Property crime and private protection in cities*

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Abstract: In Canada, rich neighborhoods are less exposed to property crime, there is no correlation between income and victimization, rich households are more victimized than their neighbors, and rich households and neighborhoods invest more in protection. We provide a theory consistent with these facts. Criminals in a city choose a neighborhood and pay a search cost to compare potential victims, whereas households invest in self-protection. As criminals' return to search increases with neighborhood wealth, households in rich neighborhoods are more likely to enter a rat race to ever greater protection that drives criminals towards poorer areas. A calibration of our model broadly reproduces the Canadian pattern of victimization and protection by household and neighborhood income.

Keywords: Economics of crime; Search frictions; Private protection; Alarms

J.E.L. classification: K42; C78

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1 Introduction

Property crimes impose a significant burden on our economies. For instance, about 630,000 break-in incidents took place in Canada in 2009, affecting more than 3% of all households in the country. Restricting these incidents to the only cases known by the police, Easton et al (2014) estimate the total cost in terms of pain and suffering is above 6 billions dollars. Property crimes generate additional costs: a substantial share of households invest in protection and install costly locks or alarms in their houses. Roughly 30% of all Canadian households have ever installed an alarm. For a cost per alarm over $300, Easton et al estimate that the yearly spending in alarms is close to 1 billion dollars. Private protection is highly heterogenous, however, and presumably interacts in complex ways with criminals' decisions. These issues have been mostly neglected by economists, so far, despite their quantitative importance.[1]

Our analysis aims to fill this gap. We first document four key stylized facts on property crimes and protection from detailed data of Canada's General Social Survey. We then build a parsimonious theoretical model able to rationalize these facts. In our model, households decide how much to invest in protection while criminals decide in which neighborhood to operate and how much effort to exert to find a profitable opportunity. We show that strong complementarities emerge between households' and criminals' decisions. Finally, we investigate a main prediction of our framework on household-level data. We find suggestive evidence that, indeed, a household's investment in protection is strongly and positively affected by his neighbors' investments and the local incidence of property crime.

Section 2 presents the following four facts: (i) Rich neighborhoods are less victimized than poor ones. The yearly mean victimization rate is about 3.4% and neighborhoods below the median income experience victimization rates 35% higher than neighborhoods above the median income. (ii) Conditional on neighborhood income, rich households are more victimized than poor ones. (iii) Victimization and household income are uncorrelated or slightly positively correlated. Victimization is roughly the same for households below and above the median household income. (iv) Rich households as well as rich

[1] The supply factors of criminal activities have been extensively studied, e.g., the size of the police force (Levitt, 1997), the incarceration rate (Levitt, 1996), overall inequality (Freeman, 1999, Nilsson, 2004, Brush, 2007), wage inequality (Machin and Meghir, 2004), unemployment (Fougère et al, 2009), and geographic location (Glaeser and Sacerdote, 1999, Hémet, 2016). Less has been done to understand the demand side of crime. Early analyzes on protection can be found in Shavell (1991) and Hotte and van Ypersele (2008).

neighborhoods invest more in protection. The percentage of households equipped with an alarm is about 30-35% larger among households above the median income than among households below the median income.

Section 3 describes a theory consistent with these facts. We build on Becker (1968) and suppose that criminals are rational. There is a city composed of two neighborhoods, a rich one and a poor one. The supply of criminals is exogenous at city level but responds to a non-arbitrage condition at neighborhood level. Once in a neighborhood, criminals choose if they pay a search cost to compare different households or simply pick one randomly. Meanwhile, households invest in private protection to damage criminals and reduce the loss in case of break in. The two main mechanisms of the model are as follows. First, criminals' search implies that households make heterogenous protection investment. Households who expect to be compared to each other invest in protection to divert criminals' attention towards neighbors. Second, protection heterogeneity motivates criminals' search. Thus there is strategic complementarity between criminals' search efforts and households' protection investments.

A calibration of our model reproduces the patterns displayed in Section 2. In the absence of protection investment, the rich neighborhood is more attractive to criminals. However, its residents also invest more in protection, which repels criminals. Indeed, criminals in the rich neighborhood are more willing to pay the search cost than in the poor neighborhood. Thus rich households expect to be frequently compared to their neighbors. This affects both the mean (people invest more on average) and the dispersion of protection investments (there are still some people who choose not to invest, whereas others invest more). That the rich neighborhood invests more in protection implies low returns to crime, and therefore criminals may be more attracted to the poor neighborhood. Meanwhile, rich households are more victimized than poorer ones in each neighborhood.

This paper develops the first model of protection investment and search for theft opportunities. Protection is modeled in the spirit of Shavell (1991), Helsley and Strange (2005), and Hotte and van Ypersele (2008). Adding search allows us to generate protection heterogeneity and endogenous comparison of households within neighborhoods. Search frictions are a natural ingredient in a market for illegal and informal activities.[2] We build on a specific form of search on goods (initiated by Burdett and Judd, 1983),

[2] There already exist search models of crime, but they do not focus on protection (see, e.g., Burdett et al, 2003, 2004; Huang et al, 2004; Engelhardt et al, 2008, and Galenianos et al, 2012).

jobs (Acemoglu and Shimer, 2000, Albrecht et al, 2006, and Galenianos and Kircher, 2009) and education (Moen, 1999). These papers share a common feature: a subset of workers deciding on their human capital investment, firms advertising for their vacancy or for their good may be compared to each other by another party. This local comparison due to search implies that similar agents make heterogenous decisions (educational investment, posted wage or price). In turn, heterogeneity promotes comparison efforts to yield, in our case, an equilibrium with positive search effort and a non-degenerate distribution of protection investment. We bring, in particular, two new elements to a classical search framework. First, we consider two separate marketplaces, i.e., neighborhoods, that are interconnected through the return to property crime. Second, we introduce within-neighborhood heterogeneity. Both elements are key to help make sense of the data.

Our paper also contributes to the literature on crime and social interactions. Existing studies have focused, so far, on strategic complementarity between individuals to engage in criminal activities (see Glaeser et al, 1996, Zenou, 2003, Calvo-Armengol et al, 2007, and Patacchini and Zenou, 2008). We highlight a novel mechanism through which social interactions affect criminal outcomes. Households invest more in protection when their neighbors also invest in protection. This interacts with criminals' decisions and may create multiple equilibria.

2 Motivating facts

This section documents four Canadian facts on income, property crime and private protection. Namely, (i) income and victimization are uncorrelated (or weakly positively correlated) at household level and (ii) negatively correlated at neighborhood level, (iii) rich households are more likely to be victimized than their neighbors, and (iv) private protection is positively correlated with income at household and neighborhood levels. We first present our data and then show the four facts.

Data.—We use cross-sectional individual data from the victimization part of Canada's General Social Survey (GSS). This survey is conducted every five years. We consider years 1999, 2004, and 2009. We supplement the GSS with the Census to compute the mean neighborhood income and neighborhood poor proportion. Years do not exactly match. We consider the following Census years: 1996, 2001, and 2006. The GSS is representative at Census Metropolitan Area (CMA) level. Each individual is located by a six-digit postal code. The first three digits define Forward Sortation Areas (FSAs), our neighborhoods.

FSA is not a common geographic unit in the Census and so we use a table mapping Dissemination Areas in the Census with FSAs. FSAs are exceptionally shared by several CMAs. When this happens, the FSA is divided into several sub-neighborhoods belonging to different CMAs. Household income is declared in 10 classes. We attribute the class mean to each income class.

We use two variables of protection. Respondents declare whether they have ever installed an alarm and if they have ever installed locks or bars. The variable PR is equal to 0 when neither bars / locks nor an alarm have ever been installed. It is equal to 1 when only bars / locks have been installed, to 2 when only an alarm, and to 3 when both have been installed. The quantitative values taken by this variable are arbitrary. Thus the other variable $PA = 1$ when there is an alarm and $PA = 0$ otherwise. For robustness purposes, we also consider the dummy variable $PA2$, which takes the value one when the household has installed an alarm or bars / locks, and $PA3$, which takes the value one when the household has installed an alarm, or bars / locks or the respondent holds a gun.

The main variable of victimization BE is equal to one when the household experienced a successful or attempted break-in over the past 12 months before the interview date. Here again, we have alternative measures. The dummy $BE2 = 1$ when a break-in occurred, or something was destroyed in the property like a window. The dummy $BE3 = 1$ when $BE2 = 1$ or something was stolen in the property but outside the house. Mean neighborhood protection $\overline{PA}$ and mean victimization $\overline{BE}$ are computed by aggregation of household observations. We use sample weights for the GSS and arithmetic means for the Census.

Facts.—Table 1 shows the mean victimization rate and the mean protection investment by household income. Victimization is slightly higher and protection much larger for households above the median income ($Y > Y_{50}$) than for those below the median income ($Y < Y_{50}$). This statement remains true for all measures of property crime and private protection. Table 1 also displays mean figures for the different quartiles of the household income distribution. They confirm that there is no relationship (or a very weak one) between household income and victimization, whereas private protection investment strongly increases with household income.

Table 1: The distribution of victimization and protection by household income

	BE	BE2	BE3	PA	PA2	PA3	PR
overall	0.032	0.063	0.098	0.350	0.506	0.633	1.037
std. dev.	0.001	0.001	0.001	0.002	0.002	0.003	0.006
$Y < Y_{50}$	0.031	0.060	0.094	0.280	0.446	0.570	0.866
std. dev.	0.001	0.002	0.002	0.003	0.003	0.004	0.008
$Y > Y_{50}$	0.033	0.067	0.101	0.410	0.557	0.684	1.182
std. dev.	0.001	0.002	0.002	0.003	0.003	0.003	0.008
$Y < Y_{25}$	0.031	0.058	0.090	0.229	0.399	0.514	0.742
std. dev.	0.002	0.002	0.003	0.004	0.005	0.005	0.010
$Y_{25} < Y < Y_{50}$	0.032	0.061	0.098	0.331	0.495	0.628	0.992
std. dev.	0.002	0.002	0.003	0.005	0.005	0.005	0.012
$Y_{50} < Y < Y_{75}$	0.032	0.067	0.103	0.431	0.576	0.721	1.227
std. dev.	0.002	0.002	0.003	0.004	0.004	0.004	0.011
$Y_{75} < Y$	0.034	0.066	0.099	0.386	0.534	0.643	1.130
std. dev.	0.002	0.002	0.003	0.005	0.005	0.005	0.011

Notes: The variable Y denotes neighborhood income and Y_{25}, Y_{50} and Y_{75} are, resp., its 25th, 50th and 75th percentiles. Reading: 3.1% of Canadian households in the 1st quartile of the income distribution experienced a break-in or an attempt of break-in in the past 12 months. Source: Canada's GSS.

Table 2 features similar statistics for the different quartiles of the neighborhood income distribution. In all cases, property crime decreases with neighborhood income and private protection increases with it. Households leaving in neighborhoods below the median neighborhood income ($\bar{Y} < \bar{Y}_{50}$) are between 23% (BE2) and 40% (BE) more exposed to property crime than households leaving in neighborhoods above the neighborhood median income ($\bar{Y} > \bar{Y}_{50}$).

Table 2: The distribution of victimization and protection by neighborhood income

	BE	BE2	BE3	PA	PA2	PA3	PR
overall	0.032	0.063	0.098	0.350	0.506	0.633	1.037
std. dev.	0.001	0.001	0.001	0.002	0.002	0.003	0.006
$\bar{Y} < \bar{Y}_{50}$	0.038	0.070	0.109	0.320	0.479	0.606	0.963
std. dev.	0.001	0.002	0.002	0.003	0.003	0.004	0.008
$\bar{Y} > \bar{Y}_{50}$	0.027	0.057	0.088	0.378	0.530	0.657	1.104
std. dev.	0.001	0.002	0.002	0.003	0.003	0.003	0.008
$\bar{Y} < \bar{Y}_{25}$	0.040	0.070	0.110	0.302	0.461	0.596	0.922
std. dev.	0.002	0.002	0.003	0.004	0.005	0.005	0.011
$\bar{Y}_{25} < \bar{Y} < \bar{Y}_{50}$	0.037	0.070	0.108	0.336	0.496	0.614	1.002
std. dev.	0.002	0.003	0.003	0.004	0.005	0.005	0.011
$\bar{Y}_{50} < \bar{Y} < \bar{Y}_{75}$	0.027	0.060	0.093	0.363	0.519	0.646	1.070
std. dev.	0.002	0.002	0.003	0.005	0.005	0.005	0.011
$\bar{Y}_{75} < \bar{Y}$	0.026	0.055	0.083	0.392	0.541	0.667	1.136
std. dev.	0.001	0.002	0.003	0.005	0.005	0.005	0.011

Notes: Neighborhoods are FSAs in Canada's GSS. The variable $\bar{Y}$ denotes neighborhood income and $\bar{Y}_{25}$,$\bar{Y}_{50}$ and $\bar{Y}_{75}$ are, resp., its 25th, 50th and 75th percentiles. Reading: 4.0% of Canadian households leaving in neighborhoods of the 1st quartile of the neighborhood income distribution experienced a break-in or an attempt of break-in in the past 12 months (BE). Source: Canada's census for BE and PA and Canada's GSS for income.

Tables 1 and 2 show that income provides incentive to protection investment, either at household or neighborhood levels. However, they also show richer neighborhoods are (much) less victimized, whereas household income and victimization are (slightly) positively correlated. These facts seem contradictory, but imperfect sorting on income implies they are not. Table 3 displays the mean victimization rate and the mean protection investment by household and neighborhood income. In all neighborhoods, the rich invest more in protection than the poor and are more victimized than them. This explains why victimization is weakly increasing in household income despite the rich are over-represented in rich and less victimized neighborhoods.

Table 3: The cross distribution of victimization and protection by neighborhood and household income

	$Y < Y_{50}$	$Y > Y_{50}$	$Y < Y_{50}$	$Y > Y_{50}$
	BE		PA	
$\bar{Y} < \bar{Y}_{50}$	0.036	0.042	0.270	0.380
std. dev.	0.002	0.002	0.004	0.005
$\bar{Y} > \bar{Y}_{50}$	0.026	0.027	0.292	0.430
std. dev.	0.002	0.001	0.005	0.004

Notes: Neighborhoods are FSAs in Canada's GSS. The variable Y and $\bar{Y}$ denote household and neighborhood income and Y_{25}, Y_{50} , Y_{75}, $\bar{Y}_{25}$, $\bar{Y}_{50}$, $\bar{Y}_{75}$ their respective 25th, 50th and 75th percentiles. Reading: 2.6 % of Canadian households below the median income and leaving in neighborhoods below the median neighborhood income experienced a break-in or an attempt of break-in in the past 12 months (BE). Source: Canada's census for BE and PA and Canada's GSS for income.

To summarize, property crime slightly increases with household income and strongly decreases with neighborhood income. Therefore rich households are more victimized than poor ones in both poor and rich neighborhoods. Meanwhile protection investments increase with household and neighborhood incomes. Hereafter we provide a possible scenario generating this collection of facts as equilibrium outcomes. Section 3 sketches a theoretical model where criminals choose a neighborhood and how much they compare possible victims, whereas households invest in private protection.

3 Property crime and protection: theory

We first present the model assumptions, then turn to a simplified case where households are homogenous within neighborhoods and criminals are immobile. The consideration of criminals' mobility between neighborhoods follows. Lastly, we analyze the more complex and empirically relevant equilibrium where households are heterogenous within neighborhoods. This section ends up with a calibration that replicates the main facts reported in Section 2.

3.1 The model

Model assumptions.—The model is static. There are two neighborhoods indexed by $j \in \{A, B\}$. Each neighborhood is composed of K_j residents. To begin with, residents differ across neighborhoods, but they are homogenous within each neighborhood. This assumption is relaxed in section 3.4 where we introduce within-neighborhood heterogeneity. All residents in neighborhood j have the same wealth endowment $V_j > 0$. We assume $V_A > V_B$ and refer to neighborhood A as the rich one, and to neighborhood B as the poor one.

There are also C criminals. They have limited mobility across neighborhoods. Each criminal must choose a neighborhood and then commits one crime in the neighborhood. The number of criminals in neighborhood j is C_j. Thus the crime rate in neighborhood j is $c_j = C_j/K_j$. By definition, we have $C_A + C_B = C$.[3]

Residents independently choose the level of self-protection $\theta \geq 0$. This comes at the cost $\gamma\theta V$, $\gamma > 0$. Protection reduces the loss incurred during a theft. This loss is $(\alpha - \theta)V$, with $\alpha \in (0, 1)$ and is proportional to wealth. However, this proportion is decreased by θ. The loss $(\alpha - \theta)V$ is also the criminal's gain.[4]

We denote by H_j the equilibrium distribution of protection efforts in neighborhood j. We also denote by $\Theta \subset \mathbb{R}_+$ the support of this distribution. The crime rate has the following upper bound $C/\min\{K_1, K_2\} < \gamma/2$, which ensures that the highest protection level $\bar{\theta}$ is lower than α.

Wealth and protection are imperfectly observable. Criminals who plan a robbery in neighborhood j are presented with one theft opportunity at random. They then observe the protection level θ. They may also benefit from a second opportunity. This comes at the cost s. Thus the margin of decision is whether to pay the cost and compare two households or not.

We denote by C_{j1} the expected number of criminals in neighborhood j who have a single theft option (*single-option criminals*), and by C_{j2} the expected number of criminals who have two options (*double-option criminals*). Similarly, c_{j1} and c_{j2} denote the corresponding criminal-to-household ratios.

Model agenda.—The timing is as follows.

Stage 1. Households choose their protection level θ.

[3] Our problem is to explain the allocation of criminals within cities and not between cities. Therefore the supply of criminals is exogenously fixed at city level. The number of criminals can easily be made endogenous thanks to a free-entry condition.

[4] We may distinguish the household's loss from the criminal's gain. Households may be insured, and consequently suffer smaller losses. But they may also endure psychological cost associated with crime. The model can easily be extended to cases where losses differ from gains by a factor of proportion.

Stage 2. Criminals choose a neighborhood $j \in \{A, B\}$ and whether to pay the search cost or not.

Stage 3. Criminals with two theft opportunities select the most interesting one. If indifferent, criminals select one of the two options with probability one half.

We solve the model in two steps. In the first step, we characterize the equilibrium at given criminals' location choice (equilibrium with immobile criminals). In the second step, we study the allocation of criminals across the two neighborhoods (equilibrium with mobile criminals). To simplify notations, we neglect the neighborhood index j until we discuss criminals' location choices.

Agents' payoffs.—Let Ω denote the expected payoff for a given criminal. When criminals play mixed strategies, we have:

$$\Omega = \alpha V - (1-q)\mathbb{E}(\theta)V - q\mathbb{E}(\min\{\theta, \theta'\})V - sq, \tag{1}$$

where $q \in [0, 1]$ is the probability of making the search effort. A theft opportunity is a random draw in the distribution of households' protection investments. When criminals have a single theft opportunity, their expected payoff thus depends on the unconditional mean $\mathbb{E}(\theta)$ of protection investments. When they have two opportunities, they choose the least protected household. Their expected payoff now depends on the mean of the minimum protection level.

The return to search is the difference in expected loss due to protection:

$$\Gamma = [\mathbb{E}(\theta) - \mathbb{E}(\min\{\theta, \theta'\})]\, V. \tag{2}$$

The return to search is proportional to wealth. Having two theft options is advantageous when protection levels are heterogenous. When the distribution of protection investments collapses to a single mass point, then $\Gamma = 0$ and criminals have no reason to search.

We now define the expected payoff W of a household with protection θ. Let η_1 and η_2 denote the expected number of visits by single-option and double-option criminals. We have

$$W = V - (\eta_1 + \eta_2)(\alpha - \theta)V - \gamma\theta V. \tag{3}$$

Wealth is reduced by theft and by the protection cost.

Appendix A shows that

$$\eta_1 = c_1 = c(1-q), \tag{4}$$

$$\eta_2(\theta) = 2c_2\Big[1 - H(\theta)\Big] = 2cq\Big[1 - H(\theta)\Big]. \tag{5}$$

Single-option criminals randomly sample within the household set. Thus η_1 is equal to the ratio of such criminals to households. As for the expected number of visits by double-option criminals, when a given household is compared to another potential victim, the household with the lowest protection level is robbed whereas the other stays safe. By assumption all households sample their protection investment in the distribution H. Thus the proportion of households with a protection level above θ is simply $1 - H(\theta)$.

3.2 Equilibrium with immobile criminals

We focus on protection investment and search effort at a given number of criminals, C, and corresponding crime rate, $c = C/K$. In equilibrium, protection efforts maximize households' well-being, whereas the search effort maximizes criminals' payoffs.

We start with protection efforts at given search effort. When criminals do not pay the search cost, households are never compared to their neighbors and do not invest in protection. Thus $\theta = 0$ for all households. When the probability of making the search effort differs from 0, the distribution of protection investment cannot be degenerate. This result is similar to Burdett and Judd (1983). In their model devoted to the goods market, prices are imperfectly observed. Some of the buyers sample two firms and there is an equilibrium distribution of prices as a result. Here similar households invest differently because protection is a positional good. If the distribution were not continuous, investing marginally more would achieve a mass gain through a discrete decline in the probability of victimization.

Equalizing payoffs $W(\theta, .)$ over the equilibrium support of the distribution, we obtain

$$H(\theta) = \frac{\theta}{\alpha - \theta} \Big/ \frac{\bar{\theta}}{\alpha - \bar{\theta}}, \tag{6}$$

for all $\theta \in \Theta = \big[0, \bar{\theta}\big]$, where $\bar{\theta} = \alpha x(q) = \alpha \frac{2cq}{\gamma - c(1-q)}$ is the max protection investment.

For later use, we define the variable x as the *protection attractiveness index*. Its numerator is the max victimization probability reduction, $2cq$, whereas its denominator is the marginal cost of protection, γ, net of marginal loss reduction, $c(1-q)$.

Zero protection belongs to the support of the equilibrium distribution. On the contrary, let us suppose that the lower bound is strictly positive. Investing less in protection would cost less and would not increase the probability of being visited. This contradicts the fact that the lower bound is strictly positive.

The equilibrium distribution of protection investment depends on the crime rate, c, and on the search probability, q. Both increase the expected number of visits by double-option criminals. Thus households anticipate being compared with their neighbors more frequently and invest more as a result. The first implication is that the maximum effort, $\overline{\theta}$, increases, so that the support of the distribution expands. The second implication is that the distribution becomes more concentrated around the highest values of investment.

To compute the return to search, we need to define the distribution of $\min\{\theta, \theta'\}$. Its density is equal to $2H'(\theta)[1-H(\theta)]$. Thus,

$$\Gamma = V \int_0^{\overline{\theta}} \{H'(\theta)\theta - 2H'(\theta)[1-H(\theta)]\theta\} d\theta. \tag{7}$$

The computation gives

$$\Gamma \equiv \Gamma(x(q)) = \alpha V \frac{x(q)-1}{x(q)^2}[(2-x(q))\ln(1-x(q)) + 2x(q)]. \tag{8}$$

The equilibrium resolution reduces to finding $q^* \in \arg\max_{q\in[0,1]}\{q\Gamma(x(q^*)) - sq\}$.

Figure 1 depicts the equilibrium. The protection attractiveness index, x, lies in the vertical axis. The return to search, Γ, and the search cost, s, lie on the left horizontal axis, whereas the search probability, q, lies on the right horizontal axis. The return to search only depends on the protection attractiveness degree. It is equal to 0 when criminals do not search, then increases until it reaches its maximum in $x_{\max} \approx 0.7$, and finally decreases to 0 when x is equal to one. The return to search increases with protection investment dispersion, whereas such dispersion is non-monotonic in criminals' search effort. When criminals search more, the max of the distribution increases, but the distribution becomes more concentrated at its top. The former effect dominates at low levels of search efforts and is dominated at larger ones. The effects cancel each other when x reaches $x_{\max}$. Thus,

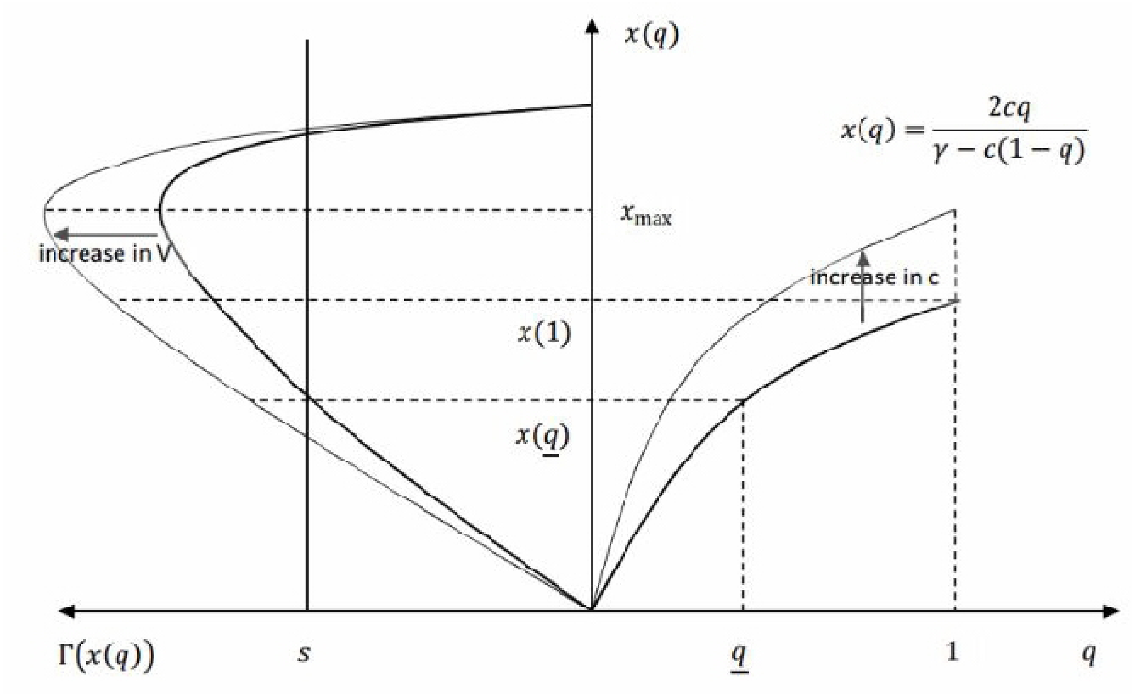

Figure 1: Properties of equilibrium with immobile criminals. The return to search, Γ, is non-monotonic in the protection attractiveness index, x, whereas x strictly increases with the search effort, q.

there are increasing social returns to searching when $x(q) < x_{\max}$ and decreasing social returns to searching when $x(q) > x_{\max}$.

Social increasing returns to searching imply there may be multiple equilibria. As the return to search is 0 when criminals do not search, there is the pure-strategy equilibrium $q^* = 0$. There is also a mixed-strategy equilibrium with $q^* \in (0, 1)$ when the return to search is equal to the expected search cost, i.e., $\Gamma(x(q^*)) = s$. Finally, the pure-strategy equilibrium $q^* = 1$ obtains when $\Gamma(x(1)) \geq s$. In Figure 1, parameters γ, c, s and V have been chosen so that $\Gamma(x(1)) > s$. Thus there are three equilibria: the two pure-strategy equilibria 0 and 1, and a mixed-strategy equilibrium $\underline{q} \in (0, 1)$. The two pure-strategy equilibria are stable, whereas the mixed-strategy equilibrium is not robust to individual deviations.

Figure 1 shows the effects of c and V. Both wealth and the crime rate favor the occurrence of search equilibria, i.e., with $q^* > 0$. Both c and V increase the return to search, but through different channels. The crime rate, c, increases the expected number of times households are compared to their neighbors. The support of the equilibrium distribution of investment widens and there is more weight at its top. In so far as $x(1)$ remains lower than $x_{\max}$, the former effect dominates the latter and the return to search increases. As for wealth, the gain that criminals expect from saving on protection damage is proportional to the property value V. Thus the return to search increases as well.

Let $x(q) \equiv x(q, c)$ to highlight the dependence with respect to c. In the remaining, we only focus on stable equilibria.

3.3 Equilibrium with mobile criminals

Criminals choose a neighborhood based on their expectations about the crime rate, the search effort made by the other criminals, and the distribution of households' protection investments.

In neighborhood j, the search effort for a given number of criminals is $q^*(c_j)$. Thus, the return to crime is

$$\Omega_j = \alpha V_j - \mathbb{E}(\theta \mid q^*(c_j), c_j)V_j + q^*(c_j)(\Gamma(x(q^*(c_j), c_j), V_j) - s). \tag{9}$$

Criminals enter neighborhoods with the highest payoffs. Therefore $c_j^* > 0$ if and only if $\Omega_j(q_j^*, H(., q_j^*, c_j^*)) \geq \Omega_{-j}(q_{-j}^*, H(., q_{-j}^*, c_{-j}^*))$. The model is closed by imposing the resource constraint $c_A^* K_A + c_B^* K_B = C$.

There always exists an equilibrium where all criminals enter the rich neighborhood, residents do not protect themselves, and criminals do not search. Though intuitive, this equilibrium is not consistent with the facts reported by Section 2 whereby victimization decreases and private protection increases with neighborhood income.

There may exist equilibria where criminals enter in both neighborhoods and search in at least one of them. The reason why all criminals enter two neighborhoods at a time is because location choices convey a congestion externality operating through protection investments. As explained in the previous section, the distribution of protection investments widens with the crime rate, the return to crime is reduced and this discourages further entry. In such equilibria, the number of criminals in a given neighborhood is disentangled from the effort they make to compare the different households. This opens room for cases where criminals are fewer in the rich neighborhood but search more than in the poor neighborhood.

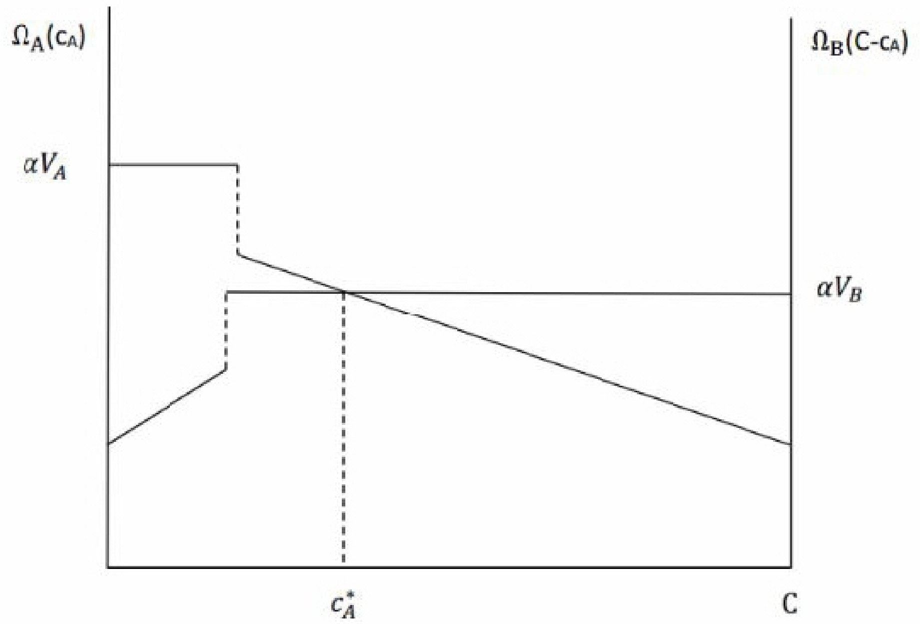

Figure 2: Interior equilibrium with mobile criminals. Population sizes are $K_A = K_B = 1$. There is an equilibrium with equal returns to crime, i.e., $\Omega_A = \Omega_B$, positive numbers of criminals in both neighborhoods, i.e., $c_A^* \in (0, C)$, more crime in the poor neighborhood, i.e., $c_A^* < C/2$, max search in the rich neighborhood and no search in the poor one, i.e., $q_A^* = 1 - q_B^* = 1$.

Figure 2 illustrates a configuration where the poor neighborhood, B, features a higher crime rate than the rich neighborhood, A. When few criminals operate in a neighborhood, they do not search and households do not invest in protection. This explains the horizontal part of the return to crime Ω_j in each neighborhood, with $\Omega_A > \Omega_B$. When the number of criminals is sufficiently large, criminals search and households invest in protection. Then, crime has decreasing returns, as more criminals stimulate protection investments.

The model can predict an equilibrium allocation of protection investment and criminal activities such that protection is larger and victimization is lower in the rich neighborhood than in the poor one. This arises despite the rich neighborhood is more attractive to criminals all else equal.

3.4 Within-neighborhood heterogeneity

We introduce within-neighborhood heterogeneity to account for the whole set of facts displayed in Section 2. In each neighborhood j, there are a fraction μ_j of poor households and the remaining fraction $1 - \mu_j$ of rich households, with $\mu_A < \mu_B$. The poor have wealth $V^P = V$, whereas the rich have $V^R = (1+\delta)V$, $\delta > 0$. Wealth heterogeneity affects households' investments and criminals' search. In the remaining, we neglect index j until we discuss criminals' location choices.

The criminals' expected payoff is still

$$\Omega = \mathbb{E}(\alpha V - \theta V) + q\Gamma - sq, \tag{10}$$

where the return to search is

$$\Gamma = \mathbb{E}[\max\{\alpha V - \theta V, \alpha V' - \theta' V'\}] - \mathbb{E}(\alpha V - \theta V). \tag{11}$$

The main difference with the homogenous case is that mean operators must account for wealth heterogeneity.

The expected numbers of visits by double-option criminals, η_2^R and η_2^P, depend on household type. A type-i household of protection θ is preferred to a household of similar type with protection θ' if and only if $\theta < \theta'$. This event occurs with probability $\Pr(\theta' > \theta \mid i) = 1 - H^i(\theta)$. When the households have different types, the type-i household is chosen if and only if $(\alpha - \theta)V^i > (\alpha - \theta')V^{-i}$. This event occurs with probability $\Pr(\theta' > \theta V^i/V^{-i} - \alpha(V^i - V^{-i})/V^{-i} \mid -i) = 1 - H^{-i}[\theta V^i/V^{-i} - \alpha(V^i - V^{-i})/V^{-i}]$. It follows that

$$\eta_2^R(\theta) = 2c_2\left[1 - (1-\mu)H^R(\theta) - \mu H^P\left(\theta(1+\delta) - \alpha\delta\right)\right], \tag{12}$$

$$\eta_2^P(\theta) = 2c_2\left[1 - (1-\mu)H^R\left(\theta/(1+\delta) + \alpha\delta/(1+\delta)\right) - \mu H^P(\theta)\right]. \tag{13}$$

As in the homogenous case, households play mixed strategies. The distribution of protection investment results from payoff equality over the support of the distribution. There are two possible equilibria, separating and pooling, which we now describe.

Separating equilibrium.—This case occurs when $x < \bar{x} \equiv \alpha\delta/(1+\delta)$. The rich are much richer than the poor and always preferred to them by criminals. For $i = R, P$,

$$H^i(\theta) = \frac{\theta}{\alpha - \theta}\frac{\alpha - \bar{\theta}^i}{\bar{\theta}^i}, \tag{14}$$

for all $\theta \in [0, \bar{\theta}^i]$, with $\bar{\theta}^R = \alpha(1-\mu)x/(1-\mu x)$ and $\bar{\theta}^P = \alpha\mu x$. These distributions are very similar to the homogenous case described in section 3.2. In particular, the support of each distribution widens when the protection attractiveness index, x, increases.

Using H^R and H^P, we obtain the return to search and the return to crime:

$$\Gamma_{\text{sep}} = \frac{\alpha V}{x^2} \langle -2x \left[(1-\mu)(\delta - x(1+\delta-\mu)) + 1 - x\mu\right] + (x-2)\left[(1+\delta)(1-x)\log(1-x) - (\delta - x(1+\delta-\mu))\log(1-\mu x)\right]\rangle , \tag{15}$$

$$\Omega_{\text{sep}} = \max_{q\in[0,1]} \left\{ \frac{\alpha V}{x^2} \langle -2qx \left[(1-\mu)(\delta - x(1+\delta-\mu)) + 1 - x\mu\right] + [q(x-2)-x]\left[(1+\delta)(1-x)\log(1-x) - (\delta - x(1+\delta-\mu))\log(1-\mu x)\right]\rangle - sq \right\}. \tag{16}$$

Pooling equilibrium.—This case happens when $x \geq \bar{x}$. Poor households who do not protect much are preferred to rich households who invest a lot in protection. Then,

$$H^R(\theta) = \begin{cases} \frac{\theta}{\alpha-\theta}\frac{1-x}{(1-\mu)x} \text{ if } \theta \in [0, \bar{x}) \\ \frac{\theta(\delta - x(1+\delta)(1-\mu)) - \alpha\delta\mu x}{(\alpha-\theta)(\delta - x(1+\delta)\mu)} \frac{1-x}{(1-\mu)x} \text{ if } \theta \in \left[\bar{x}, \bar{\theta}^R\right] \end{cases}, \tag{17}$$

$$H^P(\theta) = \frac{\theta}{\alpha-\theta}\frac{\alpha - \bar{\theta}^P}{\bar{\theta}^P} \text{ if } \theta \in \left[0, \bar{\theta}^P\right], \tag{18}$$

with $\bar{\theta}^R = \alpha x$ and $\bar{\theta}^P = \alpha[x - \delta(1-x)]$. The rich distribution, H^R, has two parts. Below the threshold $\bar{x}$, strategic interaction only involves rich households, which explains the formula's simplicity. Above the threshold, the formula accounts for cases where very protected rich are preferred to poor with low protection.

The return to search and the return to crime are

$$\Gamma_{\text{pool}} = \alpha V \frac{1-x}{x^2}\left[-2x + (x-2)\log(1-x)\right], \tag{19}$$

$$\Omega_{\text{pool}} = \max_{q\in[0,1]} \left\{ \frac{\alpha V}{x^2}(1-x)(1+\delta)\left[-2x + (qx + (q(x-2)-x)\log(1-x)\right] - sq \right\}. \tag{20}$$

With pooling, the return to search is independent from the poor proportion, μ. Any increase in this proportion translates into lower competition for the rich who invest less as a result.

In equilibrium, the return to crime must be the same in each neighborhood and the allocation of criminals must satisfy the resource constraint $C = c_A^* K_A + c_B^* K_B$. The model admits different equilibrium configurations: pooling vs separating in each neighborhood, and interior vs bounding search efforts, i.e., $q^* \in (0,1)$ vs $q^* = 0$ or $q^* = 1$. Instead of listing the properties of these different configurations, we explore one of them in detail through a calibration.

3.5 Calibration

We replicate the main features of the Canadian income-victimization nexus as reported by Section 2 in Tables 1 to 3. We focus on households who experienced a break-in or an attempt of break-in, BE, and households who have installed an alarm, PA, our most natural measures of property crime and protection. We describe the technical aspects of the calibration, the resulting parameterization and the fit with Canadian data.

We calibrate an equilibrium with pooling and interior search efforts in both neighborhoods, i.e., $(q_A^*, q_B^*) \in (0,1)^2$. Numerous simulations reveal that this equilibrium configuration is the only one compatible with Canadian data.

We normalize wealth to unity, i.e., $V = 1$, and the max proportion of wealth that criminals can steal to 50%, i.e., $\alpha = 0.5$. We also set δ to 1.5. This implies that the mean income of above-the-median households is about 2.5 times the mean income of below-the-median households, roughly what can be found in Canada's GSS.

With pooling and interior search efforts, the return to crime and the return to search do not depend on the neighborhood-specific poor proportion. We have $\Gamma_{\text{sep}}^A(x) = \Gamma_{\text{sep}}^B(x) = \Gamma_{\text{sep}}(x)$ and $\Omega_{\text{sep}}^A(x) = \Omega_{\text{sep}}^B(x) = \Omega_{\text{sep}}(x)$ for all $x \in [0,1]$. Therefore we can choose x and set the marginal search cost $s = \Gamma_{\text{sep}}(x)$. It obviously follows that $x_A^* = x_B^* = x$.

The definitions of x_A^* and x_B^* give us two relationships between γ, q_A^* and c_A^* on the one hand, and γ, q_B^* and c_B^* on the other hand. Indeed, $x_A^* = 2c_A^* q_A^* / (\gamma - c_A^*(1 - q_A^*))$ and $x_B^* = 2c_B^* q_B^* / (\gamma - c_B^*(1 - q_B^*))$. We set c_A^* and c_B^* to the Canadian values. This leaves us with two equations and three unknowns, γ, q_A^* and q_B^*.

For a given pair (c_A^*, c_B^*), the overall victimization rate is $c = kc_A^* + (1-k)c_B^*$, where $k = K_A/(K_A + K_B)$ is the share of individuals in the rich neighborhood. Therefore we set c to its empirical value and fix $k = (c - c_B^*)/(c_A^* - c_B^*)$ to ensure that this is also the equilibrium one.

The following vector of parameters remains: $(x, \mu_A, \mu_B, \gamma)$. We target victimization rates for rich and poor households in rich and poor neighborhoods. As for protection, the difficulty consists of matching a continuous prediction, i.e., the level of protection, with a categorical outcome, i.e., the household's proportion with an alarm. Let $\theta_0 \geq 0$ be the level of protection above which households install an alarm. The corresponding households' proportions are $1 - H_j^i(\theta_0)$, for household type $i = R, P$ and neighborhoods $j = A, B$. These theoretical proportions must be compared with the empirical values.

In the spirit of the method of moments, we choose the vector $(x, \mu_A, \mu_B, \gamma, \theta_0)$ to minimize the sum of squared differences between observed victimization and protection and the corresponding model predictions. We consider mean outcomes at neighborhood, household-type and neighborhood×household type levels. We account for three constraints. First, $x > \underline{x} \equiv \delta/(1 + \delta - \mu_B)$, which implies that there is a pooling equilibrium in both neighborhoods. Second, $\Gamma'_{\text{sep}}(x) < 0$ so that the equilibrium is stable. Third, $\mu_A k + \mu_B(1 - k) = 0.5$, which ensures that the poor compose 50% of the population. In practice, μ_B is free and $\mu_A = (0.5 - \mu_B(1 - k))/k$. The eight protection moments receive a small weight, 10^{-5}, so that they mostly affect the choice of θ_0 and much less the other parameters.[5] The optimal parameterization is found by scanning the parameter space.

Appendix C gives additional details on the calibration procedure. Table 4 describes the parameter set, key model variables and model fit.

[5]In Table 4, the standard deviation of victimization moments is small, around 0.001. Meanwhile the standard deviation of protection moments is large, around 0.134. Unweigthing the two sets of moments gives a lot of importance to protection for a small gain in precision. We choose to finely reproduce victimization probabilities at the cost of exarcerbating the differences between observed and predicted protection.

Table 4: Calibration of an equilibrium with interior search and pooling in both neighborhoods

				Parameters					
	V	α	δ	s	k	γ	μ_A	μ_B	θ_0
	1.0	0.5	1.5	0.040	0.522	0.053	0.355	0.658	0.393
				Model variables					
	x	q_A	q_B	z_A	z_B	σ_c	σ_θ	min	$x > \underline{x}$
	0.928	0.865	0.341	0.591	0.671	0.001	0.134	1.0×10^{-5}	True
				Crime fit					
	BE	BE_A	BE_B	BE_{AR}	BE_{AP}	BE_{BR}	BE_{BP}	BE_R	BE_P
model	0.032	0.027	0.038	0.028	0.024	0.041	0.036	0.032	0.032
data	0.032	0.027	0.038	0.027	0.026	0.042	0.036	0.033	0.031
				Protection fit					
	PA	PA_A	PA_B	PA_{AR}	PA_{BR}	PA_{AP}	PA_{BP}	PA_R	PA_P
model	0.403	0.493	0.305	0.661	0.187	0.531	0.187	0.618	0.187
data	0.350	0.378	0.320	0.430	0.292	0.380	0.271	0.410	0.280

Notes: z_A and z_B are the neighborhood-specific probabilities that a random rich household is preferred to a random poor household; σ_c and σ_θ are, respectively, the standard deviations of victimization and protection moments. The min variable is the value of the optimization criterion. See the Appendix for details on the calibration. The empirical variables BE and PA are described in Section 2.

The average neighborhood-specific search costs, sq_A^* and sq_B^*, amount to 7% of the wealth that can be stolen, αV, in the rich neighborhood and 3% in the poor one. The rich spend about 4% of αV^R in protection, against 3% of αV for the poor. The poor proportion is 36% in the rich neighborhood and 66% in the poor one. Lastly, the rich neighborhood is slightly more peopled than the poor one.

The protection attractiveness index, x, is 0.928, slightly below one, its max value. Criminals make larger search efforts in the rich neighborhood than in the poor one, $q_A^* = 0.865$ against $q_B^* = 0.341$. Consequently, the rich invest more in protection in the rich neighborhood and, therefore, are less likely to be preferred to poor households by the criminals, i.e., $z_A^* = 0.591 < z_B^* = 0.671$. The standard deviation of victimization moments is $\sigma_c = 0.001$ against $\sigma_\theta = 0.134$ for protection moments. Thus the model predicts victimization much better than protection. In particular, the calibration amplifies protection differentials between rich and poor households.

The model reproduces the GSS allocation of crime by household and neighborhood income. Perfectly mobile criminals prefer the rich neighborhood, but its households invest more in protection. This repels criminals and victimization is lower than in the poor neighborhood. In each neighborhood, the rich are more victimized than the poor. Overall, there is no relationship between victimization and income.

As for protection, the model correctly predicts that protection is larger in the rich neighborhood, the rich protect more than the poor in both neighborhoods, and the rich protect more in the rich neighborhood than in the poor one. The model also predicts equal protection for the poor in the two neighborhoods, whereas, in the GSS, the poor protect more when residing in the rich neighborhood. We cannot improve this outcome: with two pooling interior equilibria, the poor's distribution of protection does not change across neighborhoods.

4 Conclusion

We develop a model of property crime and private protection allocation within cities. Our analysis is based on four Canadian facts: rich neighborhoods are less victimized, household income and victimization are uncorrelated or weakly positively correlated, rich households are more victimized than their neighbors, and rich households and neighborhoods invest more in private protection. In our theory, criminals choose a neighborhood and whether to make a search effort to compare potential victims. In turn, households choose how much they invest in private protection. Such investments reduce criminals' gains and divert their attention to less protected neighbors. Households in a rich neighborhood are more likely to enter in a rat race to protection characterized by strong incentives to self protect and to search and a weak incentive to enter the neighborhood. When sufficiently fierce, the rat race leads criminals to prefer poorer and less protected neighborhoods. A calibration of our model reproduces the Canadian pattern of victimization by household and neighborhood income.

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APPENDIX

A Expected number of visits

We refer to theft options as *matches*. A criminal is matched with zero, one, or two households. All households draw their protection level from the continuously differentiable cdf H. The number of expected visits by single-option criminals is equal to the ratio of such criminals to households. Thus $\eta^1 = c_1$, irrespective of household's type.

We now study the expected number of visits by double-option criminals η_2. Consider a household whose protection level is θ. With probability

$$\Pi(t) = \binom{C_2}{t} \left(\frac{2}{K}\right)^t \left(1 - \frac{2}{K}\right)^{C_2 - t}, \tag{21}$$

this household is matched with t double-option criminals. When compared to another household, our household is chosen by the criminal and becomes a victim if and only if its protection level θ is lower than the other household's protection level θ'.

Let $(\theta_1, ...\theta_t)$, $\theta_1 < \theta_2 ... < \theta_t$, be the t-th order of the sub-sample of households who are connected with the victim through criminals. The victim is visited by $t - g$ criminals matched with another household if and only if $\theta \in [\theta_g, \theta_{g+1}]$. The joint density distribution (x, y) of $(g, g+1)$ order statistics is given by

$$\frac{t!}{(g-1)!(t-g-1)!} H(x)^{g-1} \left(1 - H(y)\right)^{t-g-1} h(x)h(y). \tag{22}$$

Therefore the probability that $\theta \in [\theta_g, \theta_{g+1}]$ is given by

$$\begin{aligned} p(g) &= \int_{\theta}^{\bar{\theta}} \int_{0}^{\theta} \frac{t!}{(g-1)!(t-g-1)!} H(x)^{g-1} \left(1 - H(y)\right)^{t-g-1} h(x)h(y)\ dx\ dy \\ &= \frac{t!}{g!(t-g)!} H(\theta)^g (1 - H(\theta))^{t-g}, \end{aligned} \tag{23}$$

as $\int H(x)^{g-1} h(x) dx = H(x)^g / g$ and $\int (1 - H(y))^{t-g-1} h(y) dy = (1 - H(y))^{t-g} / (g - t)$.

Thus the expected number of visits by double-option criminals is

$$\eta_2 = \sum_{t=0}^{C_2} \Pi(t) \sum_{g=0}^{t} (t - g) p(g) = 2c_2 \left[1 - H(\theta)\right]. \tag{24}$$

B Rich vs poor victimization

In Section 3.4, we claim that the victimization probability is larger for the rich than for the poor in each neighborhood. This statement is obvious in the separating case where the rich are always preferred to the poor. This is less obvious in the pooling case where some of the rich invest so much that criminals prefer poor households with low protection.

In the pooling equilibrium, suppose that a criminal is randomly matched with a poor and a rich household. The probability that the rich household is selected is

$$\begin{aligned}\Pr\left[\theta^R < \frac{\theta^P}{1+\delta} + \bar{x}\right] &= H^R(\bar{x}) + \int_{\bar{x}}^{\bar{\theta}^R} (1 - H^P(\theta(1+\delta) - \alpha\delta)h^R(\theta)d\theta^R \\ &= \frac{1}{2}\left[1 + \frac{\delta}{1-\mu}\frac{1-x}{x}\right] > 1/2, \end{aligned} \tag{25}$$

which proves the claim.

C Calibrations

We provide additional details on the calibration. The victimization probabilities are as follows:

$$BE_{AR} = (1-q_A^*)c_A^* + 2q_A^*c_A^*(\mu_A z_A + (1-\mu_A)/2), \tag{26}$$

$$BE_{AP} = (1-q_A^*)c_A^* + 2q_A^*c_A^*((1-\mu_A)(1-z_A) + \mu_A/2), \tag{27}$$

$$BE_{BR} = (1-q_B^*)c_B^* + 2q_B^*c_B^*(\mu_B z_B + (1-\mu_B)/2), \tag{28}$$

$$BE_{BP} = (1-q_B^*)c_B^* + 2q_B^*c_B^*((1-\mu_B)(1-z_B) + \mu_B/2), \tag{29}$$

$$BE_R = ((1-\mu_A)kc_{AR} + (1-\mu_B)(1-k)c_{BR})/((1-\mu_A)k + (1-\mu_B)(1-k)), \tag{30}$$

$$BE_P = (\mu_A k c_{AP} + \mu_B(1-k)c_{BP})/(\mu_A k + \mu_B(1-k)), \tag{31}$$

where $z_i = 1/2 + \delta(1-x_i^*)/(2x_i^*(1-\mu_i))$ is the probability that a random rich household of neighborhood i is preferred to a random poor household by a typical criminal.

The corresponding proportions with an alarm are

$$PA_{AR} = 1 - H_R(\theta_0, \mu_A), \tag{32}$$

$$PA_{BR} = 1 - H_R(\theta_0, \mu_B), \tag{33}$$

$$PA_{AP} = PA_{BP} = PA_P = 1 - H_P(\theta_0), \tag{34}$$

$$PA_{AR} = [(1-\mu_A)kPA_{AR} + (1-\mu_B)(1-k)PA_{BR}]/ \tag{35}$$

$$[(1-\mu_A)k + (1-\mu_B)(1-k)], \tag{36}$$

$$PA_A = \mu_A PA_{AP} + (1-\mu_A)PA_{AR}, \tag{37}$$

$$PA_B = \mu_B PA_{BP} + (1-\mu_B)PA_{BR}, \tag{38}$$

$$PA = kPA_A + (1-k)PA_B, \tag{39}$$

where

$$H_R(\theta,\mu) = \begin{cases} \frac{1-x}{(1-\mu)x}\frac{\theta}{\alpha-\theta} \text{ if } 0 \le \theta < \alpha\delta/(1+\delta) \\ \frac{1-x}{(1-\mu)x}\frac{-\delta\theta + x[\alpha\delta\mu + (1-\mu)(1+\delta)\theta]}{[x+(x-1)\delta](\alpha-\theta)} \text{ if } \alpha\delta/(1+\delta) \le \theta \le \alpha x \end{cases}, \tag{40}$$

$$H_P(\theta,\mu) = \frac{(1-x)(1+\delta)}{x-\delta+x\delta}\frac{\theta}{\alpha-\theta} \text{ if } 0 \le \theta \le \alpha(x-\delta+x\delta). \tag{41}$$

The minimization criterion is based on victimization and protection moments. As for victimization moments, we have

$$\text{crit}_c = \sum_{i=R,P;j=A,B} (BE_{ij} - \overline{BE}_{ij})^2, \tag{42}$$

where $\overline{BE}_{ij}$ is computed from BE, the empirical proportion that experienced a break-in or an attempt of break-in the last 12 months.

As for protection moments, we have

$$\text{crit}_\theta = \sum_{i=R,P;j=A,B} (PA_{ij} - \overline{PA}_{ij})^2, \tag{43}$$

where $\overline{PA}_{ij}$ is computed from PA, the empirical share of households who have installed an alarm.

The minimization criterion is

$$\text{crit} = \text{crit}_c + \lambda\text{crit}_\theta. \tag{44}$$

We set the weight λ to 10^{-5}. As explained in section 3.4, this allows us to finely reproduce victimization moments, letting parameter θ_0 adjust to fit protection moments.

The parameter vector $(x, \mu_B, \gamma, \theta_0)$ is found by scanning the parameter space over a grid of 100 elements for each parameter. Therefore there are four parameters for 13 moments, of which 8 are linearly independent. The parameter space accounts for the three constraints described in section 3.4. In particular, the return to search, Γ, must be decreasing, which we ensure by scanning x above the value maximizing this return.