, 1993) and reductions in displacements and social interactions (Liska *et al.* 1988; Miethe, 1995). Second, other indirect effects of high levels of insecurity may result in the (mis)allocation of private resources to overprotect one's security.[3] Examples of these individual proactive security activities consist of buying a watch dog to guard one's home and property, carrying a self-defense weapon, or installing extra security home devices such as burglar alarms.

The above mentioned individual costs of crime risk perception can be aggregated to account for some additional (indirect) social and economic costs of insecurity. If health services are publicly provided, then the consequences of crime risk perception turns into a collective cost. Similarly, the changes in the individual behavior can lead to reductions in the level of social capital of communities that can also translate into lower levels of trust and, at the end, can even impact economic activity (Knack and Keefer, 1997).

Also at an aggregate level, governments use an important share of public resources to prevent and control crime. There is a wide range of policies aimed at reducing criminal attitudes from which police forces seem to be the most common and important tool used. It is common sense, also supported by formal theoretical models of crime, that the probability of success of offenders decreases with deterrence variables such as police forces. Although deterrence theory justifies the need for police forces in the presence of individuals acting as criminals, police forces have adopted other roles besides influencing the probability of

[1] Note that citizen insecurity does not include concerns about terrorism.
[2] For the case of Catalonia, region where the City of Barcelona belongs, the public health survey (2010) states that 12.1% of the people above 15 consider themselves to be at risk of a mental disease.
[3] Ferraro (1995) finds that perceived risk of crime is a moderate predictor of efforts to protect oneself from crime. High levels of perceived risk are hypothesized to lead to both increased preventive and protective measures.

apprehension of criminals and potential criminals. In this sense, preventive actions are increasingly frequent and, in many cases, are linked to reducing the levels of citizens' insecurity and crime risk perception. For instance, since the mid 70's in the US, the reduction of people's insecurity has been one of the main targets for police agencies especially in central cities (Cordner, 2010) where crime is also a major concern (Glaeser, 1999). Police proximity officers are often the agents appointed to this goal.[4] For the case of the US, the Community Oriented Policing Services (COPS) Office[5] recognizes that people need not only to be safe, but also to feel safe. Therefore, as pointed out in Cordner (2010): "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 the case of Catalonia (Spain) police forces have also as one of their main goals to reduce citizens' insecurity.[6]

There is a large share of the empirical literature dealing with the economics of crime devoted to understand the impact of police forces on crime (Corman and Mocan, 2000; Di Tella and Schargrodsky, 2004; Draca *et al.,* 2009; Klick and Tabarrok, 2005; Levitt, 1997; McCrary, 2002) with no clear cut results, in part due to the difficulty and methodological challenges faced when trying to establish causal relations between both variables. Less frequent has been the study, as we do, of the impact of police forces on crime risk perception and, in general, on the determinants of citizens' insecurity.

Therefore, in this context, two issues emerge as crucial. On the one side, there is still the need to fully understand the determinants of individual crime risk perception, especially how individual and location characteristics interact in shaping people's insecurity. This analysis can help to design preventive public policies that are effective in reducing crime risk perception. On the other side, there is the need to evaluate the impact of police forces on reducing crime risk perception, and issue largely neglected in the literature but that can bring important insights regarding the effectiveness of public resources devoted to security issues, at least those also devoted to increase individual well-being, and hence, the overall well-being of the society.

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[4] Police proximity units are police officers who are closer and more visible to citizens. They normally patrol by motorbike or foot and they tend to establish contact with citizens, associations and neighbours in order to know their main problems and needs referring security issues.
[5] http://www.cops.usdoj.gov/
[6] Unlike, for instance, the case of the UK, in Spain large quantities of police agents are patrolling the streets in order to both prevent crime and make citizens to feel safer.

In this paper, using a multilevel ordered logit model, we estimate the main (individual and neighborhood) determinants of people's insecurity for the case of the city of Barcelona (Spain).[7] The novelties of this paper are various and substantial. First, we bring new evidence on the (individual and neighborhood) determinants of individual perceived insecurity (measured as the crime risk perception). Second, we focus on the effect of police proximity on people's crime risk perception controlling for spatial effects of citizens' evaluation of police performance as well as other neighborhood characteristics.

By using a unique individual victimization survey for various years at a urban setting[8] we are able to address the various issues regarding crime risk perception. Moreover, in Barcelona since 2006 police forces strategic plans present a special focus on reducing citizens' levels of insecurity. Although not initially intended to do so, our database allows us to account for the effects of police proximity on crime risk perception and we are lucky to encounter in the victimization survey itself enough information to overcome the likely problem of endogeneity between police proximity and the individual level of insecurity. Given that we use neighborhood characteristics as determinants of the crime risk perception we also deal with the issue of individuals sorting across neighborhoods.

The paper is structured as follows. Section 2 briefly reviews the relevant literature dealing with both crime risk perception and the impact of police forces on crime. Section 3 describes the victimization survey used. Section 4 presents our empirical approach and the potential estimation problems. Section 5 presents the results obtained. Finally, section 6 summarizes the main conclusions of the paper.

2. Literature Review

2.1 Crime risk perception and its determinants

First it is important to clarify the interpretation of the main crime concept we address in this study, that is, citizens' insecurity. Insecurity, in the broad literature dealing with it, has

[7] Barcelona is a large, modern, touristic, and highly populated Spanish city where petty crime is increasing. Newspapers are increasingly focusing on the impact of pick-pocketing and home robberies on crime risk perception; see for instance La Vanguardia (2012); http://www.lavanguardia.com/sucesos/20121129/54355929103/consecuencias-psicologicas-robos-domicilios.html.

[8] Note that the literature on crime acknowledges that the urban setting is the optimal to analyze the determinants and the impacts of criminal behaviours. For instance, cities show higher crime rates than rural areas and, moreover, in urban settings social interactions (crucial nowadays to understand criminal attitudes) can be considered as larger (Glaeser and Sacerdote, 1999).

often different interpretations. Thus, the literature dealing with insecurity mainly distinguishes between fear of crime and crime risk perception. LaGrange and Ferraro (1987) suggest that fear of crime can be conceived as the emotional of affective component of perceptions, while crime risk perception is the cognitive component of perception. Therefore, both concepts are different and the results of the studies explaining their determinants vary considerably. Rountree and Land (1996) show that certain individual and neighborhood characteristics may explain risk but not fear. LaGrange *et al.* (1992) suggests that perceived risk mediates the effect on emotionally generated fear. That is, the higher the crime risk perception, the higher the fear of crime. This is confirmed by Wilcox and Land (1996) that show the existence of important alignments between these two concepts.

The information available in the Barcelona's victimization survey is closer to the concept of crime risk perception, measuring the cognitive state related to a general anxiety about crime, and leaving aside the affective aspects of the worries about personal safety. However, it is worth mentioning the fact that fear of crime is, as LaGrange *et al.* (1992) pointed out, affected by the crime risk perception, our in other words, someone presents a high level of concern about crime (fear of crime) if she perceives a high crime risk in its neighborhood. The results obtained in this paper are directly related to the concept of crime risk perception. However, indirectly can be extrapolated to the affective aspect of the crime perception (fear of crime) through the channel pointed out by LaGrange *et al.* (1992).

The theoretical frameworks explaining fear of crime and crime risk perception are diverse; however, the bulk of the theoretical literature is focused on the determinants of fear of crime. For instance, within the "*broken window*" thesis (Wilson and Kelling, 1982) many scholars have explained how personal and neighborhood characteristics may explain fear of crime and even, crime. This thesis links three important concepts in neighborhoods: disorder, fear and crime. Specifically, this thesis states that the link of 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. Consequently, people may start to distrust and behave differently staying more at home and socializing less with the neighbors. In turn, this will lead to a reduction in the natural surveillance allowing consequently to further disorder and minor crimes. Skogan (1990) was the first to test this thesis concluding that disorder plays an important role in sparking urban decline. However, other authors such as Taylor (2001) proved that fear and crime cannot be linked as previously presented, concluding that the thesis was over-simplistic.[9]

Theoretical alternatives to the "*broken window*" thesis are for instance the Collective Efficacy theory of Sampson and Raudenbush (1999).[10] These authors point out that concentration of inequality, racial, ethnic and socioeconomic structures of neighborhoods are important in explaining fear of crime. Note that this theoretical view is easier to empirically test, for instance with cross section data, than the "*broken window*" thesis that needs a temporal dimension in order to be tested. This is the reason why the vast majority of studies have explained the determinants of fear of crime by means of the Collective Efficacy thesis.

At the empirical level, the study of the determinants of the fear of crime and crime risk perception has been one of the main targets for experts on different fields during the last decades. Recent psychological studies such as Russo *et al.* (2010 and 2011) present the analysis of the individual and collective determinants of crime risk perception. They find that individual characteristics are important in explaining crime risk perception but county/neighborhood characteristics are not. Criminologists have also studied the fear of crime and crime risk perception determinants focusing often on different aspects. For instance, incivilities in neighborhoods have been a key target for Taylor (2001), Robinson *et al.* (2003) and Wyant (2008). Taylor (2001), using a multilevel model, studies the effect of incivilities in Baltimore neighborhoods. In the same line, Robinson *et al.* (2003) analyze by means also of a multilevel model, the impact of incivilities on different dimensions of fear of crime at the street block level and the neighborhood level.[11] Wyan (2008) analyzes also the incivilities impact on fear of crime but taking into account the spatial autocorrelation of fear of crime across neighborhoods.

Focusing on prior victimization, Skogan (1986) for the case of the US, and Zarafonitou (2000) and Tseloni and Zarafonitou (2008) for the case of Greece, analyze the impact of

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[9] Taylor's studies have derived the "*broken window*" thesis into the currently known as the "*incivilities thesis*".

[10] Collective efficacy is understood as linkage of cohesion and mutual trust with shared expectations for intervening in support of neighbourhood social control.

[11] This distinction comes from the "*broken window*" thesis. This was first formulated at the street block level but later, Skogan (1990) broadens the thesis at the neighbourhood level.

having been victimized (direct and indirect victimization) on fear of crime. The results show that direct and indirect (knowing a victim) prior victimization affect positively fear of crime.

2.2 The effect of police forces on crime risk perception

Also related to this work, some authors have assessed the impact of certain police policies on the fear of crime and crime risk perception. Since the 1970s, US police policies have focused on the reduction of fear of crime and crime risk perception. Prior to that date, the dominant view of traditional policing was not to reduce fear of crime, but to solve crimes and capture criminals by focusing on motorized patrols, rapid responses to service calls and retrospective crime investigations (Della-Giustina and Silverman, 2001). As a result, the literature has focused on the US case to analyze if certain policies, such as foot patrols or other policies actions that approximates police to citizens, have lead to a reduction in the levels of fear of crime; even in the case that citizens were unaware of such polices (Pate *et al.* 1987). For instance, the Flint experiment showed that when foot patrols were highly visible and established contact with citizens often, fear of crime was reduced (Trajonowicz, 1982; Moore and Trojanowicz, 1988). This is also confirmed by Groff *et al.* (2013) showing by means of a control and treatment group that foot patrols interact more with citizens and are able to reduce specially violent crime. On the contrary, Moore and Trojanowicz (1988) found also that some policies such as victims contact or letters informing on the main issues in the neighborhood do not help reducing the level of fear of crime.

Taking into account the "*broken window*" thesis, Braga (2001) and Hinkle and Weisburd (2008) studied the effect of police crackdowns on hot spots. They find that polices aiming at reducing minor disorders could lead to reductions in the fear of crime but, simultaneously, these strategies could increase it since people perceive that they are living in a hot spot area. Ferguson and Mindel (2006) find a similar result in their estimations; the simple fact of seeing the police can boost the fear of crime.

Within the economic literature, parallel to the fear of crime, several authors have aimed to isolate the endogeneity of the police interventions on criminal activity. Police resources may be allocated geographically according to the level of criminal activity across specific areas. Therefore, unless the police intervention is random and exogenous, one would be capturing that more police officers increase criminal activity. Electoral cycles (Levitt, 1997; McCrary, 2002), lagged values of police officers (Corman and Mocan, 2000), police deployment after terrorist attacks (Di Tella and Schargrodsky, 2004; Draca *et al.,* 2009), changes in terror alert levels (Klick and Tabarrok, 2005) and police hiring subventions (Evans and Owens, 2007) have been used as instruments for the number of police officers to test the effect of police on crime.

All the above economic and criminological studies have addressed the effect of police on crime rates but, so far, the effect of police policies and police interventions on fear of crime and crime risk perception has driven less attention. Moreover, quantitative studies linking crime, crime risk perception and police forces are scarce for the European case. The British case is the most common in the literature using the well-known British Crime Survey (Hales *et al.* 2000; Gray *et al.* 2006). Other cases are, for instance, Greece by Tseloni and Zarafonitou (2012) and for Spain the only work relating fear of crime and police interventions is Medina (2003) who shows that so-called Belloch's Plan[12] did not have any impact on people's fear of crime but it had an effect on people's police perception.

In a nutshell; 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 it, we focus in this study, on the individual and neighborhood determinants of crime risk perception giving a special attention to the evaluation of the impact of police proximity on it. This analysis constitutes a novelty not only for Spain but also for the European case, and serves to confront the obtained results with the broad existing literature focused, as previously reviewed, mainly for the US case.

3. Victimization Survey: data and variables

In order to analyze the determinants of citizens' crime risk perception as well as the effect of police proximity on it, we present a brief summary of the city of study and the main sources and characteristics of the data.

[12] This plan, named after the head of the Spanish Home Office the socialist Juan Alberto Belloch (1994-1996), consisted of the increase in 1995 of the number police officers in the Spanish main cities in order to increase public safety, decrease fear of crime and decrease the time response of the emergency calls.

3.1 The City of Barcelona

Barcelona is one of the main cities in Spain with over 1.5 million inhabitants in 2011. It is located in the autonomous community of Catalonia, on the East coast of Spain. Barcelona constitutes one of the leading tourist destinations in Spain. Barcelona is a modern, open and international city with modern infrastructures organized in 38 neighborhoods and 10 districts.[13] With regard police organization there are mainly four police forces with jurisdiction over the City.[14] The Spanish decentralization process allowed Catalonia to have its own police forces, *Mossos d'Esquadra*, which is the force mainly responsible of security in the region. Moreover, Barcelona has a local police force, the *Guardia Urbana*, also with competences of security at the city level. The main Spanish police forces, the *Cuerpo Nacional de Policia* and the *Guardia Civil*, keep some competences in Barcelona after the autonomous police deployment in 2005, such as administrative duties (ID/passport expedition and immigration documentation) or regarding terrorisms and some specific types of crime (drug trafficking, organized crime, etc). In our case, we aim at investigating the impact of both local and regional police forces on crime risk perception given that they are known to be the closest to the citizens.

3.2 Individual survey data

For the individual level data, we use data from the Barcelona public security survey which is a victimization survey carried out annually by the Barcelona City Council.[15] This survey was first carried out in 1984 and it consists of between 4,500 and 6,000 phone interviews per year to Barcelona residents across the 38 neighborhoods. The survey collects information for the Barcelona citizens' at the neighborhood level not just regarding prior victimization, but also socio-economic and personal information. The survey is divided in three parts. One related to personal information, the second regarding victimization and

[13] It is worth pointing out that in 2007 the City Council changed the administrative division of the city splitting the 38 neighbourhoods into 73. This does not represent any problem unless data is unavailable which happens from 2009 onwards.
[14] There is a fifth police force, the "Harbor Police", but it just has traffic competences within the harbor territory and, hence, it is totally irrelevant for common typologies of crime such as property crimes or crimes against the person.
[15] Table 1 in the annex presents the descriptive statistics of the data.

information about the criminal acts, and the third (which is just carried out for 50% of the surveyed citizens) regarding opinions about police forces and safety.

Specifically, we use data for the years 2006, 2007 and 2008. For earlier years the survey presents homogeneity problems which may affect our results while later years are not comparable since Barcelona changed its territorial division. The total sample after removing missing values consists of 13,589 observations. The survey is not conceived as a panel since individuals from one year to the other are not the same. Hence, in order to take advantage of all the data available, we construct a pooled cross-section database for the three years of study including all the variables of interest.

Dependent variable

Our main dependent variable, "*crime_risk_perception*" is the result of the following survey question: "*Asses from 0 to 4 the level of insecurity in your neighborhood where 0 means very unsafe and 4 means very safe*". This insecurity measurement is closer to the concept of crime risk perception given that assess the cognitive component of perception more than the emotional component of such perception. Therefore, from now on we will refer to the dependent variable as the individual crime risk perception. Note that we reverse the valuation of the response in order to ease the interpretation of the empirical results (being 0 very safe and 4 very unsafe). Figure 1 presents the distribution of the dependent variable across the possible responses, while map 1 presents the mean variable distribution across the 38 neighborhoods. Note, from figure 1, that up to 40% of respondents have a low level of crime risk perception and that the number of respondents with high levels of crime risk perception is decreasing. According to map 1, some neighborhoods present a high number of respondents with high levels of crime risk perception especially in the north-east and the south-west of the city. We will see that these neighborhoods are geographically related to some of the socio-economic variables we account for.

[Insert figure 1 around here]

[Insert figure 2a with maps 1-4 around here]

Individual explanatory variables

We include several variables that may affect people's crime risk perception. First, we account for physical and social vulnerability of individuals by including from one hand, a dummy variable ("*gender*") that takes value 1 if the individual is a woman and 0 otherwise. We also include the age of the individual ("*age*") since, like women (Ferraro, 1996), elderly people are expected to present also less physical strength and competence (Clemente and Kleiman, 1977) and, hence, higher degrees of crime risk perception.[16]

The literature has also pointed out the strong relationship between crime risk perception and prior direct or indirect (knowing a victim) victimization (Ho and McKean, 2004; Mesch, 2000; Rountree and Land, 1996; Skogan, 1986; Tseloni and Zarafonitou, 2008). This relationship has been found to be both positive and negative. For the former, being victimized eliminates people's believe to be invulnerable to negative events and of living in a substantially benevolent and meaningful world (Janoff-Bulman, 1989). For the latter, Hill *et al.* (1985) and McGarrell *et al.* (1997) point out that previous victimization might lead some individuals to believe that they are at greater risk for 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. In our empirical model we include the variable "*victim_property*" and "*victim_agression*" that accounts for prior victimization related to property or interpersonal violence crime but with some restrictions. First, it just accounts for direct victimization since no questions about friends' victimization are made and, second, the survey just asks regarding victimization experiences during the previous year. Map 2 plots the overall victimization index and shows that the spatial distribution of the victimization index does not necessarily coincide with the spatial distribution of crime risk perception.

We include a variable called "*foreing_born*" which takes value 1 if the individual is foreign born and 0 otherwise. By adding this variable we want to account for the effect of immigration on crime risk perception (map 5 presents the distribution of male immigrants across the 38 Barcelona neighborhoods).

[16] Rountree and Land (1996) showed that this result may be the opposite if instead of crime risk perception, one uses as the dependent variable the emotive fear of crime.

We also include the level of education "*education*" (see map 6) which may influence the levels of crime and, therefore, the levels of crime risk perception. Lochner and Moretti (2007) find that education increases capacity of socializing and the opportunity of obtaining legitimate rents from the legal labor market, thus it may affect negatively both property and violent crime (except for youth which violent crime seems to increase with education) and consequently it may lead to a reduction in the crime risk perception. By including the level of education we both measure the income level of each individual (given the correlation of income and education) and, also, the general level of knowledge that the individuals possesses. In this sense, seem reasonable to assume that more educated people perceive reality clearer since their information sources are wider. They tend to socialize more and read more often newspapers which imply that information of the reality of the neighborhood can be clear and almost instant. The variable is taken from the survey and takes value 1 if individuals have less than 5 years of education and 9 if they have a university degree.

Finally, at the individual level, 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 the value 1 if there has been contact between the individual and police forces either by phone call (request of help, complain about something or request of information) or personally (file a complaint to the police) and 0 otherwise. Note, however, that this variable can suffer form reverse causality problems given that the level of risk perception of people can determine the propensity of individuals to contact the police. To overcome this problem, we make use of an exogenous (to the individual crime risk perception) variable that indicates police proximity. In this case, "*police_stop*" is also a dichotomous variable taking value 1 if someone has been randomly stopped by a police officer and 0 otherwise.[17] Our sample contains 21.2% of the individuals having had contact with police of the type of "*police_call*" and 16.24% of the type of "*police_stop*" that is, being randomly stopped by police officers. Maps 3 and 4 present the distribution across neighborhoods of both variables. Note that the distribution of "*police_call*" resembles much the distribution of the

[17] Police can randomly stop individuals for various reasons, mostly because of alcohol test when driving, routine traffic controls (documentation) or because individuals are suspicious for the police officer.

victimization index, as expected and, hence, this can also determine a higher presence of police officers. Note, though, that given its nature the spatial distribution of "*police_stop*" seems not to show any pattern related to the victimization index. Therefore, we make use of this "exogeneity" to identify the impact of police contact on crime risk perception.

[Insert figure 2b with maps 5-8 around here]

3.3 Neighborhood data and variables[18]

As previously mentioned, we undertake our estimates having into account also neighborhood characteristics as possible determinants of crime risk perception, in a multilevel framework. Neighborhood data comes from official statistics from the Barcelona City Council. Since at the individual level we use data for three years, we have to homogenize the neighborhood yearly data. We do this by simply taking the average of each variable and neighborhood along the three years of study. By doing this, we cancel out yearly fluctuations (white noise) of the neighborhood variables (Hoogue *et al.*, 2011). We implicitly assume, hence, that there exists a certain stability of the neighborhoods' characteristics.

For that data unavailable from the Barcelona Council statistics department we use data from the survey clustered at the neighborhood level. For instance, the level of perceived incivilities at the neighborhood level is the average of the perceived incivilities for all the individuals in the victimization survey belonging to a certain neighborhood.

In our database individuals are clustered across the 38 neighborhoods of Barcelona and, therefore, they might present some similarities regarding the neighborhood characteristics. We include the victimization index of each neighborhood "*N_crime_rate*" to account for the effect of total neighborhood victimization crime rate on individual crime risk perception (Roundtree and Land, 1996). The "*broken window*" thesis states that incivilities or minor disorders influence a chain of events that can affect crime risk perception, to test it, we include the average of individuals' incivilities perception "*N_incivilities*" in order to approximate these minor disorders. This variable is defined from 0, many incivilities perceived in the neighborhood, to 10, no incivilities perceived (see map 7). Also the

[18] To distinguish from individual variables, we name the neighbourhood variables as "*N_namevariable*".

neighborhood social composition may affect people's crime risk perception since people living in a more "immigrant neighborhood" may feel an invasion of various racial and ethnic groups (Skogan, 1995). For this reason, we include the variable "*N_male_immigrant*". Moreover, we also control for the number of youths "*N_youth_male*" since, as Buonanno and Montolio (2009) point out for the Spanish case, young people are more prone to be involved in criminal activities. The socio-economic status is one of the main determinants of crime risk perception as Wyant (2008) points out. Therefore, we take the average of the income "*N_average_income*" of individuals in each neighborhood to obtain an approximation of the socio-economic status.

We also take into account a proxy for the level of social capital in the neighborhood since community values, relationships between individuals and involvement in public affairs may create some sort of community trust and union. We include the variable an approximation to social capital, "*N_election_partc*", which is the voter turnout in the local elections in 2006 (see map 8). Social capital is an increasing function of participation in civic life. 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 more the implication of individuals in public affairs and, therefore, one could expect a negative effect on crime risk perception.

Finally, we also control for the average perception assessment of police officers made by surveyed individuals in each neighborhoods. This variable, "*N_police_perception*", takes the value from 0 (to represent total dislike of police forces) to 10 (highest valuation of police forces). A priori, one would expect that the better the police act in solving neighborhood criminal problems, the higher the assessment given by individuals.

Table 1 presents the basic descriptive statistics of the variables used in the empirical estimations described above.

[Insert table1 around here]

4. Empirical approach: a multilevel ordered logit model

In order to explain the main individual and neighborhood determinants of individual crime risk perception and the impact of police proximity on it, and since we measure crime risk perception scaled from 0 (non crime risk perception at all) to 4 (maximum level of crime risk perception) as our dependent variable, we have to use a link function. The link function may be either logit or probit although for the sake of simplicity we opt for the logit function.[19] The dependent variable may take up to four values and, hence, the probability of each response is denoted by:

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

y represent our dependent variable and π_k is the probability of response *k.* As the data is ordered, we can define the cumulative response probabilities which reflect the ordering of the values of y. We define γ_k the cumulative probability of being in category *k* or lower as:

$$\gamma_k = \Pr(y \leq k) = \pi_1 + \pi_2 + ... + \pi_k \,. \tag{2}$$

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

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

where α_k refers to a threshold parameters or intercepts at each category of the dependent variable. Since individuals are clustered into neighborhoods (denoted by *j*) the individuals may follow a certain distribution in each neighborhood and, hence, we need to take into account this fact by using a multilevel approach. The use of multilevel models is justified mostly by statistical reasons. If observations are clustered into categories and Ordinary Least Squares (OLS) is used, estimations will be unbiased but inefficient since the variances of errors could be underestimated leading to incorrect inferences. One potential

[19] Both functions are similar and the results do not vary considerably when using a probit model. In the case of the logit specification taking exponentials of the estimated coefficients give the odd ratios and, therefore, are easily interpretable.

way to deal with clustered data could be to introduce dummy variables that account for the cluster specific effect. However, one could not observe cluster specific errors nor 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 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 the estimation of the between-group and within group variance.

The estimation is performed by Maximum Likelihood (ML), implying some OLS starting values that are given and, then, by an iterative procedure the Likelihood function converges to the efficient and unbiased values. If both the coefficients and the random effects are included into the likelihood function we are using a Full Maximum Likelihood (FML) procedure. Alternatively, if we include just the random effects we are using the Restricted Maximum Likelihood (RML) procedure. The former presents certain advantages over RML such as easier computations as well as the possibility to test differences between two nested models that differ only in the fixed part. Here we present the general multilevel logit ordered model to be estimated:

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

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

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

The above model presents three equations. Eq. (4) represents the level 1 or individual level with threshold parameters of the single level logit model. However, this model differs from Eq. (3) in two aspects. First, β_{0jk} is the intercept (see Eq. 5) and represents the level 2 which varies across neighborhoods and its composed by a fixed part $\gamma_{0k} + \sum_l \beta_{mlk} Z_{lj}$ where the latter are the *l* explanatory variables of neighborhood *j*, and a random part $\eta_{jk} \sim \text{N}(0, \sigma^2{}_{\text{u0}})$. Finally, Eq. (6) is the random and fixed part for the coefficient *m* of neighborhood *j*. It is also composed by 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.

4.1 Endogeneity issues of crime risk perception and police contact

First we run a multilevel cumulative logit model where we introduce some individual and neighborhood level control variables. Then, we introduce our variables of interests. First the variable "*police_call*" that, as previously explained, can be potentially endogenous. That is to say, that the coefficient estimated for this variable may be biased since individuals who present a higher crime risk perception are more likely to call the police when seeing something uncommon. For instance, someone with a high crime risk perception who sees some youths at the park at late hours may dispatch a call to the police because she believes they are likely to provoke problems (fights, public facilities damage). Therefore, police contact may reflect a positive impact (negative estimated sign in our multilevel ordered logit model) on crime risk perception.

We deal with the endogeneity issue by using an alternative measure of police contact. We make use of the variable "*police_stop*" which takes into account citizen's-police contact when citizens are stopped by police officers. This is, a priori, exogenous since police traffic controls usually randomly stop citizens.[20] On one hand, police officers stop citizens independently of their individual crime risk perception. On the other hand, the location of police officers when stopping individuals for car/documentation controls is also exogenous to the neighborhood crime level given that some of the controls are performed outside the City of Barcelona. Consequently, the estimations of police-citizen contact can be seen as causal using this variable and not driven by reverse causality issues. The expected results of the effect of police-citizens contact in a police control could be, in principle, either positive or negative. A positive impact (negative estimated sign in our

[20] It is worth pointing out that there exists the typical individual stereotype that police tend to pull over. Red cars, youths and late hour and weekend drivers are more likely to be stopped. However, it is worth pointing out that this fact is true for drugs and alcohol driving tests. General police car controls for documentation may stop any citizen independently of their age, resemblance or car. In our sample, a *t* test of mean differences at the neighbourhood level show that there is no statistically difference between the means of the main individual characteristics of those being stopped by police officers and those who are not.

multilevel ordered logit model) would imply that someone who has been stopped by police officers is more likely to present lower levels of crime risk perception than someone who has not (feeling protected). On the contrary, a negative impact could also be found if people increase their crime risk perception when being in contact with police officers (feeling in danger). In fact, Braga (2001) and Hinkle and Weisburd (2008) already point out the fact that people leaving in a neighborhood where police crackdowns are carried out may have negative effects for crime but positive impacts on the levels of citizen's crime risk perception.

4.2 Controlling for spatial issues and endogenous sorting of individuals

An important aspect to be taken into account when working in urban settings is the spatial dependence. Individuals do not make their choices independently; their decisions and perceptions are also the consequences of their social environment (such as neighbors, friends or ethnic groups). This peer influences are known in the literature as the social interactions theory (Akerlof, 1997). Since we are measuring in our dependent variable an opinion expressed by an individual, responses are likely to be influenced not just by the neighborhood characteristics, but also by the characteristic of surrounding neighborhoods, expecting that closer neighborhoods are more likely to have an influence (Borjas, 1995).

To address this important issue we include spatial lags with first order contiguity matrixes using the queen criteria[21] (Anselin, 1988) for the dependent variable as well as for the "*N_crime_rate*", "*N_incivilities*" and "*N_police_perception*". We consider that these variables can affect citizens' crime risk perception but given the small distance and high mobility between neighborhoods, we consider that neighborhoods' general crime risk perception, victimization indexes, incivilities perceptions and police assessment can also affect individuals' crime risk perception.

Regarding the sorting problem, as the above issue, this should not have any impact in our main variable of interest ("*police_stop*"). However, the effect of the main neighborhood explanatory variables on crime risk perception may be influenced by other characteristics. For instance, regarding the "*N_crime_rate*" variable one could expect a positive (negative

[21] Rook criteria and higher orders of the matrices have been used and are available under request. The results are similar when using the first order contiguity matrix with rook criteria but seem to be less and even non significant when using up to third order matrixes.

estimated sign in our multilevel ordered logit model) effect on crime risk perception. However, the correlation could be simply driven by the presence of unobservable factors and/or by an endogenous sorting of individuals into areas, i.e. people with higher levels of crime risk perception may tend to live in areas with lower levels of crime. Hence, we would find no effect of this variable on the crime risk perception. If one does not deal with this issue, the estimated standard errors of the neighborhood level characteristics will be biased and, thus, can lead to misleading inference.

In order to deal with the sorting problem, we restrict our sample just to those individuals who have been living at the same place for over 5 years. The intuition of this empirical strategy is that these individuals had to choose where to live several years before taking into account the characteristics of each neighborhood (victimization indexes, number of immigrants, etc) in that moment. These characteristics 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 3 presents the evolution of the victimization index for the ten Districts of Barcelona for the available years of the 1983-2008. It may be seen that the aggregate evolution of the victimization index has considerably changed over the years which support our strategy.

[Insert figure 3 around here]

5. Empirical results

Tables 2, 3 and 4 present the results for all the approaches used in the paper. 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 rather than 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. Alternatively, if applying $\frac{\exp(\beta)}{1+\exp(\beta)}$ to the coefficients we would obtain predicted probabilities. Regarding the cut-offs or interceptions, each α_k (if taking exponentials) represents the predicted probability of being in the "*k*" category or lower and due to the ordering of the dependent variable it is increasing with the response variable.

Before explaining in detail the results obtained, it is worth determining the percentage of the variance of the crime risk perception which is due to neighborhood characteristics. We estimate Eq. (4) and Eq. (5) with no explanatory variables (we will test the random coefficient model in Eq. (6) later on). The results show that approximately 5.4% of the variance in the individual's crime risk perception is due to neighborhood characteristics.[22] This seems to be lower than other studies[23] such as Taylor (1997) which finds that 11% of the variance was due to neighborhood characteristics and Wyant (2008) with 12%. Figure 4 confirms the need to account for the differences across neighborhoods since several neighborhoods are statistically different from the mean.

[Insert figure 4 around here]

Column 1 in table 2 presents the results for the estimation of the determinants of crime risk perception using the multilevel ordered logit model. The intercepts represent the log-odds of being in each category or lower. The approximation to physical and social vulnerability of individuals "*age*" and "*gender*" present a positive and significative sign, meaning that the older the person the higher the crime risk perception and being a woman increases also this risk. Women ("*gender*" = 1) and older people 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 also a positive sign meaning that people who have suffered recent prior victimization (the year before) are more likely to report a higher crime risk perception. In fact, we find results that are in line to the ones found previously in the fear of crime literature by Quang and Thing (2002). Suffering property crimes affects more crime risk perception than suffering crimes against the person. This result is somehow unexpected since we expected that people suffering directly a crime against the person (for instance, an aggression) would be more likely to be scared. However, the results seem to be driven by

[22] It is worth pointing out that when using a sample of a single year, this variance is similar to the one found by other authors.
[23] It is worth mentioning that these studies measure the fear of crime instead of the crime risk perception.

the fact that the majority of property crimes suffered are mugging or larceny which differs from a house entry in the fact that victims do actually spot criminals.[24]

[Insert table 2 around here]

Foreign born individuals seem to present a positive sign, indicating that their perception of crime is lower than residents. This result could be explained by the fact that many foreign born individuals (from developing countries) are used to (even worst) criminal atmospheres in their countries of origin and therefore, in relative terms, living in Barcelona may be perceived as safer for them. We find opposite results regarding this variable since Skogan and Maxfield (1981) found that racial and ethnic minorities tend to be more fearful. The difference may be driven either because we are analyzing crime risk perception (instead of fear of crime) or because in our case, the racial issue is not explicitly taken into account (we control for country of origin instead of race).

The variable "*education*" presents a positive sign indicating that more educated people have a lower probability of having high values of the variable crime risk perception. Social interactions of higher educated citizens may decrease individuals' crime risk perception. Moreover, more educated people tend to inform themselves better consequently knowing the reality of their neighborhoods better.

Regarding neighborhood determinants of crime risk perception, results seem to indicate that just two of the variables are in line with the expected effect. "*N_incivilities*" has a positive impact on crime risk perception. This means that the lower the citizens' assessment of civilities in the neighborhood, the higher the probability of reporting a lower level of crime risk perception. In quantitative terms, an increase of 1 point in the assessment of the civilities in the neighborhood increases the predicted probability of being in a lower category by 0.62. This effect is strongly significant proving that "fear in the urban environment is above all a fear of social disorder" (Hunter, 1978). Unexpectedly, "*N_crime_rate*" seems to have no effect on crime risk perception. This result has been

[24] If one controls for the fact of spotting the offender, the results show that crimes against the person have a greater impact on crime risk perception.

previously found when using fear of crime as the dependent variable by Perkins and Taylor (1996).

On the other hand, the variable capturing the social capital of each neighborhood, "*N_election_partic*" presents also a positive and significant effect on crime risk perception meaning that the higher the participation (the higher the levels of trust and civic involvement in community decisions making) the higher the probability of reporting a lower level of crime risk perception.

In relation to our main variables of interest capturing police proximity to citizens, the results when using the variable "*police_call*" seem to show the opposite expected impact. The negative estimated sign means that the fact of having had contact with the police decreases the probability of reporting a lower level of crime risk perception. As previously pointed out, people that are more prone to feel unsafe may present a higher propensity of contacting the police. The sign presented for this variable seems to match with the previous hypothesis. Therefore, column 2 in table 2 presents the results when using the alternative variable for police proximity: "*police_stop*". Since the fact of being stopped by a police officer is completely random, we can trust the estimated coefficients obtained. The predicted probability of reporting a lower category of crime risk perception for someone who has been pulled over is 0.52 higher. Although the effect, as expected, is not quantitatively very high, it is worth pointing out that the approximation for police proximity of "*police_stop*" accounts just for the fact of being stopped in a police control in the last year.

Column 3 in table 2 relaxes the proportional odds assumption made so far, that is, we have assumed that the effect of, for instance, the variable "*police_stop*" is the same across different types of respondents. However, the effect of having contact with police forces could differ across individual depending on their crime risk perception. For instance, someone who is more fearful, in general, may be negatively (or positively) affected by having contact with the police. On the contrary, someone who does not perceived crime risk may not be affected by the fact of having contact with the police. By allowing the effect of the independent variable to vary across the intercepts we can capture these differences. The results show that the effect of having contact with the police is more likely to affect those people who present a high crime risk perception. In fact, those reporting 0 or 1 in the crime risk perception variable are not affected by police contact.

Further results

We present in figure 5 the predicted probabilities for the multilevel model using the interaction of "*police_stop*" and "*age*" in order to account for the different effect that having contact with the police may have on young and elderly people.[25]

[Insert figure 5 around here]

First, the blue line in figure 5 represents the people who have not been in contact with the police ("*police_stop*" = 0) is steeper for any crime risk perception level. The effect of being stopped by a police officer increases the probability of being in a lower category of crime risk perception (the green curve is flatter). However, for young people, the fact of being stopped by a police officer seems to increase their crime risk perception. This positive effect holds for people younger than 25 years. The explanation of this effect could be the attitude of young people towards police forces. Since, on average, young people tend to be more likely to commit offences (Buonanno and Montolio, 2009) they may perceive that police is not crime preventing institution but a threat to them.

We have also estimated Eq. (4) jointly with Eq. (5) that defines the random intercept and Eq. (6) that defines the random coefficient. The results show that the effect of being stopped by police forces does vary across neighborhoods. This result, indeed, proves the randomness of the independent variable used.

Spatial patterns

Table 3 presents the results for the multilevel ordered logit model when one takes into account spatial effects of some of the variables of interest. The prefix W reflects the spatial lag of the variable named after it. Column 1 includes the spatial lag of our dependent variable which reflects that neighborhoods' crime risk perception affect individuals' crime

[25] The plots have been made maintaining the other variables in their representative shares in the sample and just for Spanish individuals.

risk perception but with the unexpected sign. This means, higher crime risk perception in our neighborhoods diminishes our perception of crime. So far, the only study accounting for spatial matters is Wyant (2008) that accounts for the spatial lagged value of the fear of crime. The results show a positive and significant spatial autocorrelation of the dependent variable.

[Insert table 3 around here]

Column 2 includes the spatial lag of the incivilities perceived in contiguous neighborhoods. We obtain that the better the assessment of a contiguous neighborhood (in terms of lower incivilities) the higher the probability of dropping to a lower category of crime risk perception. The results for rest of the variables seem to remain invariant except for the case of "*N_male_immigrant*" which seems to affect negatively (positive sign) crime risk perception (in table 2 the results for this variable is not statistically significant). Column 3 includes the spatial lag of "*N_police_perception*" which shows the expected positive sign indicating that the higher the valuation of police forces in contiguous neighborhoods the higher the probability to report a lower category of crime risk perception. Column 4 includes victimization indexes of the neighborhoods but the sign obtained seem to be the opposite of which one would expect. Finally, column 5 includes simultaneously all the spatial lags considered. In the most complete model the sign and significance of the variables seem to be as expected except for the case of the victimization index which significance disappears when taking into account other spatial effects. Moreover, in column 5 of table 3 the neighborhoods' crime risk perception presents a positive effect on individual's crime risk perception, as one would expect. Regarding our main variable of interest "*police_stop*" we may see that the coefficients remain unchanged confirming again the results previously obtained.

Endogenous sorting

Table 4 presents the results for the restricted sample constructed to avoid possible problems of sorting of individuals into certain neighborhoods. The sample is composed by those citizens living in the same place for 5 years or more. Note that there are fewer observations (1,985) in the sample due to the fact that the question regarding residence length was first introduced in 2008 and only for 50% of the individuals surveyed. Having fewer observations can remove potential to our estimations, however, we perform the estimations as far as it is the only way to deal with the potential endogeneity arising from the neighborhood variables and the sorting of individuals on those neighborhoods. Therefore, these results must be taken into account very carefully since the individual observations may not be representative at the neighborhood level.

Our variable of interest presents the same effect as before. Citizens' with high crime risk perception are positively affected (reduction in crime risk perception) by the fact of being stopped by the police. Also at the individual level, the variables seem to present the same signs except for "*age*" and "*Victim_person*" which seem to be non significant anymore. These individual variables should not change their significance since restricting the sample should just affect the neighborhood variables. However, we believe these changes in the individual data may be driven by the lack of observations in the sample.

[Insert table 4 around here]

Regarding neighborhood variables, the neighborhood victimization index still does not affect citizens' crime risk perception even thought it presents the expected sign. Moreover, note that incivilities are still positive and significant at the 1% level. "*N_average_income*" presents now a positive sign depending on the spatial lag used. This implies that richer neighborhoods affect negatively crime risk perception. The neighborhood level of education and the voter turnover seem to be positive and significant meaning that the higher the level of education and the voter turnover (social capital) the higher the odds of reporting a lower category of crime risk perception.

Regarding the spatial variables, they seem to present the same signs than before except for the case of the spatial lag of crime risk perception. When using all spatial lags (column 5) only the spatial lags of incivilities and police assessment turn out to be significant and with the expected sign.[26]

[26] In fact, when running a Moran-I test of spatial global autocorrelation for the dependent variable; the test does not reject the null hypothesis of independence of the spatial units (neighbourhoods in this case).

6. Conclusions

So far this paper has attempted to analyze the main individual and neighborhood determinants of crime risk perception giving special attention to the role of police proximity on citizens' level of crime risk perception. In order to account for the hierarchical structure of the data (individual and neighborhood level) and for the ordering of the dependent variable capturing the individuals' crime risk perception, we use an ordered multilevel logit model. This model allows us to account for the differences within neighborhoods and across them obtaining robust estimations.

The results show that individual characteristics such as being older, being a woman, being native, being a victim or being poorly educated are personal characteristics that increase the level of crime risk perception. Regarding neighborhood characteristics, the level of perceived incivilities and the level of social capital (measured by means of the voters' turnout) seem to affect crime risk perception in the expected way. This is, the lower the assessment of the neighborhood (more incivilities) the higher the level of crime risk perception. In the same line, the voters' turnover as a measure of social capital reduces 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 not only the level of social capital, incivilities and citizens' police assessment affect crime risk perception but also the neighborhoods' level of these variables.

We tackle the potential issue of individual sorting across neighborhoods by using a subsample consisting of those individuals living more than 5 years in the neighborhood. The results seem to be unchanged for the majority of the variables confirming the results obtained.

Regarding our main variable of interest, police proximity, and once controlling for the potential endogeneity coming from the fact that individuals with higher crime risk perception are more prone to contact the police, we find that the simple fact of being randomly stopped by a police officer is a signal of police proximity that decreases the level of crime risk perception. This result seems to be different across age and across different levels of crime risk perception. For young people, the fact of being stopped by a police officer is crime risk perception enhancing. However, once turning into 22 years or more, people start to asses positively police institutions and, therefore, the fact of being stopped by a police officer decreases the individual level of crime risk perception. In relation to the effect of police on individuals' crime risk perception we find that just the most worried individuals (those reporting higher levels of crime risk perception) are affected by the contact with the police.

These results give also some important policy implications especially for police policies since it reinforces the socializing role of the police officers. This is, patrolling the streets trying to prevent crime is not the only role of police proximity officers. The fact of stopping people in car controls and interact with them has a greater role than prevention itself since people have not just to be safe, but also to feel safe. Police officers should receive even greater levels of socializing techniques in order to know how to be closer to citizens' and how to handle the situations in order to make people feel safer.

Finally, this socializing role of the police officers should be taken into account when calculating efficiency proxies of police forces since just taking into account crime clear-up rates could be misleading. Public expenditure in police officers' must be seen as an investment in deterring crime and an investment in individual, and overall, well-being since, as we show in this paper, there exist individual benefits of police proximity.

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Figures and Maps

Figure 1: Crime risk perception distribution.

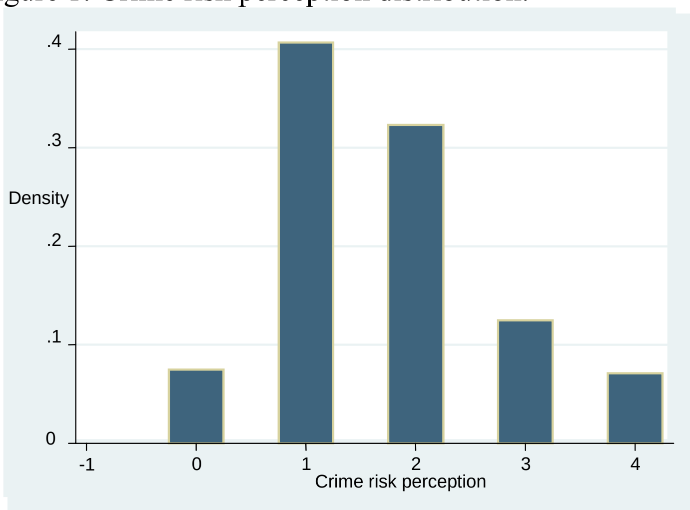
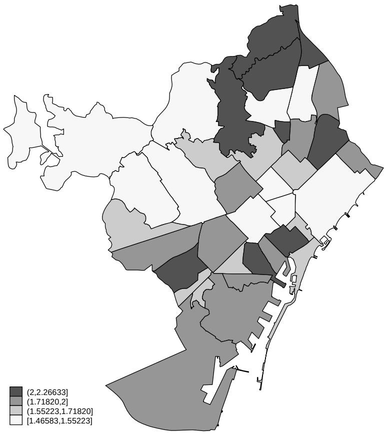
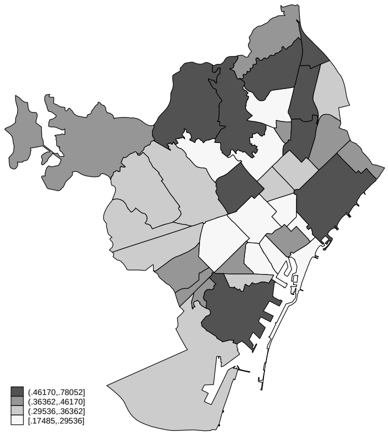


Figure 2a: Maps for main variables of interest

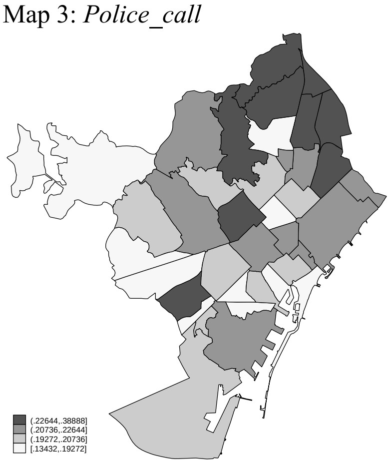
Map 1: Crime risk perception



Map 2: Distribution of victimization index



Map 3: *Police_call*



Map 4: *Police_stop*

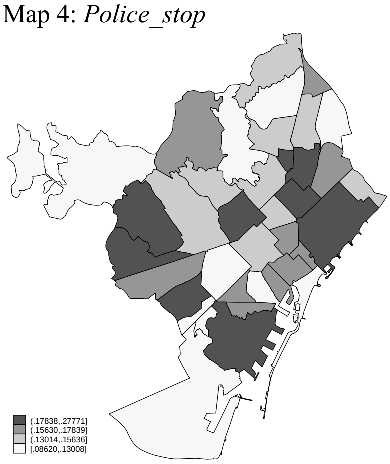
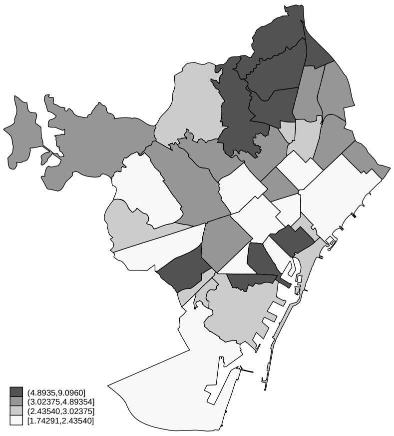
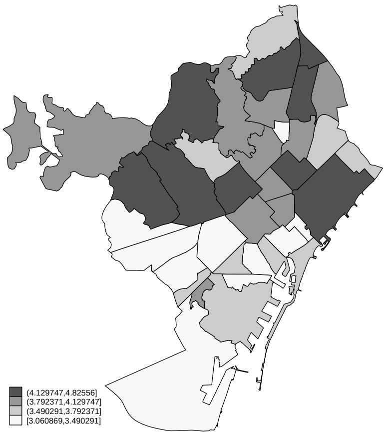


Figure 2b: Maps for main explanatory variables

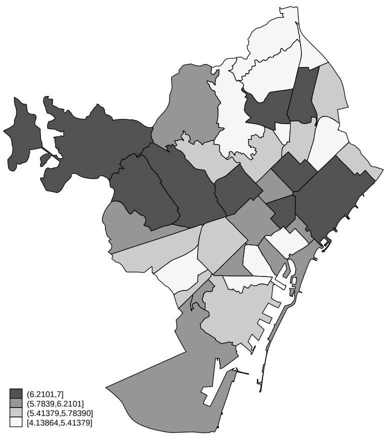
Map 5: Distribution of male immigrants



Map 6: Distribution of educational level



Map 7: Distribution of perceived incivilities



Map 8: Distribution of electoral participation

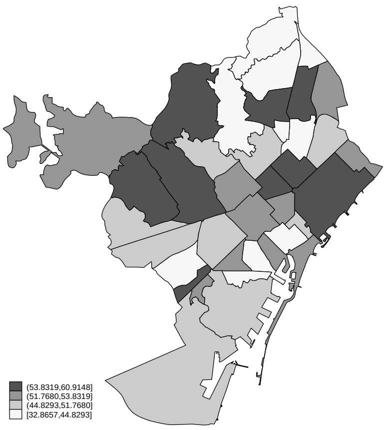


Figure 3: Victimization index for Barcelona Districts.

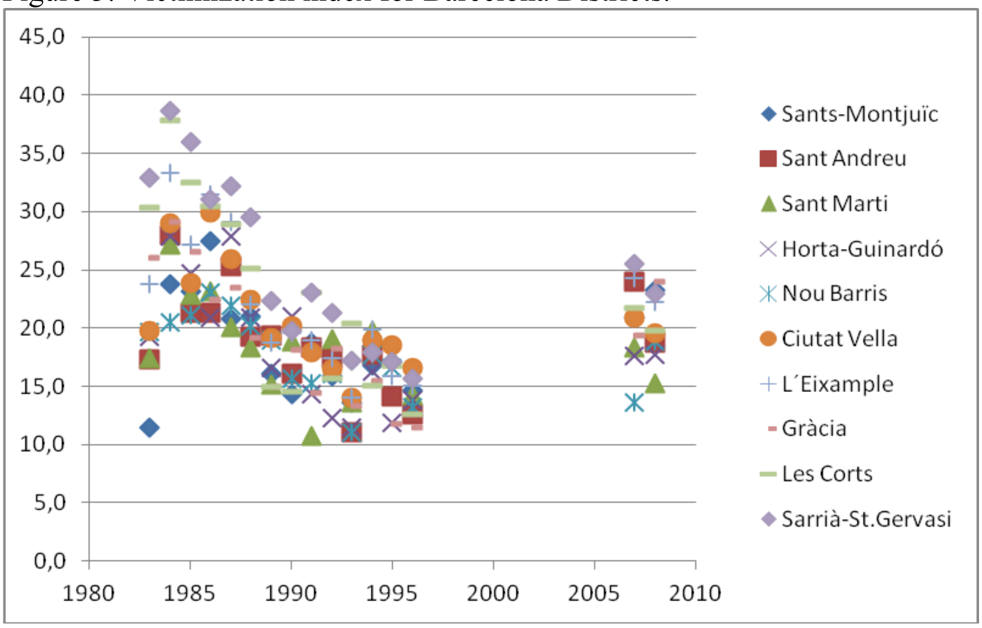


Figure 4: Estimated residuals for the 38 Barcelona neighbourhoods.

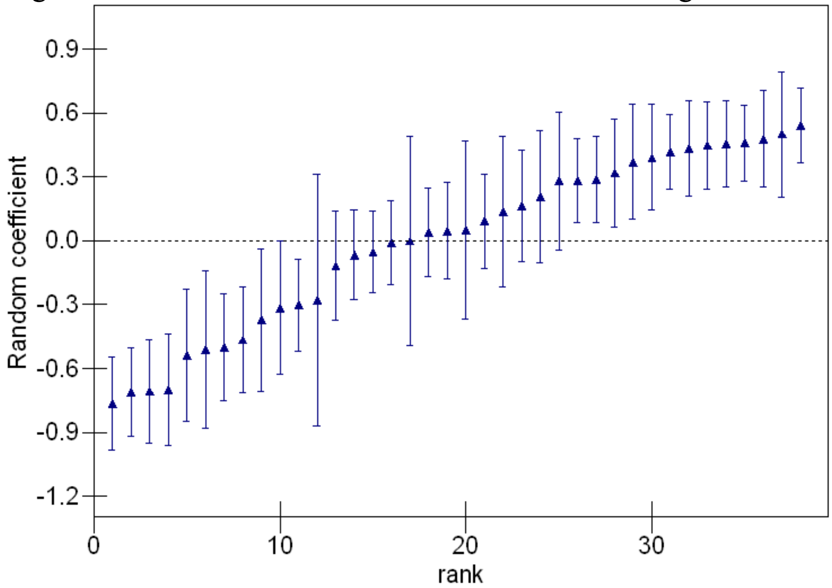
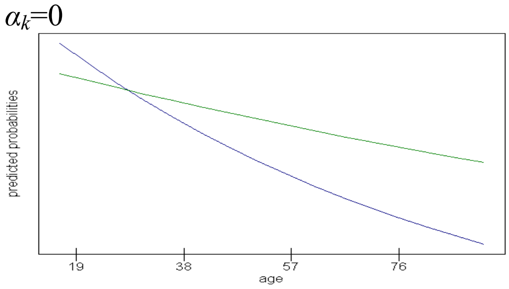
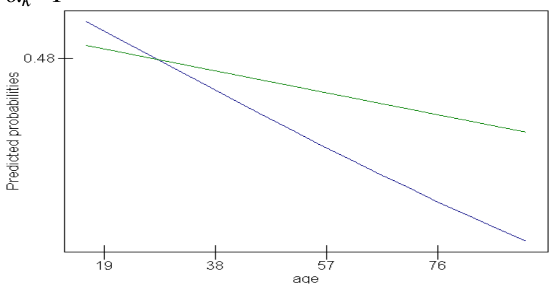


Figure 5: Predicted probabilities of crime risk perception for age and “*police_stop*”=0 (blue line) and “*police_stop*”=1 (green line).

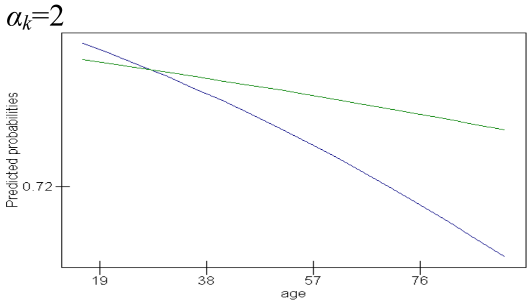
α_k=0



α_k=1



α_k=2



α_k=3

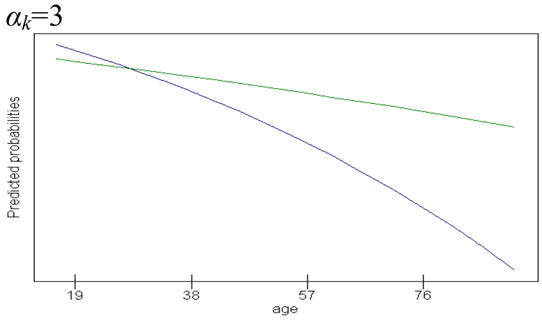


Table 1: Descriptive statistics.

	Obs	mean	standard dev	min	max
Individual variables					
crime_risk_perception	13,589	1.710795	1.015171	0	4
police_call	13,589	0.21201	0.408747	0	1
police_stop	13,589	0.162411	0.368841	0	1
age	13,589	46.97446	18.32439	16	98
gender	13,589	0.520568	0.499595	0	1
foreign_born	13,589	0.088233	0.283644	0	1
victim_property	13,589	0.329826	0.470167	0	1
victim_agression	13,589	0.058356	0.234424	0	1
education	13,589	3.92516	1.563937	1	9
Neighbourhood variables					
N_crime_rate	13,589	0.371885	0.137898	0.122931	0.849057
N_incivilities	13,589	5.828322	0.578406	4.138643	7
N_education	13,589	3.908535	0.47474	3.060869	4.82556
N_youth_male	13,589	9.776968	1.690212	7.333746	17.85484
N_male_immigrant	13,589	3.457683	1.780285	1.742918	9.09662
N_average_income	13,589	2.873647	0.117088	2.333333	3.206186
N_police_perception	13,589	5.678534	0.213067	5	6.056522
N_election_partc	13,589	51.65278	5.618084	32.86573	60.91486

Table 2: Multilevel estimations for *police_call* and *police_stop*.

	Police_call	Police_stop	Proportional odds
VARIABLES	(1)	(2)	(3)
α_0	-8.818***	-8.980***	-8.965***
	(1.436)	(1.444)	(1.447)
*police_stop*_0			0.105
			(0.0946)
α_1	-6.224***	-6.389***	-6.297***
	(1.435)	(1.443)	(1.445)
*police_stop*_1			0.0135
			(0.0503)
α_2	-4.596***	-4.766***	-4.885***
	(1.435)	(1.443)	(1.444)
*police_stop*_2			0.268***
			(0.0587)
α_3	-3.363**	-3.537**	-3.586**
	(1.435)	(1.443)	(1.445)
*police_stop*_3			0.183**
			(0.0874)
Individual level variables			
police_call	-0.306***		
	(0.0397)		
police_stop		0.101**	
		(0.0450)	
gender	-0.190***	-0.198***	-0.199***
	(0.0321)	(0.0325)	(0.0325)
age	-0.00645***	-0.00625***	-0.00625***
	(0.000955)	(0.000961)	(0.000961)
victim_property	-0.717***	-0.732***	-0.730***
	(0.0365)	(0.0366)	(0.0366)
victim_person	-0.604***	-0.637***	-0.633***
	(0.0687)	(0.0684)	(0.0684)
foreign_born	0.939***	0.924***	0.924***
	(0.0591)	(0.0591)	(0.0591)
education	0.0877***	0.0837***	0.0839***
	(0.0115)	(0.0115)	(0.0115)
Neighborhood level variables.			
N_crime_rate	-0.129	-0.150	-0.152
	(0.159)	(0.159)	(0.159)
N_incivilities	0.510***	0.513***	0.513***
	(0.118)	(0.119)	(0.119)
N_education	-0.0182	-0.0220	-0.0235
	(0.0406)	(0.0408)	(0.0408)
N_youth_male	-0.0497	-0.0528	-0.0521
	(0.160)	(0.161)	(0.161)
N_malei_mmigrant	0.0564	0.0616	0.0617
	(0.0457)	(0.0460)	(0.0460)
N_average_income	0.0998	0.0945	0.0994
	(0.303)	(0.305)	(0.305)
N_police_perception	0.216	0.213	0.211
	(0.170)	(0.171)	(0.171)
N_election_partc	0.0325**	0.0330**	0.0327**
	(0.0144)	(0.0145)	(0.0145)
η_{jk}	0.0244***	0.0248***	0.0249***
	(0.00842)	(0.00853)	(0.00854)
Observations	13,589	13,589	13,589
Number of groups	38	38	38

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

Table 3: Percieved risk perception with spatial lags.

	W_insecurity	W_incivil	W_police_perc	W_crime_rate	W
VARIABLES	(1)	(2)	(3)	(4)	(5)
α_0	-8.937***	-9.020***	-9.034***	-8.702***	-9.674***
	(1.091)	(1.118)	(1.094)	(1.112)	(1.165)
police_stop_0	0.107	0.107	0.107	0.106	0.107
	(0.0942)	(0.0944)	(0.0942)	(0.0945)	(0.0939)
α_1	-6.263***	-6.348***	-6.360***	-6.031***	-7.000***
	(1.088)	(1.115)	(1.091)	(1.109)	(1.162)
police_stop_1	0.0122	0.0121	0.0119	0.0126	0.0104
	(0.0503)	(0.0503)	(0.0503)	(0.0503)	(0.0504)
α_2	-4.849***	-4.933***	-4.946***	-4.618***	-5.585***
	(1.087)	(1.114)	(1.090)	(1.109)	(1.161)
police_stop_2	0.267***	0.266***	0.267***	0.267***	0.266***
	(0.0589)	(0.0588)	(0.0589)	(0.0588)	(0.0590)
α_3	-3.550***	-3.634***	-3.647***	-3.319***	-4.285***
	(1.088)	(1.115)	(1.091)	(1.110)	(1.162)
police_stop_3	0.183**	0.182**	0.183**	0.183**	0.183**
	(0.0878)	(0.0877)	(0.0878)	(0.0876)	(0.0880)
Individual level variables					
gender	-0.199***	-0.198***	-0.199***	-0.199***	-0.200***
	(0.0325)	(0.0325)	(0.0325)	(0.0325)	(0.0325)
age	-0.00624***	-0.00624***	-0.00623***	-0.00625***	-0.00622***
	(0.000961)	(0.000961)	(0.000961)	(0.000961)	(0.000961)
victim_property	-0.732***	-0.731***	-0.732***	-0.731***	-0.732***
	(0.0366)	(0.0366)	(0.0366)	(0.0366)	(0.0366)
victim_person	-0.633***	-0.633***	-0.633***	-0.632***	-0.635***
	(0.0684)	(0.0684)	(0.0684)	(0.0684)	(0.0684)
foreign_born	0.926***	0.926***	0.926***	0.926***	0.925***
	(0.0591)	(0.0591)	(0.0591)	(0.0591)	(0.0591)
education	0.0840***	0.0840***	0.0840***	0.0840***	0.0838***
	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)
Neighborhood level variables					
N_crime_rate	-0.0959	-0.107	-0.0963	-0.113	-0.0970
	(0.159)	(0.159)	(0.159)	(0.159)	(0.157)
N_incivilities	0.536***	0.539***	0.539***	0.529***	0.526***
	(0.112)	(0.115)	(0.112)	(0.115)	(0.107)
N_education	-0.0220	-0.0289	-0.0249	-0.0359	-0.0302
	(0.0382)	(0.0391)	(0.0382)	(0.0398)	(0.0391)
N_youth_male	-0.143	-0.131	-0.143	-0.152	-0.159
	(0.137)	(0.139)	(0.137)	(0.142)	(0.134)
N_malei_mmigrant	0.0705*	0.0745*	0.0728*	0.0746*	0.0783*
	(0.0426)	(0.0436)	(0.0426)	(0.0439)	(0.0411)
N_average_income	0.0234	-0.000231	0.0114	0.0467	0.0995
	(0.290)	(0.297)	(0.290)	(0.295)	(0.283)
N_police_perception	0.236	0.249	0.251	0.219	0.374**
	(0.162)	(0.165)	(0.162)	(0.165)	(0.175)
N_election_partc	0.0325**	0.0314**	0.0319**	0.0322**	0.0328**
	(0.0134)	(0.0136)	(0.0134)	(0.0137)	(0.0130)
Spatial lags					
W_insecurity	0.0170**				-0.204*
	(0.00702)				(0.105)
W_incivil		0.0106**			0.0860**
		(0.00504)			(0.0381)
W_police_perc			0.00849**		0.163**
			(0.00346)		(0.0728)
W_crime_rate				0.102**	0.0633
				(0.0493)	(0.116)
η_{jk}	0.0201***	0.0214***	0.0201***	0.0218***	0.0164**
	(0.00734)	(0.00766)	(0.00732)	(0.00776)	(0.00639)
Observations	13,589	13,589	13,589	13,589	13,589
Number of groups	38	38	38	38	38

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

Table 4: Percieved risk perception with spatial lags and restricted sample.

VARIABLES	W_insecurity (1)	W_incivil (2)	W_police_perc (3)	W_crime_rate (4)	W (5)
α_0	-14.18***	-14.81***	-14.45***	-13.65***	-14.11***
	(2.425)	(2.390)	(2.392)	(2.411)	(2.694)
*police_stop*_0	0.0788	0.0736	0.0784	0.0762	0.0790
	(0.249)	(0.249)	(0.250)	(0.249)	(0.250)
α_1	-11.47***	-12.10***	-11.74***	-10.94***	-11.40***
	(2.414)	(2.379)	(2.381)	(2.400)	(2.685)
*police_stop*_1	0.177	0.172	0.176	0.176	0.176
	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)
α_2	-9.878***	-10.51***	-10.15***	-9.343***	-9.801***
	(2.411)	(2.375)	(2.377)	(2.397)	(2.682)
*police_stop*_2	0.376**	0.369**	0.374**	0.372**	0.372**
	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)
α_3	-8.137***	-8.766***	-8.407***	-7.597***	-8.056***
	(2.416)	(2.379)	(2.382)	(2.402)	(2.684)
*police_stop*_3	0.101***	0.0910***	0.0970***	0.0910***	0.0920***
	(0.0275)	(0.0275)	(0.0275)	(0.0275)	(0.0275)
Individual level variables					
gender	-0.276***	-0.274***	-0.275***	-0.274***	-0.275***
	(0.0866)	(0.0865)	(0.0865)	(0.0865)	(0.0866)
age	-0.00354	-0.00353	-0.00352	-0.00359	-0.00357
	(0.00254)	(0.00254)	(0.00254)	(0.00254)	(0.00254)
victim_property	-0.677***	-0.675***	-0.677***	-0.672***	-0.676***
	(0.0969)	(0.0969)	(0.0969)	(0.0968)	(0.0970)
victim_person	0.200	0.217	0.210	0.208	0.214
	(0.190)	(0.190)	(0.190)	(0.190)	(0.192)
foreign_born	0.917***	0.917***	0.918***	0.901***	0.910***
	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)
education	0.0753**	0.0755**	0.0755**	0.0732**	0.0740**
	(0.0298)	(0.0298)	(0.0298)	(0.0298)	(0.0298)
Neighborhood level variables					
N_crime_rate	-0.181	-0.148	-0.164	-0.241	-0.190
	(0.405)	(0.404)	(0.403)	(0.397)	(0.406)
N_incivilities	0.723***	0.692***	0.721***	0.713***	0.733***
	(0.244)	(0.239)	(0.241)	(0.240)	(0.243)
N_education	0.133**	0.121*	0.130**	0.100	0.113*
	(0.0661)	(0.0651)	(0.0654)	(0.0647)	(0.0686)
N_youth_male	-0.106	-0.103	-0.107	-0.138	-0.130
	(0.220)	(0.217)	(0.217)	(0.219)	(0.221)
N_malei_mmigrant	-0.0689	-0.0599	-0.0649	-0.0570	-0.0590
	(0.0553)	(0.0540)	(0.0543)	(0.0540)	(0.0583)
N_average_income	0.861*	0.830*	0.837*	0.801	0.810
	(0.508)	(0.503)	(0.503)	(0.504)	(0.504)
N_police_perception	0.619**	0.721**	0.675**	0.604**	0.669*
	(0.299)	(0.298)	(0.296)	(0.296)	(0.354)
N_election_partc	0.0224***	0.0262***	0.0219***	0.0212***	0.0181***
	(0.00368)	(0.00360)	(0.00363)	(0.00363)	(0.00371)
Spatial lags					
W_insecurity	0.0396***				-0.0342
	(0.0109)				(0.173)
W_incivil		0.0290***			0.0127***
		(0.00781)			(0.00597)
W_police_perc			0.0199***		0.0345***
			(0.00533)		(0.0116)
W_crime_rate				0.290***	0.175
				(0.0768)	(0.194)
η_{jk}	0.0199***	0.0186***	0.0196***	0.0220***	0.0191***
	(0.00190)	(0.00186)	(0.00189)	(0.00196)	(0.00187)
Observations	1,985	1,985	1,985	1,985	1,985
Number of groups	37	37	37	37	37

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