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Abstract

This paper explores the relationship between unemployment rate and crime victimization at the neighborhood level, using data from the French victimization survey. The very local nature of the data enables me to tackle the endogenous location selection issue: once I control for the characteristics of a larger area into which household select their location, the remaining variation of observables across neighborhoods within this larger area can be considered as exogenous. The contribution of this paper to the economics of crime literature is then twofold. First, I show that, at the very local neighborhood level, unemployment rate is an important factor explaining victimization. Second, I take advantage of the precise localization of the data to compare the effect of unemployment rate in the reference neighborhood and in adjacent neighborhoods. The results support the idea that criminals are mobile across neighborhoods for more serious economic crimes, but that petty crimes and vandalism do not involve any mobility.

JEL Classification: K42, R23, J64

Keywords: crime victimization, neighborhood effects, unemployment

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1 Introduction

Some factors such as a high population density or a large unemployment rate, are known for rising crime rates. Living in a deprived US county, Italian province or French department hence puts one at a higher risk of being victim of a criminal event than living in a prosperous region. Yet, such a statement may hide important spatial disparities: a region characterized by well-defined social and economic attributes generally encompasses very heterogeneous areas. As we zoom in and focus on smaller and smaller areas, the relationship between social, economic or demographic characteristics and crime rates established at more aggregate levels may be altered. Consider for instance two adjacent neighborhoods, a prosperous one and a depressed one. Admittedly, unemployment breeds crime, so that the depressed neighborhood will be a nest for criminals.[1] Those criminals may act in their own neighborhood, but they may as well travel to the more attractive adjacent neighborhood. This could lead to a dual crime market, with different types of crimes committed in different neighborhoods (*e.g.* vandalism in poor neighborhoods and burglaries in wealthy areas). This simple example illustrates the idea that studying crime from a more disaggregate perspective can challenge some of the established results, and lead to a better understanding of the mechanisms behind criminal events. In particular, adopting a local approach allows the researcher to ask or revisit the following questions. Does unemployment increases crime? To what extent is the probability to be victim of a criminal event in a given neighborhood affected by unemployment levels in the surrounding areas? Can we observe a duality in crimes, with some crimes explained by intrinsic neighborhoods characteristics and others explained by the characteristics of more distant areas?

This paper answers these questions taking advantage of the French victimization survey that provides detailed information localized at a very low geographic level (a 2,000 inhabitants neighborhood). Note upfront that the survey asks whether individuals have been victims of any criminal event, that is *victimized*, but does not inform about people committing crimes.[2] Hence, I am able to characterize the circumstances of a crime and the victim, but not the criminal. Two important findings emerge from this study. First, among the various neighborhood characteristics considered, unemployment rate appears as the most relevant fac-

[1] I use the term "crime" in a very broad sense, encompassing various types of offenses, from misdemeanor to felony. In this respect, "criminals" can designate simple delinquents.

[2] I will henceforth use the term *victimized* to refer to someone having been victim of any criminal event (from property to violent crimes and vandalism). Similarly, a *victimization* will refer to the criminal event making one a victim.

tor having a positive effect on victimization. Second, going beyond the local neighborhood and looking at the surrounding neighborhoods, I find that the effect of unemployment rate in surrounding neighborhoods is stronger than the effect in the reference neighborhood for crimes such as burglaries and thefts of objects from cars, while the reverse is true for smaller crimes.

The present work differs from the previous literature by exploring the determinants of victimization at a very low geographic level. The geographic unit considered, called IRIS, is a 2,000 individuals neighborhood and is the smallest census tract unit for which representative indicators can be constructed in France. Instead, existing results are generally obtained using more aggregate data: Gould et al. (2002) and Kelly (2000) rely on US counties, which add up to 3,140 units for the whole country; Buonanno et al. (2009) and Bianchi et al. (2012) are based on 95 Italian provinces; Machin and Meghir (2004) rely on 43 police force areas for England and Wales; and Fougère et al. (2009) use data from the 96 French *départements*. An exception is Bell et al. (2010) who study the impact of immigration on crime using data from 371 local authorities across England and Wales. Although I am not questioning the validity of the results based on aggregate data, I think that they present an important drawback. As a consequence, these studies ignore the heterogeneity across smaller locations (municipalities, neighborhoods) within the spatial unit of analysis, and thus miss part of the mechanisms through which economic conditions can relate to crime. By contrast, I argue that according to the type of crime and the expected pay-off, criminals might either operate in their own neighborhood or travel to a remote area. It is for instance reasonable to think that thieves are more likely to live in deprived neighborhoods and to steal from wealthier (possibly neighboring) areas, while young delinquents will not have any incentives to bear transportation costs in order to vandalize cars in a distant neighborhood. Zenou (2005) provides some theoretical background for this idea in an urban economics model explaining the link between crime and location by highlighting the role of the housing market. In particular, distance to the city center (where jobs and crime opportunities are located) affects the decision to commit crime instead of working by increasing commuting costs and reducing housing rents. The idea that distance and mobility matter in criminal decision also finds some empirical support in the criminology literature. It documents that the places where perpetrators commit crimes often differ from their area of residence, and that the distance between the two locations varies with the accessibility of the target area, the type of crime and the offender's characteristics (see Bruinsma (2007) for a detailed survey on the Netherlands, and Bernasco and Luykx

(2003) for an analysis of criminals' target location choice). Working at a very local level enables me to add a spatial dimension to the study of crime, which is a key input to the literature. I am indeed able to compare the effects of the characteristics of adjacent neighborhoods on crime and therefore to capture more precisely the mechanisms behind the relationships obtained with aggregate data.

In addition to allowing for the localization of the surveyed individuals at the neighborhood level, the victimization survey data used in this paper present several valuable features. First, in some cases, it is possible to know where the victimization took place, and hence to control for the characteristics of this location. By contrast, studies relying on police data usually consider the location of the police station where the crime was reported rather than the location of the event itself. Second, these data provide detailed information on individuals, so that relevant individual characteristics pertaining to potential victims' attractiveness can be taken into account, while they are ignored in most of the existing literature. Finally, victimization surveys are known for avoiding the under-reporting issue from which reported police data suffer. Not only are individuals less likely to report personal offenses or small property crimes to the police, but criminal attempts or threats are also not always taken into account by police forces. Relying on victimization survey data is thus particularly insightful regarding petty crimes and assaults. Distinguishing between petty crimes such as vandalism and more important economic crimes shows quite relevant, as these different types of crimes turn out be driven by different channels.

The nature and the quality of these data enable me to answer the questions asked above. Regarding the local determinants of crime, I show that social, economic and demographic neighborhood characteristics strongly matter to explain victimization. In particular, among the various neighborhood characteristics considered, unemployment rate appears as the most relevant factor, while factors such as the share of immigrants in the neighborhood are not important in explaining victimization. The subsequent results of this paper hence focus on the role of unemployment on victimization. The coefficient for local unemployment rate is positive and its magnitude is particularly strong for small crimes such as motorbike theft or vandalism. Therefore, it seems that crimes committed in more deprived areas relate more to social disorganization theory (e.g. Shaw and McKay, 1942) than to rational economic crime theory *à la* Becker. Note that these results are obtained after correcting for the biases related to endogenous sorting, as will be explained below.

Finally, following the intuition that perpetrators may move across neighborhoods to commit economic crimes, I adopt a spatial approach that consists in controlling for both reference neighborhood and adjacent neighborhoods characteristics. The results show that for crimes such as burglaries and thefts of objects from cars, the effect of unemployment rate in distant neighborhoods is stronger than the effect in the reference neighborhood, while the reverse still holds for smaller crimes. Otherwise stated, for a given local unemployment rate, being surrounded by higher unemployment areas increases the probability of being burgled, but does not affect vandalism. Rather, vandalism is boosted by larger local unemployment rates for a given level of unemployment in the surrounding neighborhoods. This tends to support the idea of criminals mobility for some types of crime, e.g economic crimes, in line with Becker's theory, but not for other types of crimes (petty crimes and vandalism), relating instead to the social disorganization theory. This result is, to my opinion, the most important finding of this work. It helps understand the mechanisms behind the finding that, at larger geographic level, unemployment increases crime: unemployment would have a direct local effect on small crimes versus a remote effect on more serious economic crimes. Not only does it mean that the relationship between unemployment and crime is not trivial as we focus on smaller areas, but that this relationship also depends on the type of offense. This result shows the importance of taking criminals' mobility into account, and implies that distance, geography and transport infrastructure might be worth getting more attention in future research on crime.

This paper obviously relates to the large economics of crime literature, initiated by Becker (1968) and Ehrlich (1973). The hypothesis developed in these seminal papers is that the decision to engage into criminal activities is the result of a rational cost-benefit analysis. Most empirical research on the economics of crime aims at testing this hypothesis, which implies that economically weaker individuals (e.g. unemployed workers) have a higher propensity to commit crime because they face lower opportunity costs. Part of the literature hence focuses on economic factors, revealing that lower wages (Gould et al., 2002), larger unemployment rates (Fougère et al., 2009) or more inequality (Kelly, 2000) generate higher crime rates. Alternatively, several studies concentrate on demographic factors such as population density: Glaeser et al. (1996) show that crime is rifer in denser and more populated areas due to extended social interactions. A similar idea is developed by Calvó-Armengol et al. (2007) and Patacchini and Zenou (2008) who show the importance of social relationships, in particular of weak ties,[3] in criminal behavior. A growing literature also focuses on the role

[3]Weak ties are simple acquaintances, doing contrast to strong ties which are usually close friends and close relatives

played by immigration, and provides evidence that its causal impact on crime is not significant or only very moderate. For instance, Bianchi et al. (2012) demonstrate that the share of immigrants in Italian provinces has only a marginal effect on crime rates through robberies. Other studies, such as Spenkuch (2010) or Bell et al. (2010) show that the effect is driven by the most economically deprived immigrants. On another aspect, Buonanno et al. (2009) insist on the role of social norms and show that they tend to reduce property crimes.

Incidentally, the low geographic focus of this study binds it to the literature on neighborhood effects. A major concern in this literature is that households usually sort across neighborhoods in a non-random fashion. It is then possible that some unobserved household or individual characteristics influence both the propensity to be victim of a criminal event and neighborhood characteristics, therefore biasing the results. Several methods have been used in the literature to overcome this endogenous sorting issue, such as randomized experiments or instrumental variables, that will be detailed more carefully in the paper. The approach adopted in this study follows Bayer et al. (2008) and builds on the very local nature of the data. The idea is that although households are able to select a given area in which they want to live, they are, however, unable to select a precise neighborhood within this given area. Therefore, once the characteristics of the larger selected area are controlled for, the remaining variation of unemployment rates across the smaller neighborhoods can be considered as exogenous.

The rest of the paper is organized as follows. I describe the victimization survey and explain the particular geographic structure of the data in Section 2. In Section 3, I present the strategy used to bypass the issue related to endogenous location selection, and propose several arguments and tests of the identifying assumption. The baseline empirical specification and the corresponding results are presented in Section 4. Section 5 is then devoted to studying the role of unemployment not only in the reference neighborhood, but also from surrounding areas. Section 6 concludes.

2 Data overview

The French victimization survey (*Cadre de Vie et Sécurité* - Living Environment and Security, INSEE, CVS henceforth) is a repeated cross section, representative of mainland France households. It has been conducted annually since 2007 and each wave contains approximately 16,000 observations (one per household). The latest wave I use is the 2011. For each type of victimization considered in the CVS survey, the respondent is asked whether it occurred at least once over the two years preceding the survey. Various types of victimization affecting households in general are considered. These are mostly property thefts (or attempts) and acts of vandalism: burglary, attempt of burglary or theft without breaking in the main home (*burglary*), car theft or attempt, (*car theft*), motorbike (or scooter) theft or attempt (*motorbike theft*), *bike theft*, act of vandalism on the main home (*home vandalism*), act of vandalism on the car (*car vandalism*), and theft of objects from the car (*car objects theft*). I will henceforth refer to these types of victimization as household victimization. In addition, one randomly selected individual in each household is asked about his/her personal experience of victimization over the past two years.[4] In this paper, I will consider three types of individual victimization: *robbery*, *theft* and *assault*.[5] The shares of households and individuals victims of a given type of victimization at least once over the previous two years are displayed in the first column of Table 1. These figures are obtained pooling the 2007 to 2011 waves of the victimization survey. The other columns report the figures for various types of urban units, according to their population size and their degree of urbanization. Expectedly, the probability of victimization is higher in larger urban units (more than 50,000 inhabitants) and in the Paris urban unit than in less populated and rural areas. It is also clear from this table that occurrences of victimization are very rare events, which does not ease their study. The survey reveals that very few households or individuals report repeated occurrence of a given type of victimization, so that considering the occurrence of an event or its number does not make a large difference (this is not in the table).

When a victimization is reported, the respondent gives details about the circumstances, declaration to the police, consequences (physical injuries, protection behavior), and offender (e.g. when s/he was seen or arrested). The data also contain detailed information on households such as income, home ownership status or number of children, as well as individual characteristics such as age, gender, socio-economic category, education, income and national origins. Descriptive statistics of household and individual characteristics are reported in Table 2. In addition, the survey describes the neighborhood: the pollster characterizes the type of housings in the neighborhood and indicates whether s/he observes evidence of vandalism (burnt cars for instance). The respondent also reports whether s/he was aware of any crime or alcohol or drug related incident in the neighborhood and characterizes the general quality of the neighborhood (street light, green

[4] The member of the household selected to answer to the individual part of the survey is the person above 14 years old whose birthday is the closest to the 1st of January.

[5] The survey also informs about threats or insults, but I decide to let these types of victimization aside.

spaces, buildings aspect, bunch of people hanging around). Finally, the respondent rates her/his feeling of insecurity.

All this information is available in the public version of the survey. I also have access to more sensitive information, through a Secure Remote Center of Access to the Data (*Centre d'Accès Sécurisé Distant*, CASD). In particular, I am able to localize the precise neighborhood where the surveyed households live. This local area, called IRIS (*Ilots Regroupés pour l'Information Statistique*) is the smallest census tract unit for which representative indicators can be constructed in France. All French municipalities with more than 10,000 inhabitants and most of the municipalities with more than 5,000 inhabitants are divided into several IRISes. Each IRIS is defined so as to be an homogeneous area in terms of living environment, and its borders follow the main topographical and landscape frontiers (e.g. roads, railways and rivers). The target size of an IRIS is 2,000 inhabitants, so that IRISes actually include between 1,800 and 5,000 inhabitants.[6] To give an idea of the level of aggregation, there are about 50,000 IRISes in France (for around 36,000 municipalities). By comparison, there are 96 *départements* in France, the geographical unit used by Fougère et al. (2009).[7]

For the sake of illustration, Figure 1 shows a map of two cities. Paris is represented on the top left panel, and the top right panel focuses on the 18^{th} district (*arrondissement* in French), which is colored in darker grey on the map. To give an idea, Paris is divided into 992 IRISes for about 2.2 millions inhabitants, and the 18^{th} district comprises 75 IRISes where around 200,000 people lived in 2011. The same year, around 114,000 inhabitants lived in the city of Rouen, in Normandy, in one of 46 IRISes. The surface area of the 18^{th} district of Paris is of 6 km^2 while that of Rouen is of 21 km^2, so that Paris 18^{th} district is more than six times denser than Rouen. As a consequence, IRISes in Paris are quite small compared to other cities. In the remainder of the paper, I will interchangeably refer to IRIS or neighborhood.

[6]The IRISes are thus comparable in terms of population size, but not necessarily in terms of geographical space. Typically, a small village in the countryside is not divided into IRISes and is actually an IRIS of its own, while cities with more than 5,000 inhabitants are divided into several IRISes. The denser the city considered, the smaller the size of its IRISes.

[7]Bianchi et al. (2012) rely on Italian Provinces, that adds up to a total of 95 units, and most studies on the US are done at the county level, that adds up to 3,140 units.

Figure 1: Neighborhoods divisions (IRIS) in two cities: Paris (left top panel – with a focus on the 18^{th} arrondissement, right top panel) and Rouen (bottom panel)

Because each wave of the CVS survey comprises about 16,000 observations, there are very few observations in each IRIS (2.3 observations per IRIS per year on average). Working at such a small scale thus prevents me from computing representative victimization rates at the IRIS level. Instead, I use variables indicating whether each individual or household has ever experienced victimization over the past two years. On the bright side, working at the IRIS level presents a major advantage: it enables me to supplement the victimization data with social, economic and demographic characteristics representative of the IRIS. Indeed, the INSEE designed the IRIS to be the primary statistical unit of the census. Most of the French statistical data sources are therefore based on this geographical unit, so that it is easy to match information at the IRIS level. Using the French population censuses from 2006 to 2009, I can enrich the CVS survey data with socio-economic and demographic characteristics of the IRIS, at the time of the survey. Since 2004, the population census has been conducted annually, in a continuous way, and each wave contains information collected over five consecutive years.[8] For instance, the 2006 census was conducted over the 2004 to 2008 period. Individuals living in municipalities of less than 10,000 inhabitants are all surveyed once over the period. For

[8]Prior to 2004, the population census was conducted every decade on average, the latest one dating back from 1999.

municipalities of more than 10,000 inhabitants, 8 % of the population is surveyed each year, so that 40 % of the population is included in the final census data. Because the CVS survey data of a given year concern events that happened over the previous two years, I match them with the census data of the previous year, to be as close as possible in terms of dates: the 2007 wave of the CVS survey is hence matched with the 2006 census data and so on. To be more precise, I enrich the CVS survey data with the following characteristics, representative at the IRIS level: unemployment rate, share of single-parent households, share of immigrants, share of public housing units, share of households arrived less than two years ago and share of 14-18 years old. Furthermore, I can retrieve the IRIS median household income (per consumption unit) from tax surveys. The median household income of a given IRIS is averaged over two consecutive years (weighted by the number of consumption units) and then matched to the following wave of the CVS survey. For instance, the observations from the 2007 wave of the CVS survey are matched with the average median income of 2005 and 2006. Table 3 describes the most relevant contextual variables accounting for households' living environment.

When a victimization is reported in the survey, information is gathered about its circumstances. In particular, the respondent indicates whether it took place in his/her own neighborhood or in some non-specified other place. As I am interested in the local determinants of victimization, I restrict the victimization occurrence to the events that happened in one's own neighborhood, which I am actually able to identify and to characterize. I can then control for the socio-economic environment of the IRIS where the event occurred. Hence, for all types of victimization considered, the dependent variable takes on value 1 if the household or the individual was offended in his own neighborhood and 0 otherwise, i.e. if the offence happened outside the neighborhood or if no offence happened at all. Table 4 documents the extent to which victimization happens in the neighborhood. It shows that most of the household victimization happens in the neighborhood, while the reverse is true for individual victimization. Limiting the study to victimization that happened in the victim's neighborhood can hence be an issue for individual victimization, but it is the only way to control for contextual characteristics.

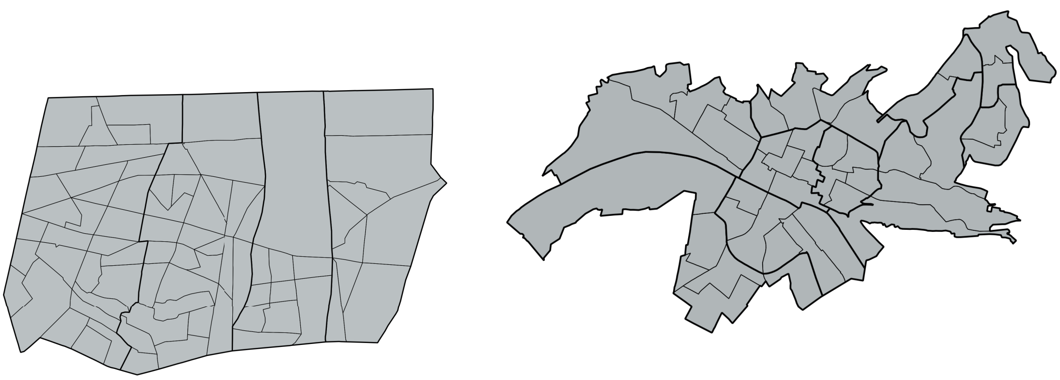
3 Addressing the issue of endogenous location selection

A major concern when working with local issues, pervasive in the literature on neighborhood effects, is that households usually sort across neighborhoods in a non-random fashion. It is then possible that some unobserved household or individual characteristics influence both the propensity to be victim of a criminal event and neighborhood characteristics, therefore biasing the results. Several methods have been used to overcome this endogenous sorting issue, that I briefly summarize here. A first approach consists in using a measure of the variable of interest aggregated to a higher geographic level as an instrument for this variable. For instance, Evans et al. (1992) instrument neighborhood poverty with metropolitan area poverty. An alternative method is to rely on randomized experiments designed such that the choice of neighborhood is actually exogenous. On of the most famous examples is the Moving To Opportunity program in the US, through which randomly selected households are given housing vouchers, enabling them to relocate in richer neighborhoods. In particular, and related to the topic of the present study, Ludwig et al. (2001) and Kling et al. (2005) use this experiment to examine the role of neighborhood characteristics on juvenile crime. These are, to the best of my knowledge, the only two existing studies researching the impact of neighborhood effects on crime. However, the very particular setting in which these results are derived brings some concern regarding their validity in a more general context. Bayer et al. (2008) review more extensively these alternative methods and discuss their limitations.

The approach adopted in this paper builds on the very local nature of the data. It follows Bayer et al. (2008) who study the role of neighbors on work location, and more recent work by Hémet and Malgouyres (2018) and Solignac and Tô (2018) who investigate neighborhood effects using French data. The idea is that although households are able to select a given area in which they want to live, they are, however, unable to pinpoint a precise neighborhood within this given area. This assumption means that even if households are able to choose a given residential area, there will not be any correlation in unobserved factors affecting risk of victimization among individuals living in the same neighborhood *within the larger selected area*. As a consequence, once we control for the characteristics of the larger area selected by the individual, the remaining spatial variation of characteristics across neighborhoods within the larger area is supposed to be exogenous. Empirically, this is done through the inclusion of fixed effects of these larger areas. In particular, in this paper, I assume that the area into which households select corresponds to what is literally called a *Large*

Neighborhood in the French statistical jargon (*Grand Quartier*). Large enough municipalities are divided into several *Large Neighborhoods*, which themselves encompass several contiguous IRISes. As for IRISes, Large Neighborhoods are following obvious physical boundaries (e.g. streets, rivers...) and are designed by the French Statistical Institute so as to be as homogeneous as possible in terms of living environment. Figure 2 depicts the four Large Neighborhoods of Paris 18^{th} district and the ten Large Neighborhoods of Rouen, which are delineated by thicker lines. Although there is no formal evidence that large neighborhood is the geographical unit targeted by households when looking for a housing, this area makes a reasonable reference neighborhood compared to the IRIS.[9] Importantly for my argument, these large neighborhoods are generally labeled by a "common-knowledge" name referring to a neighborhood to which people can actually refer (e.g. "city-hall" or "station" neighborhood). In other words, households can easily identify these Large Neighborhoods, by contrast with IRISes as explained below. In the case of Paris, Large Neighborhoods correspond to "administrative neighborhoods" upon which a number of public services are administered. In particular, each of these administrative units possess a police station. Relying on the assumption that households decide upon the Large Neighborhood where they want to live, but do not pick a specific IRIS *within* this Large Neighborhood, I can subsequently estimate local neighborhood effects once including Large Neighborhoods fixed effect: the identification comes from the remaining variation of characteristics across IRISes within a given Large Neighborhood.

Figure 2: Large Neighborhoods in Paris 18^{th} (left panel) and Rouen (right panel)



[9] An alternative and maybe more obvious selection zone would be shools' catchment areas. Although it is not easy to get access to the corresponding maps, except for some specific regions, I intend to focus on these areas as an alternative selection zone.

It is now in order to present a few arguments supporting this assumption. First, because the housing market is very tight, it is reasonable to think that a household targeting a given area very unlikely has a choice over the precise neighborhood where it will end up in this area. This would indeed require that at least one housing unit satisfying the other decision criteria of the household (e.g. size) be vacant in each neighborhood within the larger area at the time when the household is looking for a new place. A second consideration is that it may be difficult for prospecting households to identify neighborhood-by-neighborhood variation in neighbors and contextual characteristics, prior to moving into the neighborhood. To put it differently, although the household may have a realistic *ex-ante* view on the characteristics of the targeted area, it is less likely to be actually able to identify differences in these characteristics across the various neighborhoods of the area. This makes even more sense in the context of victimization, for which *ex-ante* information is particularly difficult to gather. Finally, an interesting feature of the French neighborhoods studied here (the IRISes) is that they do not follow any kind of administrative frontier. For instance, they are distinct from police districts, and from school zones determining to which school children must go. Rather, the neighborhoods considered here were designed to encompass 2,000 inhabitants on average, and to be homogeneous in terms of living environment, with borders following the main topographical and landscape frontiers (e.g. roads, railways and rivers). People ignore where these borders are, and more generally do not even know what an IRIS is, as it is only used for statistical purpose. For those reasons, it is practically impossible that households purposely decide to live in a given IRIS rather than in a contiguous one. All these arguments support the validity of the assumption that there should be no correlation in unobserved factors affecting victimization among neighbors living in the same neighborhood (IRIS) *within the larger selected area*.

In addition to these general arguments, I now turn to a more formal statistical test of this assumption: I want to verify whether there is sorting across local neighborhoods based on individual observable characteristics, and whether this sorting remains after controlling for selection into Large Neighborhoods (*i.e.* I want to test for the presence of sorting across IRISes within Large Neighborhoods). The test I propose here is inspired by Hémet and Malgouyres (2018) who rely on a similar strategy but on different spatial units. I first check whether there is sorting across neighborhoods. To this aim, I randomly pick one individual in each IRIS and regress a given observable characteristic (*e.g.* origin or education) on the IRIS-neighbors average of this characteristic, excluding the individual and members of her household. This procedure is repeated 100 times. The average R-squared from these regressions for different observable characteristics are reported in column 1 of Table 5. As expected, they are rather large, suggesting a substantial degree of spatial sorting.

I now want to test the assumption that there is little sorting remaining after including fixed effects for larger selection areas. I first regress any given individual characteristic on fixed effects for larger geographic areas into which households are likely to self-select, from the largest to the smallest (*départements*[10], municipalities and IRISes), and I store the residuals from these regressions. I then store the residuals obtained after running the same regressions using instead the corresponding neighborhood average as the dependent variable. Both residuals simply measure deviation from the area average. If households do not actually select in which particular IRIS they settle *within* a given larger area, there should be no association between the two residuals. To test this, we regress the residual from the individual regression on the residual from the neighbors-average regression, and we eventually store the the corresponding R-squared. I repeat this procedure 100 times and compute the average R-squared, which are eventually reported in columns 2 to 4 of Table 5. Looking at the R-squared reported in column 4, obtained when fixed effects for Large Neighborhoods are included, we can note that they are much smaller than those reported in the previous columns, and in particular than those obtained in the unconditional regressions in column 1. This supports the assumption that the amount of *within-Large Neighborhood* sorting based on the various observable characteristics is negligible.

Finally, Solignac and Tô (2018) also work at the IRIS level to study how local employment influences labor market outcomes of young graduates, and rely on the same identifying assumption. In their paper, they propose an alternative statistical test of the validity of this assumption that I summarize here. This test consists in showing that the spatial autocorrelation in observed characteristics between local neighborhoods is limited once these local neighborhoods are nested within Large Neighborhoods. To this aim, the authors rely on Moran indices, which are designed to capture spatial autocorrelation in a given variable between all units (here, IRISes) belonging to the same geographical area. This statistic is large and positive if local neighborhoods with similar characteristics tend to be clustered spatially, and it gets close to zero if local neighborhoods are randomly spread out. Using data from the 1999 census, they compute Moran indices for a set of IRIS characteristics, taking alternative larger spatial units as the reference area. For all characteristics considered, the distribution of standardized Moran statistics is much less dispersed when the reference unit

[10] *Départements* are large administrative units: there are 96 such units in mainland France.

(*i.e.* the unit within which spatial autocorrelation is measured) is the Large Neighborhood compared to larger areas such as the municipality. This means that households tend to sort themselves between local neighborhoods within municipalities for instance, but not within Large Neighborhoods where spatial autocorrelation remains quite limited, providing additional support to our common identifying assumption.

4 Empirical specification and baseline results

Let i, j and k indicate respectively individual, household and IRIS. For each outcome considered, I estimate the following equation.

$$VICT_{(i,j),k} = \alpha + \beta U_{k(i,j)} + X_{i,i(j)}\gamma + Y_{j(i),j}\delta + Z_{k(i,j)}\kappa + \mu F_{year} + \nu F_{LN} + \varepsilon_{(i,j),k} \qquad (1)$$

where $VICT_{(i,j),k}$ is a dummy variable indicating the occurrence of a given type of victimization at least once over the preceding two years. More precisely, in the case of a household victimization the dependant variable is $VICT_{j,k}$, while it is $VICT_{i,k}$ when it turns to individual victimization, with k standing for the IRIS where the surveyed household lives. U_k stands for local neighborhood unemployment rate, so that β is the main parameter of interest. X is a vector of individual observables characterizing the surveyed individual or the head of households according to the type of victimization considered (individual or household respectively), Y is a vector of household characteristics and Z_k a vector of social, economic and demographic characteristics of the IRIS, along with other contextual variables that are detailed below. I also include year fixed effects (F_{year}) to account for specific time trends related to a change in economic conditions or policy orientation for instance. Finally, *Large Neighborhoods* fixed effects (F_{LN}) are included for the sake of identification, as explained in the previous section. All results presented below derive from the estimation of a linear probability model, using OLS estimates, with robust standard errors clustered at the IRIS level.

Two broad sets of variables are used in the regressions: one to control for the living environment in a general sense (Z_{IRIS}) and another to control for individual and household characteristics (X and Y). Regarding contextual variables, I control for social, economic and demographic neighborhood (IRIS) characteristics: median annual household income (in log), share of immigrants, share of households living in the public housing sector, share of 14- to 18-year-old individuals, share of single-parent families (*monoparental*) and share of households that have been living in the IRIS for less than two years (*recent movers*). I also include a variable from the CVS survey describing the type of buildings in the neighborhood (dispersed houses out of the city, houses in a lot or in the city, apartment blocks in the city or in the suburbs). Regarding household characteristics, the following controls are used: household monthly income (in three categories), ownership status (owner, tenant in the private housing sector or tenant in the public housing sector) and number of children in the household. As far as individual (respectively household head) characteristics are concerned, age, gender, nationality, occupation status and socio-economic category of the surveyed individual (respectively household head) are included in regressions of individual (respectively household) victimization.

Table 6 summarizes the results of the regressions including large neighborhood fixed effects. The coefficients for the variables other than IRIS characteristics are not presented for the sake of space-saving, but are available upon request, and are commented below.

The estimates reveal that living in a neighborhood with a larger share of immigrants would reduce the probability of being burgled and robbed. This is particularly striking given that people's feeling of insecurity is strongly positively correlated with the share of immigrants in the neighborhood. Living in a poorer area would also lower the likelihood of robberies compared to richer neighborhoods, which goes in the expected direction given the incentives. The share of single-parent households appears to drive car thefts and car vandalism, as well as thefts of objects from cars, but to a lesser extent. The share of recent movers is also an important characteristic explaining vandalism. A possible interpretation is that the larger the share of recent movers, the less neighbors know each other, and hence the less likely they are to organize some sort of collective neighborhood watching. Another interpretation pertaining to the social disorganization theory is that weaker social ties undermine the ability of a community to exercise informal control over its members. This alternative explanation is also relevant to the previous results on single-parents families.

Local unemployment rate emerges as one of the most important determinants of crime victimization, both in terms of the number of victimization types in which it is involved and in terms of magnitude of the coefficient. The effect of unemployment rate is particularly large for car vandalism. Because this is a non-lucrative and violent offense, this result also seems in line with social disorganization theory, resulting from social rather than financial deprivation. The strong relationship of unemployment with burglaries is less intuitive, as it suggests that burglars live and burgle in the same neighborhood. One interpretation could be that the burglaries happening in high unemployment neighborhoods are committed by amateurs, out of despair and as a last resort, who seek to steal goods for their personal use (e.g. TV sets, video game consoles, food) rather than for reselling them (e.g. jewelry, pieces of art). An alternative explanation can be borrowed from sociology: the routine activity theory (Cohen and Felson, 1979): one's neighbors are easy to observe on a daily basis, up to knowing when they are absent from home and when they will return (the routine), facilitating burglaries.

The type of neighborhood is also particularly relevant for most types of victimization. As expected, households living in residential areas made of groups of houses are more likely to be offended than those living in isolated houses in the countryside. Households living in apartments buildings are less likely to be burgled, but more likely to have their car vandalized, especially if they live in the suburbs.[11] Now taking a quick look at household and individual characteristics, we can see that wealthier households suffer more of home vandalism, but less of car vandalism, while their members are less likely to be assaulted. The result for cars is probably explained by the fact that wealthier household park their cars in a closed or secured space. Households with an unemployed head are more likely to be victims of burglary, home vandalism, and car theft. Similarly, unemployed individuals are more likely to suffer from violent crimes (robberies and assaults). Older individuals tend to be less victimized. Gender does not affect the probability of theft or robbery, but males are more victims of assaults than females.

Although I do not present the naive estimates in the paper (those estimated without including Large Neighborhood fixed effects, controlling only for larger regions), a few remarks are in order. To a very large extent, the coefficients on IRIS characteristics are smaller once *Large Neighborhoods* fixed effects are included. In particular, for the share of immigrants, the coefficients for *theft of objects from cars* and *theft* are significantly positive in the naive regression and are now driven down to zero (in part due to an increase in the standard errors), while some of the coefficients that were not significantly different from zero are now significantly negative (*burglary* and *robbery*). This suggests that controlling for large neighborhood fixed effects actually corrects a bias induced by the fact that immigrants tend to settle in more criminogenic areas, because of lower rents for instance. The estimates for unemployment are rather stable for burglary, car vandalism and assault. Yet, they are driven down to zero for car theft, motorbike theft and bike theft once we control for *Large Neighborhoods* characteristics. The exception is for robbery, where it becomes slightly

[11]They are also less likely to have their home vandalized, but this is mechanically due to their home type.

positive.

5 Going beyond one's own neighborhood

An important dimension to take into account in the study of crime is criminals' mobility. To put it simply, if criminals are not mobile, the larger the number of criminals living in a neighborhood, the more likely the other inhabitants of this neighborhood experience victimization. On the other hand, if criminals are mobile, then even individuals living in a criminal-free neighborhood may face a risk of victimization if they are located at some reasonable distance of a neighborhood populated with criminals. Consider for instance a high unemployment neighborhood, more likely to breed criminals according to Becker's theory. The potential offenders could commit crime in the neighborhood where they reside, if, for instance, they cannot afford the cost of commuting to a more distant neighborhood, or if they benefit from observing their neighbors' habits and routine activities (Cohen and Felson, 1979). Alternatively, they could decide to commit a crime in a more distant neighborhood if they fear to be more easily identified in their own neighborhood, or if their neighborhood is too deprived to be attractive. Whether an offender decides to act in his own neighborhood or in a remote one thus reflects a weighting of the expected gains, the direct costs and the opportunity costs of committing crime in another neighborhood. Therefore, even if we find that unemployment increases victimization on average, the effect might actually depend on where one lives relative to high unemployment neighborhoods.

Although the question of criminals' mobility seems highly relevant when studying determinants of victimization, it is not addressed in the economics of crime literature, mainly due to the fact that most studies rely on aggregate data. By contrast, because I work with data localized at a low geographic level, I am able to connect individuals not only to the characteristics of the neighborhood where they live, but also to the characteristics of the neighborhoods that are further away. This new spatial approach enables me to indirectly account for criminals mobility.[12] To this aim, I consider the IRIS where the surveyed individual lives as the reference neighborhood, and I construct two successive circles of adjacent IRISes to represent more distant neighborhoods. More precisely, all the IRISes contiguous to a given IRIS constitute the first ring of adjacent neighborhoods (denoted as *IRIS 1*), while all the IRISes contiguous to those in the first ring, excluding the

[12] It is not direct as I have no information about the offenders, so I am not actually able to locate them.

reference IRIS and the first ring of IRISes themselves, constitute the second ring of adjacent neighborhoods (denoted as *IRIS 2*). Figure 3 illustrates the three geographic levels on which I rely for the 18^{th} district of Paris (left) and the city of Rouen (right). On each map, the reference IRIS (*i.e.* where the individual lives) is colored in black, while the first and second rings of surrounding IRISes are colored in dark grey and in light grey respectively.

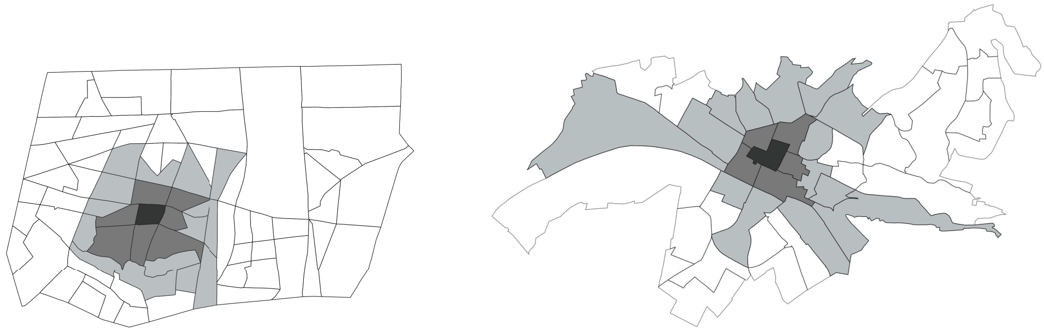
Using this setting, it is possible to relate any individual or household in the survey to the characteristics of the neighborhood where it lives, as well as to those of the first and second rings of adjacent neighborhoods. Thus, I can explore whether a given factor matters more within the neighborhood or from a remote one. In the following empirical analysis, I will focus on one particular factor: the unemployment rate. First, as noted at the end of the previous section, this factor shows the most relevant in explaining victimization. Second, I make this choice in order to avoid a likely collinearity issue with other IRIS characteristics. The unemployment rate of a given neighborhood is indeed highly correlated with most of the other IRIS characteristics (share of immigrants, median income, share of single parents families and share of public housing), as can be seen from Table 7. Concretely, I compute the average unemployment rate over all the first and second rings of IRISes respectively, weighted by the size of the active population in each IRIS. To summarize, and using the same notation as in section 4, I estimate the following equation:

$$VICT_{(i,j),k} = \alpha + \beta_0 U_{k(i,j)} + \beta_1 U_{k+1(i,j)} + \beta_2 U_{k+2(i,j)} + Y_{j(i),j}\delta + Z_{k(i,j)}\kappa + \mu F_{year} + \nu F_{LN} + \varepsilon_{(i,j),k} \quad (2)$$

Where U_k is the unemployment rate in the reference IRIS, U_{k+1} the average unemployment rate in the first ring of adjacent IRISes, and U_{k+2} the average unemployment rate in the second ring of adjacent IRISes.

This geographical approach has some drawbacks. First, as I do not have any information for the road or transportation networks, I am not effectively capturing transportation time or cost, which are key determinants of mobility. This could be addressed using the information about road networks provided by the French Institute of Geography (IGN), and performing a Geography Information System analysis. However, because I do not have access to these data nor to the technology necessary to deal with it, I keep this step for future research. Second, this approach with adjacent IRISes does not enable me to directly capture distance, as IRISes are heterogeneous in terms of size. As mentioned in Section 2, only municipalities with more

Figure 3: Examples of two reference neighborhoods (black) with their first (dark grey) and second (light grey) rings of surrounding neighborhoods, in Paris 18^{th} and Rouen.



than 5,000 inhabitants are divided into IRISes, and the target size of an IRIS is 2,000 inhabitants so that denser cities tend to have smaller IRISes. To deal with this issue, I restrict the sample to municipalities that are actually divided into IRISes, hence reducing the variation in the size of the IRISes. Such a restriction typically excludes rural villages, which are quite large IRISes (in terms of surface).

The estimated effects of the unemployment rate in the three successive neighborhood rings (IRIS, IRIS 1 and IRIS 2) on the various types of victimization are reported in Table 8. The first set of results displayed are the estimates obtained when no other control is included, while the second set of results is obtained including the full set of controls. Note that for each specification, I control for large neighborhood fixed effects to avoid the endogeneity issue, as discussed in the previous section. Let us first look at the burglaries in column (1). In the no other control specification, only the unemployment rate in the first ring of adjacent IRISes is positive and significant at the 10% level. In the full specification, both the IRIS and the IRIS 1 unemployment rates are significant at the 5% level, with a larger coefficient for the latter. The results are similar for thefts of objects from cars. The unemployment rate in the first contiguous neighborhoods is the only significant one that in the full specification. This suggests that economic types of crimes such as burglary and theft of objects from cars are better explained by the unemployment rate from more distant places than from the immediate neighborhood. This is in line with the idea that when it turns to economic crimes, offenders are more likely to travel to some remote area. Several considerations can help rationalize this: stealing from one's direct neighbors is not financially attractive when one lives in a more economically deprived neighborhood; the expected financial gain from an economic crime allows the offender to afford the cost of traveling to a more distant neighborhood; and the criminal limits the chance to be identified by witnesses when committing an offense in a different place than the one where he lives. It is then a bit puzzling that the unemployment rate in the reference IRIS still matters for burglaries. A possible explanation is that there are two types of burglars: those who travel to a remote place to steal expensive goods they can resell such as jewelry and works of art, and those who steal very basic goods such as food or TV sets from their own neighbors for their personal consumption. An alternative explanation could be that the habits and general behavior of one's direct neighbor are more easily observed, so that it simplifies the planning of the crime (Cohen and Felson, 1979). It is also surprising not to find any significant effect on car and motorbike thefts. A possible explanation could be that stealing this type of goods requires an even longer distance, so that it is more easy to stock or use the car.

On the other hand, Table 8 also shows that the unemployment rate in the immediate neighborhood is particularly relevant in explaining non-economic and violent crimes such as acts of vandalism, whether on the home or on the car, and assaults. In this case, the social disorganization theory is more appropriate to understand the mechanisms than the Beckerian approach.

The concern linked to the IRIS size may persist, with the existence of very small IRISes in densely populated cities such as Paris. In this case, the distance between two IRISes may not be relevant, with a null transportation cost across the three contiguous rings of IRISes. In what follows, I therefore exclude the observations of the three largest cities (Paris, Lyon and Marseille), hence getting rid of the smallest IRISes. The regressions presented above are then replicated on this sub-sample. The estimates for unemployment rates in the successive rings of IRISes in the full specification are reported in Table 9. The previous results are robust to this sample restriction. The results are stable for burglaries, with a positive effect of direct (IRIS) unemployment rate and a larger positive effect of more distant (IRIS 1) unemployment. Note that the gap between the two coefficients is even slightly larger than in the previous table. The estimates for both acts of vandalism, theft of objects from car and assaults are also similar to those presented above. There are however two differences compared to the regressions including large cities: the coefficient for IRIS unemployment rate is now significantly positive (at the 10% level) in the motorbike theft and in the robbery equation. To the extent that robberies are violent crimes by opposition to thefts, this new result tends to comfort the idea that the direct exposure to unemployment affects violent rather than economic crimes. The result for motorbike theft could be at odds with this intuition, unless most of the thefts observed apply to motorcycles rather than to more powerful motorbikes.

Because the unemployment rates of the adjacent local neighborhoods are averaged over the first and second rings of adjacent IRISes, this measure of unemployment may fail to capture important spatial disparities in terms of economic conditions. For instance, a given average unemployment rate may be obtained with a set of IRISes characterized by the same unemployment rate, or with a set of IRISes in which some have a very low unemployment rate and some a very large one. Thus, a given average unemployment rate may hide very different situations. Even if my level of analysis is quite small, it is possible that a given IRIS has very heterogeneous neighbors, so that looking at mean unemployment rates might not be the most relevant metrics. I therefore estimate the same equation as above, but considering the largest unemployment rate among the various IRISes in the first and second rings, rather than the average.

The corresponding estimates are displayed in Table 10, where estimates in Panel A are obtained using the main sample, while those in Panel B are obtained excluding Paris, Lyon and Marseille. The main results are robust to this change in specification.

6 Conclusion

This paper is, to the best of my knowledge, the first study on victimization at the neighborhood level. This local approach brings new insights to the economics of crime literature as it enables me to characterize precisely the context (both location and victim) in which criminal events occur. By contrast with previous papers based on aggregate police data, I am therefore able to distinguish between factors related to the opportunity cost of committing crime (e.g. unemployment, wages) and factors pertaining to the attractiveness of the victims (e.g. wealth). I find that household and individual characteristics are minor determinants of household and individual victimization respectively, while the economic situation of the neighborhood actually matters. In other words, victims (individuals or households) are not directly targeted (except in the case of assaults): rather, it is the neighborhood where the mischief occurs that is coveted. In particular, local unemployment rate is found to be strongly related to household victimization. In order to address the endogenous neighborhood selection issue, I included "large neighborhood" fixed effects in order to control for the characteristics of the larger area that the households are likely to have actually selected. Most of the estimates of neighborhood characteristics are attenuated once selection is corrected for. Yet, the local unemployment rate remains a strong predictor of several types of victimization.

This paper also sheds new light on the mechanisms behind this relationship, through the adoption of an original spatial approach. I take advantage of the precise location of the data to control for the characteristics of both the reference neighborhood and the first and second rings of adjacent neighborhoods. That way, I can account for heterogeneity across neighborhoods and hence indirectly for criminals mobility. This is an improvement over the existing literature which ignores this dimension. The results reveal that for burglaries and thefts of objects from cars, unemployment rate in the adjacent neighborhoods have a stronger explanatory power than unemployment in the precise neighborhood where the misdeed occurred. On the contrary, local unemployment rate dominates over more distant unemployment rates in explaining vandalism and assaults in particular. A natural interpretation of these findings is that criminals are mobile for economic crimes but not for violent crimes. In other words, they can afford some transportation cost when they expect a financial reward from their mischief, in line with the Beckerian theory of crime. On the other hand, violent crimes and vandalism escape from this logic and relate more the the social disorganization theory. This new method helps understanding more precisely criminal behavior according to the different types of crimes, and is therefore a key contribution to the literature.

Naturally, the empirical design endorsed in this paper presents some drawbacks and will be subject to future improvements. For instance, considering only two rings of adjacent neighborhoods is somehow arbitrary and is an important limitation as criminals may travel from more remote areas. In particular, car thefts may involve longer distances so as to reduce the risk of apprehension. This could explain why none of the unemployment rate estimates (IRIS, IRIS1 and IRIS2) is significant for this type of crime. One of the next developments of this work will therefore be to take into account all neighborhoods in an exhaustive fashion. The idea would be to express crime as a function of the sum of unemployment rates in all surrounding neighborhoods, weighted by distance or transportation costs. In other words, this would consist in adapting the market-potential function developed in the new economic geography literature (e.g. Harris, 1954; Hanson, 2005) to the economics of crime literature. Because it reveals the relevance of a spatial approach and stresses its necessity, the present paper is a first step in this direction.

Table 1: Share of households or individuals victimized at least once over the past two years.

		Full Sample (1)	Rural Areas (2)	Less than 50,000 inhab. (3)	More than 50,000 inhab. (4)	Paris Urban Unit (5)
Household victimization						
Burglary	Mean	4.61 %	3.81 %	4.01 %	5.20 %	5.18 %
	StDev	(.210)	(.191)	(.196)	(.222)	(.222)
	N	85141	16211	19175	35755	13895
Car Theft	Mean	3.36 %	1.59 %	2.97 %	4.19 %	4.87 %
	StDev	(.180)	(.125)	(.179)	(.200)	(.215)
	N	69226	14953	16599	28183	9413
Motorbike Theft	Mean	5.34 %	2.25 %	4.42 %	7.28 %	8.91 %
	StDev	(.225)	(.148)	(.205)	(.260)	(.285)
	N	10051	2633	2470	3755	1181
Bike Theft	Mean	3.71 %	1.14 %	2.56 %	5.52 %	6.34 %
	StDev	(.189)	(.106)	(.158)	(.228)	(.244)
	N	46321	10974	11687	17877	5730
Home Vandalism	Mean	4.13 %	1.93 %	3.93 %	5.68 %	3.69 %
	StDev	(.199)	(.138)	(.194)	(.231)	(.188)
	N	85142	16214	19177	35751	13895
Car Vandalism	Mean	10.46 %	5.66 %	8.46 %	13.42 %	14.48 %
	StDev	(.306)	(.231)	(.278)	(.341)	(.352)
	N	69192	14955	16593	28170	9396
Car Object Theft	Mean	6.71 %	3.52 %	5.41 %	8.16 %	10.79 %
	StDev	(.250)	(.184)	(.226)	(.274)	(.310)
	N	69227	14953	16598	28186	9412
Individual victimization						
Robbery	Mean	0.95 %	0.29 %	0.54 %	1.13 %	2.09 %
	StDev	(.097)	(.054)	(.073)	(.106)	(.143)
	N	85154	16213	19177	35759	13900
Theft	Mean	3.38 %	2.46 %	2.88 %	3.74 %	4.62 %
	StDev	(.181)	(.155)	(.167)	(.190)	(.210)
	N	85148	16211	19176	35759	13897
Assault	Mean	2.42 %	1.76 %	2.03 %	3.09 %	2.34 %
	StDev	(.154)	(.132)	(.141)	(.173)	(.151)
	N	85142	16212	19171	35758	13896

Table 2: Sample characteristics: households and individuals characteristics.

	Household Characteristics			
	[Min - Max]	Mean	(StDev)	Med
Household monthly income:				
$w \leq 1500$	[0 - 1]	0.313	(0.464)	0
$1500 < w \leq 2500$	[0 - 1]	0.294	(0.456)	0
$w > 2500$	[0 - 1]	0.393	(0.488)	0
Ownership Status:				
Owner	[0 - 1]	0.598	(0.490)	1
Rent in private market	[0 - 1]	0.213	(0.410)	0
Rent in public housing	[0 - 1]	0.144	(0.351)	0
Other	[0 - 1]	0.045	(0.207)	0
Household composition:				
Head with a partner	[0 - 1]	0.569	(0.495)	1
Number of children	[0 - 11]	0.644	(0.993)	0

	Household Head				Individual			
	[Min - Max]	Mean	(StDev)	Med	[Min - Max]	Mean	(StDev)	Med
Age	[15 - 101]	53.25	(17.87)	52	[14-102]	47.19	(19.62)	46
Gender	[0 - 1]	0.622	(0.485)	1	[0 - 1]	0.479	(0.500)	0
Nationality:								
Native French	[0 - 1]	0.908	(0.290)	1	[0 - 1]	0.907	(0.290)	1
Naturalized French	[0 - 1]	0.043	(0.203)	0	[0 - 1]	0.042	(0.201)	0
EU 15	[0 - 1]	0.021	(0.142)	0	[0 - 1]	0.019	(0.136)	0
Other EU (after 2004)	[0 - 1]	0.001	(0.037)	0	[0 - 1]	0.001	(0.037)	0
Maghrebian	[0 - 1]	0.013	(0.115)	0	[0 - 1]	0.014	(0.118)	0
Other African	[0 - 1]	0.005	(0.073)	0	[0 - 1]	0.006	(0.075)	0
Other nationality	[0 - 1]	0.009	(0.092)	0	[0 - 1]	0.010	(0.100)	0
Employment status:								
Employed	[0 - 1]	0.559	(0.496)	1	[0 - 1]	0.488	(0.500)	0
Unemployed	[0 - 1]	0.041	(0.198)	0	[0 - 1]	0.059	(0.235)	0
Inactive	[0 - 1]	0.340	(0.490)	0	[0 - 1]	0.453	(0.498)	0
Socio-economic Category:								
Farmer	[0 - 1]	0.014	(0.117)	0	[0 - 1]	0.012	(0.108)	0
Craftsman, shopkeeper	[0 - 1]	0.046	(0.209)	0	[0 - 1]	0.034	(0.182)	0
Higher occupation	[0 - 1]	0.111	(0.314)	0	[0 - 1]	0.078	(0.269)	0
Intermediate occupation	[0 - 1]	0.150	(0.357)	0	[0 - 1]	0.128	(0.334)	0
Employee	[0 - 1]	0.130	(0.336)	0	[0 - 1]	0.165	(0.371)	0
Factory worker	[0 - 1]	0.155	(0.362)	0	[0 - 1]	0.131	(0.337)	0
Retired	[0 - 1]	0.353	(0.478)	0	[0 - 1]	0.286	(0.452)	0
Other inactive	[0 - 1]	0.041	(0.198)	0	[0 - 1]	0.166	(0.372)	0

Reading: The head of the average household is 53 years and 3 months old. The average surveyed individual is about 47 years and 2 months old. 55.9 % of household have an employed head. 48.8 % of individuals are employed.

Table 3: Sample characteristics: households living environment

Contextual Variables:	[Min - Max]	Mean	(StDev)	Med
IRIS Characteristics:				
Share of immigrants	[0 - 0.794]	0.079	(0.074)	0.055
Median income (log)	[7.69 - 10.98]	9.792	(0.258)	9.784
Unemployment rate	[0 - 0.741]	0.112	(0.056)	0.100
Share single-parent families	[0 - 0.673]	0.137	(0.068)	0.127
Share hh in public housing	[0 - 1]	0.136	(0.187)	0.064
Share of recent movers	[0 - 0.935]	0.129	(0.061)	0.116
Share of 14-18 y.o.	[0 - 0.239]	0.056	(0.017)	0.056
City density (log)	[-1.09 - 10.55]	6.297	(1.955)	6.292
Type of neighborhood:				
Dispersed houses	[0 - 1]	0.176	(0.381)	0
Houses Lot / in cities	[0 - 1]	0.443	(0.497)	0
Apartment block (city)	[0 - 1]	0.231	(0.422)	0
Apartment block (suburbs)	[0 - 1]	0.091	(0.288)	0
Mixed	[0 - 1]	0.059	(0.235)	0
Size of the Urban Unit:				
Rural Areas	[0 - 1]	0.226	(0.418)	0
Less than 50,000	[0 - 1]	0.251	(0.433)	0
More than 50,000	[0 - 1]	0.365	(0.481)	0
Paris Urban Unit	[0 - 1]	0.158	(0.165)	0

Reading: The average household lives in an IRIS where there are 7.9 % of immigrants. 59.8 % of households own their home. The head of household lives with a partner in 56.9 % of households.

Table 4: Probability that the incident occurs in own's neighborhood

	Mean	(StDev)	N
Household Victimization			
Car theft	0.724	(0.447)	2,052
Motorbike theft	0.643	(0.479)	497
Bike theft	0.755	(0.430)	1,620
Vandalism on the car	0.657	(0.475)	6,581
Theft of object from car	0.289	(0.454)	4,080
Individual Victimization			
Robbery	0.396	(0.489)	633
Theft	0.301	(0.459)	2,308
Assault	0.372	(0.484)	1,725

When at least one offence is reported, more details are asked about the latest event. In particular, the respondent indicates whether the incident happened in one's "own village or neighborhood". Reading: 72.4 % of the latest car theft happened in the owner's neighborhood. 37.2 % of the latest assaults occurred in the victim's neighborhood.

Table 5: Sorting test based on observable characteristics

Variable	(1) **Unconditional**	(2) **Département FE**	(3) **Municipality FE**	(4) **Large N'hood FE**
North African	5.5 %	4.5 %	2.9 %	1.6 %
Master, PhD	10.4 %	5.3 %	2.5 %	1.3 %
Graduate	0.56 %	0.43 %	0.26 %	0.17 %
Undergraduate	0.07 %	0.03 %	0.02 %	0.01 %
Lower undergraduate	0.11 %	0.07 %	0.04 %	0.03 %
Technical Baccalaureate	1.54 %	0.55 %	0.15 %	0.07 %
Lower degree	0.67 %	0.25 %	0.11 %	0.06 %
Drop-out	5.6 %	4.5 %	3.03 %	1.8 %
Age	3.65 %	2.82 %	1.89 %	1.48 %

In each IRIS, we randomly draw an individual and compute the average characteristics among her neighbors (excluding members of her own household). For each observed characteristic, we regress the individual's observation on IRIS-neighbors' average observation and look at the within-group R-squared of the regression. We repeat this process 100 times and compute the average R-squared, which are reported in the table. Column 1 displays the average R-squared from the unconditional regressions, while Columns 2, 3, and 4 display the mean R-squared from regressions including *département*, municipality, and Large Neighborhood fixed effects, respectively.

Table 6: Determinants of victimization: including large neighborhood fixed effects

	Household victimization							Individual victimization		
	Burglary	Car Theft	Motorbike Theft	Bike Theft	Home Vandalism	Car Vandalism	Theft of car objects	Robbery	Theft	Assault
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share of Immigrants	-0.118**	0.024	0.049	0.079	0.024	-0.038	0.036	-0.022*	0.017	0.006
	(0.043)	(0.038)	(0.165)	(0.056)	(0.041)	(0.063)	(0.035)	(0.013)	(0.021)	(0.020)
Median Income (log)	-0.026*	-0.001	0.074	0.024	-0.012	-0.006	0.009	-0.004	0.004	0.011*
	(0.014)	(0.012)	(0.051)	(0.018)	(0.013)	(0.020)	(0.011)	(0.004)	(0.007)	(0.006)
Unemployment rate	0.105**	0.007	0.181	0.059	-0.003	0.216***	-0.017	0.026*	-0.026	0.041**
	(0.044)	(0.039)	(0.169)	(0.056)	(0.042)	(0.064)	(0.035)	(0.013)	(0.022)	(0.020)
Share Monoparental	-0.027	0.061**	-0.032	0.070	-0.018	0.152**	0.048*	0.009	0.016	0.021
	(0.035)	(0.030)	(0.126)	(0.043)	(0.034)	(0.050)	(0.027)	(0.011)	(0.017)	(0.016)
Share Public Housing	-0.008	-0.024**	0.071	-0.021	0.028**	-0.040**	-0.004	-0.007*	0.001	0.004
	(0.012)	(0.011)	(0.047)	(0.016)	(0.012)	(0.018)	(0.010)	(0.004)	(0.006)	(0.006)
Share Recent Movers	0.042	0.021	0.021	0.060	0.089**	0.104**	0.050**	0.014	0.036**	0.003
	(0.031)	(0.026)	(0.115)	(0.038)	(0.030)	(0.044)	(0.024)	(0.010)	(0.015)	(0.014)
Share 14-18 y.o.	0.098	0.087	-0.099	0.040	0.095	0.141	0.076	-0.027	-0.060	-0.038
	(0.096)	(0.082)	(0.339)	(0.115)	(0.092)	(0.135)	(0.074)	(0.029)	(0.047)	(0.044)
N	63,586	52,453	7,891	35,665	65,588	52,428	52,455	63,655	63,653	63,649

In addition to the IRIS characteristics reported here, the regressions include the following controls: city density (log), type of neighborhood, household characteristics, household head (respectively individual characteristics) in the household (respectively individual) victimization regressions. They also control for year and large neighborhood fixed effects.
* p<0.10, ** p<0.05, *** p<0.001

Table 7: Correlation between IRIS characteristics

	Share Immigrants	Median Income	Unemployment Rate	Share Single Parent	Share Public Housing	Share Recent Movers	Share 14-18 y.o.
Share Immigrants	1.000						
Median Income	-0.255	1.000					
Unemployment Rate	0.528	-0.645	1.000				
Share Single Parent	0.496	-0.457	0.671	1.000			
Share Public Housing	0.505	-0.527	0.661	0.697	1.000		
Share Recent Movers	0.066	0.049	0.126	0.191	-0.104	1.000	
Share 14-18	0.128	-0.158	0.225	0.161	0.292	-0.151	1.000

These correlations are obtained using one observation per IRIS per year. The numbers in the columns of the first line correspond to the numbers in the lines of the first column. For instance, (1) stands for the Share of Immigrants, so that "-2.255" is the correlation between the share of immigrants in an IRIS in a given year and the median income in the same IRIS and year.

Table 8: Unemployment rate in adjacent neighborhoods.

	Household victimization							Individual victimization		
	Burglary	Car Theft	Motorbike Theft	Bike Theft	Home Vandalism	Car Vandalism	Theft of car objects	Robbery	Theft	Assault
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
No other controls										
u_{iris}	0.005	0.049**	0.273**	0.116**	0.096***	0.353***	0.055*	0.016*	-0.012	0.051***
	(0.025)	(0.024)	(0.115)	(0.038)	(0.026)	(0.042)	(0.023)	(0.009)	(0.013)	(0.013)
u_{iris1}	0.104*	-0.009	0.145	0.054	0.034	0.133	0.286***	0.016	0.041	-0.022
	(0.058)	(0.054)	(0.266)	(0.086)	(0.059)	(0.095)	(0.052)	(0.020)	(0.031)	(0.029)
u_{iris2}	-0.028	0.049	-0.372	-0.093	-0.055	-0.211	0.140*	-0.005	0.014	-0.035
	(0.089)	(0.082)	(0.362)	(0.127)	(0.091)	(0.143)	(0.079)	(0.031)	(0.047)	(0.044)
Full specification										
u_{iris}	0.081**	0.021	0.211	0.021	0.124***	0.235***	-0.006	0.013	-0.018	0.029**
	(0.028)	(0.027)	(0.128)	(0.042)	(0.029)	(0.047)	(0.026)	(0.010)	(0.015)	(0.014)
u_{iris1}	0.144**	0.035	-0.045	0.030	0.024	0.112	0.226***	0.018	0.051	-0.011
	(0.062)	(0.058)	(0.283)	(0.090)	(0.063)	(0.100)	(0.055)	(0.022)	(0.032)	(0.031)
u_{iris2}	-0.013	0.052	-0.475	0.166	0.063	-0.189	0.001	0.004	0.028	-0.052
	(0.094)	(0.087)	(0.379)	(0.132)	(0.096)	(0.150)	(0.083)	(0.033)	(0.049)	(0.047)
N	41,781	32,191	4,264	20,502	41,780	32,170	32,194	41,826	41,826	41,822

In these regressions, the sample has been restricted to observations living in actual IRISes, so that the remaining IRISes are homogeneous in terms of size. "u_{iris}" is the local (IRIS) unemployment rate, "u_{iris1}" the average unemployment rate in the first ring of adjacent IRISes, and "u_{iris2}" the average unemployment rate in the second ring of adjacent IRISes. In the second set of results, the controls are environment characteristics (city density (log), type of neighborhood, size of the urban unit), year fixed effects, household characteristics (income, ownership status, number of children) and individual characteristics, corresponding to the surveyed individual for individual victimization and to the household head for household victimization (nationality, age (log), gender, employment status, socio-economic category). They also include large neighborhood fixed effects. Standard errors clustered at the IRIS level reported in parentheses. * p<0.10, ** p<0.05, *** p<0.001

Table 9: Unemployment rate in adjacent neighborhoods, excluding Paris, Lyon and Marseille

	Household victimization							**Individual victimization**		
	Burglary	Car Theft	Motorbike Theft	Bike Theft	Home Vandalism	Car Vandalism	Theft of car objects	Robbery	Theft	Assault
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
u_{iris}	0.074**	0.042	0.243*	0.003	0.126***	0.227***	0.002	0.017*	-0.014	0.026*
	(0.029)	(0.028)	(0.129)	(0.042)	(0.030)	(0.048)	(0.026)	(0.010)	(0.014)	(0.015)
u_{iris} 1	0.164**	0.057	0.031	0.008	0.053	0.104	0.213***	0.017	0.037	-0.009
	(0.064)	(0.059)	(0.288)	(0.090)	(0.066)	(0.103)	(0.056)	(0.021)	(0.031)	(0.032)
u_{iris} 2	-0.033	0.073	-0.308	-0.216	-0.076	-0.199	0.011	0.023	0.025	-0.052
	(0.097)	(0.088)	(0.377)	(0.132)	(0.100)	(0.153)	(0.083)	(0.032)	(0.047)	(0.049)
N	38,409	30,409	3,945	19,525	38,405	30,390	30,412	38,451	38,450	38,448

In these regressions, the sample has been restricted to observations living in actual IRISes, so that the remaining IRISes are homogeneous in terms of size. "$uiris$" is the local (IRIS) unemployment rate, "$uiris$ 1" the average unemployment rate in the first ring of adjacent IRISes, and "$uiris$ 2" the average unemployment rate in the second ring of adjacent IRISes. The controls are environment characteristics (city density (log), type of neighborhood, size of the urban unit), year fixed effects, household characteristics (income, ownership status, number of children) and individual characteristics, corresponding to the surveyed individual for individual victimization and to the household head for household victimization (nationality, age (log), gender, employment status, socio-economic category). They also include large neighborhood fixed effects. * p<0.10, ** p<0.05, *** p<0.001

Table 10: Largest unemployment rate in adjacent neighborhoods.

	Household victimization					Individual victimization		
	Burglary	Car Theft	Home Vandalism	Car Vandalism	Theft of car objects	Robbery	Theft	Assault
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Main sample								
u_{iris}	0.079**	0.026	0.099***	0.205***	-0.005	0.012	-0.015	0.027*
	(0.026)	(0.026)	(0.030)	(0.046)	(0.024)	(0.010)	(0.012)	(0.014)
$Max(u_{iris1})$	0.033	0.015	-0.039*	-0.082**	0.010	-0.002	0.028**	0.006
	(0.022)	(0.021)	(0.021)	(0.033)	(0.020)	(0.007)	(0.011)	(0.010)
$Max(u_{iris2})$	-0.013	0.047**	-0.001	-0.026	-0.008	0.008	0.012	-0.012
	(0.016)	(0.017)	(0.018)	(0.028)	(0.017)	(0.007)	(0.010)	(0.008)
Panel B: Excluding Paris, Lyon and Marseille								
u_{iris}	0.075**	0.046*	0.101**	0.194***	-0.005	0.017*	-0.011	0.023
	(0.028)	(0.025)	(0.031)	(0.048)	(0.025)	(0.010)	(0.012)	(0.015)
$Max(u_{iris1})$	0.048**	0.024	-0.044**	-0.075**	0.005	0.004	0.021*	0.006
	(0.024)	(0.021)	(0.022)	(0.034)	(0.021)	(0.007)	(0.011)	(0.011)
$Max(u_{iris2})$	-0.002	0.051**	-0.006	-0.023	-0.013	0.001	0.017*	-0.012
	(0.017)	(0.018)	(0.019)	(0.030)	(0.019)	(0.005)	(0.010)	(0.009)

In these regressions, the sample has been restricted to observations living in actual IRISes, so that the remaining IRISes are homogeneous in terms of size. "u_{iris}" is the local (IRIS) unemployment rate, "$Max(u_{iris1})$" the largest unemployment rate in the first ring of adjacent IRISes, and "$Max(u_{iris2})$" the largest unemployment rate in the second ring of adjacent IRISes. In both panels, the controls are environment characteristics (city density (log), type of neighborhood, size of the urban unit), year fixed effects, household characteristics (income, ownership status, number of children) and individual characteristics, corresponding to the surveyed individual for individual victimization and to the household head for household victimization (nationality, age (log), gender, employment status, socio-economic category). They also include large neighborhood fixed effects. The second panel is obtained after excluding Paris, Lyon and Marseille from the sample. Standard errors clustered at the IRIS level reported in parentheses. * p<0.10, ** p<0.05, *** p<0.001

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