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CRIME PROTECTION INVESTMENT SPILLOVERS: THEORY AND EVIDENCE FROM THE CITY OF BUENOS AIRES

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EFECTOS DERRAME DE LAS INVERSIONES EN PROTECCIÓN: TEORÍA Y EVIDENCIA EN LA CIUDAD DE BUENOS AIRES

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RESUMEN

Este documento estudia los efectos derrame de las inversiones en tecnologías observables para la protección entre las potenciales víctimas del crimen. Los criminales y las víctimas potenciales interactúan en un mercado friccional para los delitos. Las externalidades dentro de los dos lados del mercado surgen como externalidades comerciales y su signo y tamaño dependen de los cambios de equilibrio de las probabilidades de victimización. Este tema se explora empíricamente usando data de hogares georeferenciada de la ciudad de Buenos Aires. La ciudad muestra un nivel significativo de concentración o agrupamiento de inversiones en protecciones contra robo. Más importante, se encuentra que las inversiones hechas por los vecinos afectan la decisión de inversión individual de los hogares. Para lograr identificación, se explotó las variaciones en el estatus de inversión en protecciones de los vecinos cercanos, dentro del vecindario, inducidas por el conocimiento de crímenes sufridos por amigos, parientes, conocidos u otros ocurridos en un lugar suficientemente lejano. En efecto, se encuentra que información sobre experiencias de victimización de otras personas aumenta la inversión en protección de los vecinos, y, por ende, se puede usar como una fuente de variación exógena para lo último bajo supuestos relativamente débiles. Estimaciones de variables instrumentales muestran que las inversiones por parte de vecinos en cámaras CCTV y en alarmas aumentan la propensión de un determinado hogar a invertir en las mismas tecnologías. Sin embargo no se encuentra ningún efecto para cerraduras especiales de seguridad o iluminación de espacios externos. Tomando todo en cuenta todo lo anterior, los resultados implícitamente sugieren que la oferta de criminales de la ciudad es relativamente inelástica en relación con el promedio de intensidad de protección en ciertos lugares, o a si lo perciben las víctimas potenciales.

Palabras clave: crimen, victimización, inversión en protección, efectos derrame.

CRIME PROTECTION INVESTMENT SPILLOVERS: THEORY AND EVIDENCE FROM THE CITY OF BUENOS AIRES

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ABSTRACT

This paper studies spillover effects among potential crime victims from investment in observable protection technologies. Criminals and potential victims interact in a frictional market for offenses. Externalities within the two market sides arise as trading externalities, and their sign and size depend on the equilibrium changes in victimization probabilities. I explore the issue empirically using household-level geo-referenced data from the City of Buenos Aires. The City exhibits a significant level of spatial clustering of burglary protection investment. More importantly, investment by neighbors is shown to significantly affect individual households' investment decisions. In order to achieve identification, I exploit within-neighborhood variation in close neighbors' protection investment status as induced by their knowledge of crimes suffered by friends, relatives, acquaintances or others, occurred sufficiently far away. Indeed, information about others' victimization experiences is found to significantly increase the protection investment of neighbors, and can thus be used as a source of exogenous variation for the latter under relatively weak assumptions. Instrumental variable estimates show neighbors' investment in CCTV cameras and alarms to significantly increase a given household's propensity to invest in the same technology. No effect is found instead for special door locks, bars or outdoor lighting. Taken all together, results implicitly suggest the supply of criminals in the city to be relatively inelastic with respect to the intensity of protection in the average location, or perceived to be so by potential victims.

Keywords: crime, victimization, protection investment, spillovers.

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Crime Protection Investment Spillovers: Theory and Evidence from the City of Buenos Aires

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Abstract

This paper studies spillover effects among potential crime victims from investment in observable protection technologies. Criminals and potential victims interact in a frictional market for offenses. Externalities within the two market sides arise as trading externalities, and their sign and size depend on the equilibrium changes in victimization probabilities. I explore the issue empirically using household-level geo-referenced data from the City of Buenos Aires. The City exhibits a significant level of spatial clustering of burglary protection investment. More importantly, investment by neighbors is shown to significantly affect individual households' investment decisions. In order to achieve identification, I exploit within-neighborhood variation in close neighbors' protection investment status as induced by their knowledge of crimes suffered by friends, relatives, acquaintances or others, occurred sufficiently far away. Indeed, information about others' victimization experiences is found to significantly increase the protection investment of neighbors, and can thus be used as a source of exogenous variation for the latter under relatively weak assumptions. Instrumental variable estimates show neighbors' investment in CCTV cameras and alarms to significantly increase a given household's propensity to invest in the same technology. No effect is found instead for special door locks, bars or outdoor lighting. Taken all together, results implicitly suggest the supply of criminals in the city to be relatively inelastic with respect to the intensity of protection in the average location, or perceived to be so by potential victims.

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JEL Codes: D19, D83, K42.

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1 Introduction

Property crime typically yields both wealth redistribution and net losses. On top of the physical and psychological cost suffered by victims, the process involves a given amount of inputs (labour and capital) which could possibly be more productive if used otherwise. In particular, potential victims undertake investment in protection technologies in order to decrease their victimization probabilities. Starting with Clotfelter (1978), several theoretical contributions have specifically explored the relevance of spillovers from protection investment among potential crime victims. Given the stock of active criminals, when protection devices are observable, investors exert a negative externality on non-investors as criminal activity is diverted towards unprotected targets. However, the higher the number of protected individuals, the lower is the probability for an active criminal of successfully committing an offense. Following the decrease in expected returns from criminal activity, the crime supply side may respond accordingly, leading to a reduction of criminals which generates a positive externality on non-investors[1] (Shavell 1991; Ayres and Levitt 1998).

The purpose of this paper is to theoretically explore and empirically identify spillovers among potential victims from investment in observable property crime protection technologies. When investment decisions are decentralized, the extent to which externalities are internalized determines the scope for government intervention aimed at maximizing the total welfare of potential victims. Whether the resulting sign is positive or negative is therefore a policy relevant question. Moreover, spillovers on the side of victims can potentially be as important as social interactions mechanisms on the side of criminals in explaining the spatial and time variability of crime rates, net of observable characteristics (Glaeser et al. 1996; Zenou 2003; Patacchini and Zenou 2012; Ballester et al. 2010).

The theoretical framework for the analysis builds upon Ehrlich (1996, 2010) in the formalization of the market for offenses. The model incorporates the main mechanisms highlighted at the beginning and motivates the empirical analysis. Similarly to frictional labor market models, a *victimization function* is introduced in order to capture likely deviations from the perfectly competitive set-up. Spillovers among potential victims arise as trading externalities, and their sign and size will depend on the relative impact of the effects of protection investment of others on equilibrium victimization probabilities.

The empirical investigation is carried out focusing on burglary protection technologies, using originally collected data from the City of Buenos Aires. Geo-referenced household-level data allow to explore the extent to which neighbors' choices concerning investment in protection relate to each other. First, the data reveal significant spatial clustering of observable burglary protection technologies within the City area. Using an approach similar to Bayer et al. (2008) in their exploration of labor market referrals, the protection investment schedule of close neighbors is here shown to be significantly more similar than the one of two households located in the same neighborhood, but further apart. More specifically, I build a dataset having as units of

[1] When protection devices are unobservable, positive externalities are likely to prevail, as shown by Ayres and Levitt (1998) in their study of Lojack.

observation all pairs of surveyed households located in the same administrative neighborhood. For each household pair, I define the value of an *investment similarity score* variable, which captures the degree of analogy between the protection investment schedule of the two households in the pair. The answers to specifically designed questions in the survey allow to consider investment in private security, special door locks, bars, armor plating, alarms, CCTV cameras, outdoor lighting and staying at home not to leave the house alone. I thus compare those pairs of households located close to each other with pairs of households located in the same administrative neighborhood, but further apart. The former are shown to have a significantly higher protection investment similarity score with respect to the latter, corresponding to a 2% increase over the score mean. Such positive correlation between close neighbors' protection investment decisions is attributable to negative spillovers from protection investment, which increase the victimization probabilities of unprotected individuals and thus their likelihood to invest in protection themselves. However, results could also be driven by sorting of individuals with the same propensity to invest in protection or differences in idiosyncratic location characteristics at the within-neighborhood level.

In the second part of the empirical analysis, I tackle the causal question explicitly and ask whether neighbors' investment in protection has any impact on household's investment decisions. In order to achieve identification, I exploit within-neighborhood variation in close neighbors' investment status as induced by their knowledge of crimes suffered by their friends, relatives, acquaintances or others, occurred sufficiently far from their house. Information about others' victimization experiences can be framed as a shock to the agent's information set leading to beliefs update and changes in her optimal protection investment decisions. Indeed, information about any crime episode involving friends, relatives, acquaintances or others is shown to be strongly and positively correlated with individual household's protection investment. Variation in the neighbors' reported information about crimes occurred sufficiently far away can thus be used as a source of exogenous variation for neighbors' investment status under a set of relatively weak and partially testable assumptions. In particular, once the individual household's reported information is controlled for, neighbors' knowledge of any crime episode is assumed to be as good as randomly assigned, and to have no direct effect on individual household's investment decisions. In this respect, the potential confounding effects of information sharing and overlapping peer groups among neighbors is investigated and further taken into account by controlling for the household's reported information and beliefs, so that only residual variability in neighbors' information is used for identification. The proposed strategy shares the same framework of some recent advances in the empirical network literature on peer effects, which exploit the variation within higher-order links as a source of exogenous variation for behavior of first-order links in order to achieve identification (Bramoullé et al. 2009; Calvó-Armengol et al. 2009; De Giorgi et al. 2010; Blume et al. 2011).

Protection investment of neighbors is here shown to significantly affect household's investment decisions. Instrumenting neighbors' investment status with a dummy capturing whether they report information about any crime involving friends, relatives, acquaintances and others occurred at least 20 blocks away, I find neighbors' investment in cameras and alarms to positively and significantly affect the likelihood of a given household to invest in the same protection technology. The decision of one neighbor to install monitored alarms is found to significantly increase the probability of a given household of doing the same by around 20 percentage points. The same effect is about 10 percentage points for CCTV cameras, while no effect is found for special door locks, bars, outdoor lighting and the cumulate protection investment score. In particular, further investigation reveals that the relationship between neighbors' cumulate protection and own investment appears to be non-linear. Neighbors' cumulate investment is positively correlated with own investment when the former is lower, but the opposite holds for higher values of average cumulate neighbors' protection investment. The weakness of the correspondent first stage prevents instead from identifying the effect for other protection technologies such as private security guards, armor plating, unmonitored alarms and whether any household member permanently stays at home in order not to leave it alone. In light of the theoretical argument formalized in the model, evidence indirectly suggests the elasticity of burglary supply with respect to the fraction of protected individuals to be relatively low, or perceived to be so by potential victims.

The rest of the paper is organized as follows. The theoretical model is presented in Section 2, while the empirical analysis is carried out in Section 3. Section 4 concludes.

2 Crime and Protection in a Frictional Market Model

The reasoning behind the salience of spillovers from investment in observable property crime protection technologies can be formalized by means of a theoretical model of frictional market for offenses. As in Ehrlich (1996, 2010), observed crime rates can be rationalized in a market context as equilibrium results. The supply side of this market is shaped by the choice of criminals, who decide whether or not to become active through balancing the benefits and costs of engaging in criminal activities (Becker 1968). The demand for crime is instead determined by the decision of potential victims, who choose whether or not to invest in protection in face of its cost and their victimization probabilities.

In this framework, a crime event is nothing but a trading episode. Nonetheless, this market is supposedly far from being considered as perfectly competitive. Unobserved heterogeneity, frictions, information imperfections are likely to be increasing the cost of trading. As for frictional labor market models (Pissarides 2000), it is possible to capture such features altogether through the definition of a Constant-Returns-to-Scale (CRS) *victimization function*

$$v(\gamma, \lambda) = \gamma^{\mu}\lambda^{1-\mu} \tag{1}$$

with $\mu \in (0, 1)$, where λ is the number of unprotected individuals as a fraction of the population of potential victims, and γ is the normalized fraction of active criminals[2]. For simplicity, the protection investment decision is thought of as a binary choice. The victimization function

[2] The fraction of active criminals is normalized as a fraction of population of potential victims, whose mass is equal to one.

plays the same role of the matching function in frictional labor market models. It returns the total number of matches using as inputs the number of active criminals and the number of unprotected individuals: trading and thus crime occurs whenever one match is realized. Market frictions prevent trading opportunities from being cleared with probability one: whenever one active criminal more and one unprotected potential victim more appear in this market, the probability for them to match and thus for a crime to occur is strictly lower than one.

Individual victimization and matching probabilities can be defined accordingly. The individual probability for an unprotected potential victim to match with an active criminal and thus be victimized is given by

$$q(\gamma, \lambda) = \frac{\gamma^{\mu}\lambda^{1-\mu}}{\lambda} = \left(\frac{\gamma}{\lambda}\right)^{\mu} \tag{2}$$

By the same token, the individual probability for an active criminal to match with an unprotected potential victim is given by

$$h(\gamma, \lambda) = \frac{\gamma^{\mu}\lambda^{1-\mu}}{\gamma} = \left(\frac{\lambda}{\gamma}\right)^{1-\mu} \tag{3}$$

Market tightness shapes individual victimization probabilities as frictions are responsible for the generation of trading externalities. The decision of each agent is thus not independent from the choice of others. Consider first the protection decision of potential victims. A population of agents of mass one makes a binary investment choice. Each agent chooses $a_i \in \{0, 1\}$, where $a_i = 1$ if the observable protection investment is undertaken, and zero otherwise. Agent i maximizes her payoff function

$$u_i = a_i(w - K) + (1 - a_i)\left\{q(\gamma, \lambda)\left[w - L_i\right] + \left[1 - q(\gamma, \lambda)\right] w\right\} \tag{4}$$

where w is individual wealth, K is the cost of protection investment and L_i is the individual loss from victimization. If the agent invests in protection, she keeps all her wealth with probability one, but needs to pay the investment cost. If no protection investment is undertaken, with probability $q(\gamma, \lambda)$ the agent is victimized and suffers the correspondent loss. Otherwise, she keeps her entire wealth at no cost. Heterogeneity on this side of the market is shaped through the differences in the losses L_i from victimization, distributed according to a cumulative distribution function $H(\cdot)$. It follows that the agent decides to invest in protection ($a_i = 1$) if the expected loss exceeds the cost of the investment, meaning

$$\left(\frac{\gamma}{\lambda}\right)^{\mu} L_i \geq K \tag{5}$$

Notice that, given the stock of active criminals γ, a higher fraction of protected individuals (smaller λ) increases the likelihood of each agent to invest in protection. This is because observable protection by some potential victims diverts criminals' attention towards the rest of unprotected individuals[3]. Following Shavell (1991), this can be labeled as the *diversion effect*

[3] The problem of a social planner willing to maximize the sum of payoffs of potential victims and the resulting

of individual protection investment. Given the above equation and knowing the distribution of L_i, it is possible to identify the agent indifferent between investing or not, and define the equilibrium fraction of unprotected individuals λ^* implicitly as

$$\lambda^* = H\left[K\left(\frac{\lambda^*}{\gamma}\right)^{\mu}\right] \tag{6}$$

It is worth noticing that the equilibrium fraction of unprotected individuals diminishes with the stock of active criminals γ and increases with the protection investment cost as captured by K.

At the same time, agents from an exogenously given population of potential criminals decide whether or not to become active as captured by a binary choice variable $g_j \in \{0, 1\}$[4]. Each agent j maximizes

$$w_j = g_j\left[h(\gamma, \lambda)(\hat{L} - R)\right] + (1 - g_j)r_j \tag{7}$$

where $\hat{L}$ are expected gains from property crime as equal to the expected loss of unprotected potential victims, meaning $\hat{L} = \mathbb{E}(L_i|a_i = 0)$. R is the payoff value of the cost of crime, meaning the probability of getting caught times the correspondent loss. r_j captures instead the payoff value of a given outside option (possibly capturing ethic considerations, too). Heterogeneity is in this case shaped through such outside option value r_j, which is modeled as distributed according to a cumulative distribution function $G(\cdot)$. Similarly to potential victims, criminals decide to become active ($g_j = 1$) whenever

$$\left(\frac{\lambda}{\gamma}\right)^{1-\mu}(\hat{L} - R) \geq r_j \tag{8}$$

so that, given the fraction of unprotected individuals, the equilibrium fraction of active criminals can be defined implicitly by

$$\gamma^* = G\left[\left(\frac{\lambda}{\gamma^*}\right)^{1-\mu}(\hat{L} - R)\right] \tag{9}$$

Notice that the equilibrium fraction of active criminals increases with the expected gains from crime $\hat{L}$ and diminishes with its cost as captured by R. More importantly, it diminishes when the fraction of unprotected individuals λ is lower, provided that changes $\hat{L}$ are small enough. In other words, investment in protection has a *deterrence effect*, which reduces the profitability for criminals to become active (Shavell 1991).

The two equilibrium equations are determined simultaneously in the definition of the overall

equilibrium solution are developed in Appendix A Section 1.

[4]The existence an of exogenously given population of potential criminals can be rationalized as in Di Tella et al. (2010) by the presence of labor market frictions which prevents individuals with an earning potential lower than a given threshold to enter the labor market. These same individuals consider to become criminals in order to avoid starvation.

model equilibrium as

$$\lambda^* = H\left[K\left(\frac{\lambda^*}{\gamma^*}\right)^{\mu}\right]$$
$$\gamma^* = G\left[\left(\frac{\lambda^*}{\gamma^*}\right)^{1-\mu}(\hat{L}-R)\right] \tag{10}$$

An equilibrium always exists in this setting[5]. The simultaneous determination of λ^* and γ^* carries with it the non-trivial interaction between the diversion and deterrence effect of investment in observable protection technologies. Given the stock of active criminals, when a given agent decides to invest in protection, the victimization probabilities of other unprotected individuals increase because of the diversion effect. However, the same investment choice also diminishes the returns from criminal activities, and thus the fraction of active criminals in virtue of the deterrence effect. These two effects jointly determine the change in victimization probabilities of other potential victims, and their likelihood to invest in protection themselves as captured by equation (5)[6]. If the equilibrium fraction of active criminals was highly elastic with respect to the fraction of unprotected individuals, the deterrence effect would be prevalent. Investment by some potential victims would wipe out criminals and decrease victimization probabilities of other unprotected individuals, diminishing the likelihood to invest in protection themselves. In this case, investment in observable protection technologies would have positive spillovers. The opposite would hold if the equilibrium fraction of active criminals was relatively stable and inelastic with respect to the fraction of unprotected individuals. The diversion effect would prevail in this case, generating negative spillovers. Investment by some would then increase the likelihood of others to invest in protection themselves.

3 Burglary in the City of Buenos Aires

Results from the previous section suggest the sign and size of spillover effects among potential victims from investment in observable crime protection technologies not to be uniquely identified by theory. In what follows, the question of interest is investigated empirically using household-level data from the City of Buenos Aires. I focus on one specific crime category, *burglary*, defined by the illegal entry into a building for the purposes of committing an offense. The analysis aims at providing evidence of a systematic relationship between burglary protection investment of neighbors, with the final goal of testing the hypothesis of non-zero spillover effects.

The City of Buenos Aires (*Capital Federal*) counts approximately 3 millions inhabitants and 1.4 million dwellings[7]. The household-level data for the analysis belong to an original survey designed and administered in the Fall and Winter of 2013 in collaboration with the Research Lab on Crime, Institutions and Policies (LICIP) at Universidad Torcuato Di Tella. The main

[5]Notice that the above define a continuous mapping from a convex compact subset of the euclidean space $\mathbb{R}^2$ to itself, $f : [0,1]^2 \to [0,1]^2$. A fixed point exists by Brouwer fixed point theorem.

[6]The formal theoretical argument is developed in Appendix A Section 2.

[7]2010 Argentina Census (INDEC)

body of the questionnaire is mainly based on a previously designed survey (*Encuesta Larga*) administered by LICIP in 8 waves in between 2006 and 2010. To date, the sample counts 1192 interviewed households. I geo-referenced the data and located each of the interviewed households in the Buenos Aires City map. Figure 1 shows the City map together with the location of interviewed households as indicated by the green dots. The thick shaded lines coincide with the administrative boundaries of the 48 neighborhoods in the City.

Interviewed household members are asked a number of questions concerning their victimization experiences. In particular, 144 out of the 1192 households (12.1%) report to have suffered from burglary or burglary attempt in the 5 years before the interview. Furthermore, the survey was specifically designed in order to draw extensive information about the household's burglary protection investment behavior. In particular, households are asked whether they hire private security, have any special door locks, bars, armor plating, monitored and non-monitored alarms, CCTV cameras or outdoor lighting installed and whether any household member permanently stays at home not to leave the house alone. Nine investment dummy variables taking value one when the specific investment is undertaken can be defined accordingly. Moreover, in order to capture the household's cumulate protection investment, I define a *protection investment score* taking integer values from 0 to 9 and equal to the sum of the previously defined dummies. The percentages of interviewed households undertaking each investment is shown in Table 1, together with the summary statistics for all the variables used in the overall empirical analysis.

3.1 Spatial Clustering

Are close neighbors significantly more or less likely to implement the same burglary protection investment schedule? Is there any evidence of spatial clustering of observable protection investment in the City of Buenos Aires? In a framework similar to Bayer et al. (2008) in their exploration of labor market referrals, I consider all pairs of households located in the same administrative neighborhood. I then ask whether households located close enough have a systematically more similar burglary protection investment schedule with respect to households living in the same neighborhood but further apart. The validity of this approach rests on the use of the set of household pairs living in the same neighborhood but further apart as comparison group for immediate neighboring household pairs. It follows that results can thus be ascribed to spillover effects only to the extent to which sorting of individuals with the same propensity to implement a given protection investment schedule does not occur within the neighborhood boundaries. Also, idiosyncratic location characteristics at the within-neighborhood level could still be driving a spurious correlation between the investment schedules of close neighbors. Both issues will be addressed later in the paper, in the search of direct evidence of non-zero spillover effects.

A grid of cells of 450m edge is superimposed over the Buenos Aires City map. Figure 2 shows a detail of the Buenos Aires City map around the *Recoleta* neighborhood, together with households' location and the superimposed cell grid. The final sample is composed by all pairs of household located in the same neighborhood. Households located within the same cell are labeled as *close neighbors*[8].

Starting from the nine burglary protection investment dummy variables defined above, for each household pair (i, j) in neighborhood b it is possible to define an *investment similarity score* variable $siminv_{ijb}$ taking integer values from 0 to 9. The variable captures the degree of similarity between households' investment schedule. Its value is defined by counting the number of investment dummy variables which take the same value for both households in the pair. If none of the nine variables take the same value, the burglary protection investment schedule of the two households is completely different and the investment similarity score variable takes value 0. If all nine dummy variables take the same value, the two households in the pair implement exactly the same protection investment schedule, and the investment similarity score variable takes value 9. Values 1 to 8 correspond to intermediate cases. Table 2 shows the frequencies of each value taken by $siminv_{ijb}$ in the whole sample of household pairs located in the same neighborhood. The total number of pairs of surveyed households located in the same administrative neighborhood is equal to 24985. Over 50% of the household pairs in the sample have an investment similarity score taking values 7 or 8, while only 3 pairs refer to households implementing a completely orthogonal investment schedule. Figure 3 provides a graphical representation of how geographical proximity relate to these numbers. The fraction of close neighbors over the total number of household pairs is estimated separately for each value taken by the investment similarity score, together with the correspondent 95% confidence interval. The figure reveals a clear pattern in the data. Indeed, a higher fraction of close neighbors is found within those household pairs with higher investment similarity scores, suggesting that immediate neighboring households have a more similar protection investment schedule with respect to households located in the same administrative neighborhood, but further apart.

This pattern is investigated more rigorously through implementing the following regression specification

$$siminv_{ijb} = \gamma_b + \beta\ close_{ijb} + \mathbf{X}'_{ijb}\ \delta + u_{ijb} \tag{11}$$

where $siminv_{ijb}$ is the protection investment similarity score defined as above for the household pair (i, j) in neighborhood b, while $close_{ijb}$ is a dummy equal to 1 if i and j are located in and belong to the same cell. γ_b is neighborhood fixed effect which controls for average differences in household pairs' similarity across neighborhoods. $\mathbf{X}_{ijb}$ is a vector of pair's demographic and economic characteristics. Residual determinants of investment similarity are captured by u_{ijb}. The coefficient of interest β captures whether close neighbors have a systematically different propensity to implement the same burglary protection investment schedule with respect to neighbors located further apart[9].

[8]The choice of a specific edge size is motivated as follows. Given the sample of all household pairs living in the same neighborhood, increasing the cell size automatically increases the number of household pairs defined as close neighbors, which can be thought of as treated units. This decreases the minimum detectable effect for a given power, sample size and significance level (Duflo et al. 2008). By the same token, the assumption of absence of sorting within neighborhood and across cells is less likely to hold as cell size increases. I thus chose the edge size so to let the within-neighborhood average number of blocks per cell be at most 10% of the total number of blocks in the neighborhood. At the resulting 450m edge cell size, an average number of 11 blocks are contained into one cell, with the smallest administrative neighborhood (*San Telmo*) containing 85 blocks. As shown in Table 4, results are robust to reasonable changes in edge size.

[9]The same analysis is performed also using neighborhood (or reference group) definition different from the ad-

Point estimates for β are reported in Table 3. Given that one household belongs to more than one pair in the final dataset, consistently with Bayer et al. (2008), bootstrapped standard errors are computed and used for inference in most specification. Column 1 reports the estimate of the coefficient of interest from a simple regression of the investment similarity score over the close neighbors dummy and neighborhood fixed effects. The point estimate is significant at the 1% level. Close neighbors are shown to be significantly more likely to implement the same burglary protection investment schedule with respect to the average household pair in the same neighborhood. The point estimate is 0.166, equal to the 2.3% of the score mean and 11% of its standard deviation. In column 2 to 5, I progressively include the vectors of pair-level controls[10]. The point estimate slightly decreases, but keeps being significant at the 1% level.

Robustness of results is explored further in Table 4. In the first column, I include individual household fixed effects for each pair member. The generalized regression specification is

$$siminv_{ijb} = \lambda_{ib} + \lambda_{jb} + \beta \ close_{ijb} + u_{ijb} \tag{12}$$

Fixed effects should be thought of as capturing the households' idiosyncratic propensity to implement the investment schedule of neighbors. If individuals were sorting across cells within neighborhood according to such propensity, we would mistakenly consider proximity to be responsible of a spurious correlation generated by sorting (Bayer et al. 2008). Moreover, the inclusion of individual household fixed effects allows to correct residuals estimates $\hat{u}_{ijb}$ for a potential source of non-independence between them when the same household belongs to different pairs. The resulting point estimate in column 1 is now equal to 0.067, but still significant at the 1% level.

The issue of possibly correlated residuals can be further explored by testing the robustness of results with respect to alternative standard errors estimation techniques. Results from clustering standard errors at the neighborhood level are shown in column 2 of Table 4. The estimate of the coefficient of interest is still significant at the 5% level. Finally, in the estimation of the variance-covariance matrix of residuals, we can allow their correlation to be non-zero whenever two observations have one pair household member in common. Following Fafchamps and Gubert (2007a,b), we can thus implement a dyadic standard errors estimation which allows for $\mathbb{E}(u_{ijb}u_{gkb}) \neq 0$ whenever i or j is equal to either g or k. Column 3 shows the point estimate of interest in this case to be still significant at the 1% level.

Column 4 in Table 4 reports the same estimate of the coefficient of interest, but exploiting variation within the boundaries of police districts instead of administrative neighborhoods. The point estimate is still significant at the 1% level and now equal to 0.105. Finally, columns 5 and 6 reports estimate under alternative grid cell size definitions, with edges equal to 350m and 400m respectively. Results are found to be comparable to previous ones in terms of both magnitude and significance.

ministrative neighborhood one. As shown in Table 4, using police districts yields qualitatively and quantitatively similar results.

[10]The full set of included controls is specified in the table notes.

Results can be interpreted in light of the theoretical model presented above. Investment by close neighbors in one specific observable protection device increases the victimization probability of a given household and thus its likelihood to make the same investment. This generates a higher degree of similarity between the investment schedule of close neighbors, and implicitly suggests the relative supply of burglars in the city to be relatively inelastic with respect to the fraction of investors in the average location (or perceived to be so by potential victims). However, the same observed pattern could arise if sorting of individuals with the same propensity to implement a given protection investment schedule occurs at the cell level, or if idiosyncratic cell characteristics independently shape the investment schedules of close neighbors in the same way (correlated effects).

3.2 Protection Investment Spillovers

Evidence from the previous section suggests that immediate neighbors have a systematically more similar burglary protection investment schedule with respect to neighbors living further apart. However, it remains silent on whether protection investment of neighbors has any causal effect on individual household's investment decisions. I thus implement an alternative identification strategy where I exploit within-neighborhood variation in close neighbors' investment status, and look for a systematic relationship of the latter with a given household's investment choice.

In the same framework of Miguel and Kremer (2004) in their study of externalities from deworming treatment in Kenya, I implement the following regression specification

$$y_{ib} = \psi_b + \lambda_d \ N^y_{dib} + \phi_d \ N_{dib} + \mathbf{Z}'_{ib} \ \theta + v_{ib} \tag{13}$$

where y_{ib} is dummy variable indicating the protection investment status of household i in neighborhood b. The nine investment variables and the overall protection investment score are studied separately. N_{dib} is the total number of surveyed households within distance d from household i, while N^y_{dib} is the number of those among them who undertook the investment under investigation, meaning those for which $y = 1$. In the case of the overall protection investment score, N^y_{dib} equals the cumulate investment of surveyed neighbors. $\mathbf{Z}_{ib}$ is a vector of household-level demographic and economic controls, while the fixed effects ψ_b capture average differences across neighborhoods. The coefficient of interest λ_d captures spillovers from protection investment of close neighbors. More specifically, $\lambda_d \neq 0$ reveals systematic differences between households located in the same neighborhood and with the same number of surveyed immediate neighbors, but differing in the number of the latter who invest in a given protection technology.

Estimation of the above equation using Ordinary Least Squares (OLS) is likely to deliver a biased estimate of the coefficient of interest. First, the above equation defines the investment choice of all households simultaneously, yielding to problems of the same family of those identified by Manski (1993) in the estimation of endogenous peer effects. Second, as outlined before, within-neighborhood sorting of individuals with the same propensity of investing in a given protection technology can potentially generate a spurious positive correlation between the investment status of immediate neighbors. Third, the same would be true if idiosyncratic location characteristics at the within-neighborhood level are independently pushing the investment choices of neighbors in the same direction. Fourth, the inclusion of both spatial lags and neighborhood fixed effects yields a mechanical downward bias in OLS estimates of the same nature of the Nickell-Hurwicz bias in short time series (Nickell 1981; Guryan et al. 2009; Plümper and Neumayer 2010)[11].

In order to overcome these problems, I exploit the variation in the protection investment status of close neighbors as induced by their reported information about crimes suffered by their friends, relatives, acquaintances and others. The questionnaire specifically asks the respondent to list these crimes, if any, together with the category and whether they occurred at least 20 blocks away from the respondent's house. Crime at such a high distance from the interviewed household can be thought of as orthogonal to the protection investment of the given household and its neighbors. Such statement is supported by the empirical evidence in the economics of crime literature showing no significant spatial displacement of crime beyond the neighborhood boundaries after an exogenous increase in police presence (Draca et al. 2010; Di Tella and Schargrodsky 2004). More importantly, information about crimes involving one's contacts and others can be framed as a shock to the agent's information set. New, updated information on crime and its probability to occur is likely to induce variation in the agent's protection investment decisions. I thus implement an Instrumental Variable (IV) strategy and use within-neighborhood variation in the number of surveyed close neighbors reporting information about any crime occurred at least 20 blocks away N^v_{dib} as a source of exogenous variation for the number of surveyed close neighbors who invest in protection N^y_{dib}. In the regression specification I include the full set of neighborhood fixed effects and control for whether the household has itself information about any crime episode. The validity of this approach rests on the satisfaction of few well identified assumptions. First, conditional on the included controls, the number of surveyed close neighbors reporting information about any crime occurring sufficiently far away needs to be a strong predictor of the number of the former investing in the specific technology under investigation. Second, neighbors' reported knowledge of crime episodes has to be as good as randomly assigned to each given household, and have no direct effect on the investment schedule of the latter.

Table 5 shows OLS estimates of the coefficients from a series of regressions of the number of surveyed close neighbors reporting information about any crime occurred at least 20 blocks away N^v_{dib} over a number of variables capturing household's demographic and economic characteristics, controlling for the total number of surveyed neighbors N_{dib} and neighborhood fixed effects. Close neighbors are defined as those who are located within a distance d of 150m from the given household. Results show the neighbors' knowledge of any crime episodes occurred far away not

[11] Notice also that N^y_{dib} refers to surveyed close neighbors. Therefore, it is only an estimate of the intensity of protection adoption within the immediate neighborhood. As long as the survey sampling design is such that the number of surveyed close neighbors is randomly assigned to households, the problem can be conceptualized as one of *random measurement error* in the regressor of interest, which would result in attenuation bias in the estimate of the coefficient of interest.

to be systematically related to given household's characteristics. All coefficients of interest turn out to be negligible and/or non-significant at standard significance level. Remarkably, in the first column, a non-significant coefficient estimate indicates that the number of neighbors reporting any information about crimes occurred far away is orthogonal to a given household's knowledge of the same[12]. Moreover, no systematic relationship is found in the last column, when we look at respondent's beliefs on crime using a dummy equal to one if crime is considered to be a very serious issue, which is likely to be a relevant determinant of protection investment behavior. All this is particularly reassuring, as it shows that potential confounding effects of information sharing and overlapping of peer groups among neighbors are likely to be a minor concern in this setting. Indeed, results speak in favor of the exclusionary restriction, i.e. the assumption of no direct effect of neighbors' reported knowledge of crimes on household's information and protection investment decisions. Furthermore, no systematic relationship is found when we look at the other variables, suggesting the proposed instrument to be framed as good as randomly assigned. A significant coefficient is estimated when the probability for the respondent of being married, being a college graduate and the household's dwelling to be a flat is considered, but the point estimate is negligible in magnitude. When all variables are used as explanatory variables at the same time, results from an *F-test* of joint significance show that the hypothesis of all coefficients being jointly zero cannot be rejected (*p-value* of 0.498). Nonetheless, all these variables will be progressively included as controls in the main empirical analysis in order to evaluate the robustness of results and improve estimates' precision.

Table 6 shows OLS estimates of λ_d from equation (13) for the nine different observable protection investments under investigation (private security, special door locks, bars, armor plating, monitored and non-monitored alarms, CCTV cameras, outdoor lighting and permanently stay at home), together with the results for the overall protection investment score. Standard errors are clustered at the neighborhood level. Point estimates are negative in most specifications, from the one which only includes the total number of surveyed close neighbors and neighborhood fixed effects as controls (column 1) to the ones which include demographic and economic controls (column 2 and 3 respectively), respondent's beliefs about crime (column 4) and dwelling type characteristics (column 5). All the variables investigated in Table 5 are used as demographic or economic controls. Further variables added to the latter are dummy variables capturing ownership of specific durable goods, as listed in the bottom panel of Table 1. Despite the dummy of whether house is a flat, controls for dwelling type characteristics include distance from the closest police station. OLS estimates are significant when looking at the propensity of a given household to invest in special door locks and non-monitored alarms given the neighbors' composition of the same. The mechanical negative Nickell-Hurwicz-type bias is likely to be responsible for the results.

IV estimation results are shown in Table 7. Estimates are restricted only to those protection investment variables for which the proposed instrument is found to be relevant enough, meaning it induces meaningful variation in the endogenous variable of interest. In this respect, the table

[12]In order to take care of the mechanical Nickell-Hurwicz-type bias outlined before, the sample is here restricted to households who are at most 310m distant from each other.

displays the value of the *F-statistic* for the test of significance of the instrument in the first stage regression, which is indeed safely above 10 in all specifications. Results are ordered as in Table 6 in columns 1 to 5, where, consistently with the above, standard errors are clustered at the neighborhood level. A positive and significant effect is found when monitored alarms and CCTV cameras are considered: one close neighbor more shifting from being a non-investor to be an investor increases the probability for a given household of doing the same of 19 and 10 percentage points respectively. Note that the IV estimates are invariant to the inclusion of controls, and in particular the measure of household's beliefs towards crime in column 4.

Non-significant effects are found instead when the other technologies are considered, meaning special door locks, bars and outdoor lighting. Also, no effect is found for the cumulate investment of neighbors as captured by the overall protection investment score. In order to shed further light on this last result, Figure 4 plots the individual household's protection investment score over the average investment score of surveyed close neighbors. The relationship between the two appears to be non-linear, with own cumulate protection being positively related to neighbors' investment score when the latter takes smaller values, and negative otherwise. This suggests that high levels of cumulate neighbors' protection investment may actually exert a positive externalities on a given household's victimization probability, decreasing its likelihood of investing in protection itself. However, this result is only tentative and cannot be interpreted causally.

Overall, results from this section confirm what was found in the analysis of spatial clustering of burglary protection investments. Given household's information and beliefs, investment by neighbors is directly shown to significantly increases the likelihood of investing in protection for the average household. In light of the model, this is due to the perceived increase in household's victimization probability, implicitly suggesting the burglary supply to be relatively inelastic with respect to the intensity of protection in the average location, or perceived to be so by potential victims.

4 Conclusions

This paper explores both theoretically and empirically the extent to which observable crime protection investment of potential victims relate to each other. In theory, the impact of a marginal investment decision on the likelihood of other individuals to invest in protection themselves is far from being unambiguous. On one side, observable protection by some agents divert criminals' activity towards other unprotected targets. On the other side, it diminishes returns to engage in criminal activity and therefore the stock of active criminals. The ultimate sign and size of protection on victimization probability of other potential victims and thus their likelihood to acquire protection is thus an empirical question.

These issues are explored theoretically in a model of frictional market for offenses. Externalities among potential victims arise as trading externalities and the sources of spillovers' ambiguity is identified by theory. The issue is then taken to the data using geo-referenced household-level information from the City of Buenos Aires. Focusing on burglary protection investment decisions, close neighbors are shown to implement a more similar observable protection investment schedule than neighbors further apart. Perhaps more importantly, exploiting within-neighborhood variation in close neighbors' reported information about crimes as a source of exogenous variation for their investment status, an Instrumental Variable identification strategy reveals the latter to have a significant impact on individual household's propensity to invest. This is true when looking at the likelihood of installing monitored alarms and CCTV cameras, while it seems not to be the case for other technologies. Finally, the investigation of the relationship between neighbors' and own cumulate investment is shown instead to be non-linear, with a positive effect on own investment when neighbors' cumulate protection investment is low, and a negative effect when the latter is higher.

When interpreted in light of the theoretical model, evidence indirectly suggests burglary supply to be relatively inelastic with respect to the fraction of protected individuals, or perceived to be so by potential victims. More generally, the proposed evidence of non-zero spillover effects of protection investment calls for the need of investigating further the potential victims' side of the market for offenses. A clear understanding of its functioning and its explanatory power for the variability of equilibrium crime rates is crucial for rigorous design of crime reduction policies.

References

Ayres, I. and S. D. Levitt (1998). Measuring Positive Externalities from Unobservable Victim Precaution: An Empirical Analysis of Lojack. *The Quarterly Journal of Economics 113*(1), 43–77.

Ballester, C., A. Calvó-Armengol, and Y. Zenou (2010). Delinquent Networks. *Journal of the European Economic Association 8*(1), 34–61.

Bayer, P., S. L. Ross, and G. Topa (2008, December). Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes. *Journal of Political Economy 116*(6), 1150–1196.

Becker, G. S. (1968). Crime and Punishment: An Economic Approach. *Journal of Political Economy 76*, 169.

Blume, L. E., W. A. Brock, S. N. Durlauf, and Y. M. Ioannides (2011). Identification of social interactions. Volume 1 of *Handbook of Social Economics*, pp. 853–964. North-Holland.

Bramoullé, Y., H. Djebbari, and B. Fortin (2009). Identification of peer effects through social networks. *Journal of Econometrics 150*(1), 41–55.

Calvó-Armengol, A., E. Patacchini, and Y. Zenou (2009). Peer effects and social networks in education. *Review of Economic Studies 76*(4), 1239–1267.

Clotfelter, C. T. (1978). Private security and the public safety. *Journal of Urban Economics 5*(3), 388–402.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of Econometrics 92*(1), 1–45.

De Giorgi, G., M. Pellizzari, and S. Redaelli (2010). Identification of social interactions through partially overlapping peer groups. *American Economic Journal: Applied Economics 2*(2), 241–75.

Di Tella, R., S. Galiani, and E. Schargrodsky (2010). Crime Distribution and Victim Behavior during a Crime Wave. In *The Economics of Crime: Lessons for and from Latin America*, NBER Chapters, pp. 175–204. National Bureau of Economic Research, Inc.

Di Tella, R. and E. Schargrodsky (2004). Do police reduce crime? estimates using the allocation of police forces after a terrorist attack. *American Economic Review 94*(1), 115–133.

Draca, M., S. Machin, and R. Witt (2010, October). Crime displacement and police interventions: Evidence from londons operation theseus. In *The Economics of Crime: Lessons for and from Latin America*, NBER Chapters, pp. 359–374. National Bureau of Economic Research, Inc.

Duflo, E., R. Glennerster, and M. Kremer (2008). Using randomization in development economics research: A toolkit. In T. P. Schultz and J. A. Strauss (Eds.), *Handbook of Development Economics*, Volume 4, Chapter 61, pp. 3895–3962. Elsevier.

Ehrlich, I. (1996). Crime, Punishment, and the Market for Offenses. *The Journal of Economic Perspectives 10*(1), pp. 43–67.

Ehrlich, I. (2010). The Market Model of Crime: A Short Review and New Directions. In B. L. Benson and P. R. Zimmerman (Eds.), *Handbook on the Economics of Crime*, Chapter 1, pp. 3–12. Edward Elgar.

Fafchamps, M. and F. Gubert (2007a). Risk Sharing and Network Formation. *American Economic Review 97*(2), 75–79.

Fafchamps, M. and F. Gubert (2007b). The Formation of Risk Sharing Networks. *Journal of Development Economics 83*(2), 326–350.

Glaeser, E. L., B. Sacerdote, and J. A. Scheinkman (1996). Crime and Social Interactions. *The Quarterly Journal of Economics 111*(2), 507–548.

Guryan, J., K. Kroft, and M. J. Notowidigdo (2009). Peer effects in the workplace: Evidence from random groupings in professional golf tournaments. *American Economic Journal: Applied Economics 1*(4), 34–68.

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *Review of Economic Studies 60*(3), 531–42.

Miguel, E. and M. Kremer (2004). Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities. *Econometrica 72*(1), 159–217.

Nickell, S. J. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica 49*(6), 1417–26.

Patacchini, E. and Y. Zenou (2012). Juvenile Delinquency and Conformism. *Journal of Law, Economics and Organization 28*(1), 1–31.

Pissarides, C. (2000). *Equilibrium unemployment theory* (2. ed ed.). Cambridge, Mass. [u.a.]: MIT Press.

Plümper, T. and E. Neumayer (2010). Model specification in the analysis of spatial dependence. *European Journal of Political Research 49*(3), 418–442.

Shavell, S. (1991). Individual precautions to prevent theft: Private versus socially optimal behavior. *International Review of Law and Economics 11*(2), 123–132.

Zenou, Y. (2003). The Spatial Aspects of Crime. *Journal of the European Economic Association 1*(2-3), 459–467.

Tables and Figures

Table 1: Summary Statistics

Variable	N	Mean	St. Dev.	Min	Max
Age	1185	47.973	15.243	18	90
Female	1192	0.548	0.498	0	1
Any HH member < 18 years old	1192	0.297	0 .457	0	1
Married	1192	0.496	0.50	0	1
Owner	1192	0.569	0.495	0	1
College degree	1192	0.270	0.444	0	1
Self-employed	1192	0.352	0.478	0	1
Retired	1192	0.184	0.387	0	1
Unemployed	1192	0.049	0.217	0	1
Believes Crime is Very Serious Problem	1192	0.522	0.50	0	1
Dwelling is a flat	1192	0.522	0.50	0	1
Distance from closest Police Station (km)	1192	0.779	0.468	0.024	2.409
Reports any crime occurred > 20 blocks away	1192	0.266	0.442	0	1
Number of Surveyed Neighbors within 150m	1192	2.804	4.716	0	26
Protection Investment Variables					
Private Security	1192	0.159	0.365	0	1
Special Door Locks	1192	0.176	0.381	0	1
Bars	1192	0.210	0.407	0	1
Armor plating	1192	0.065	0.246	0	1
Alarm, monitored	1192	0.097	0.297	0	1
Alarm, non-monitored	1192	0.048	0.213	0	1
CCTV Camera	1192	0.135	0.342	0	1
Outdoor Lighting	1192	0.050	0.219	0	1
Permanently Stays at Home	1192	0.367	0.482	0	1
Individual Protection Score (0-9)	1192	1.307	1.424	0	8
Durable Goods Ownership Dummies					
Cars	1192	0.327	0.469	0	1
Cable TV	1192	0.780	0.414	0	1
DVD Player	1192	0.513	0.50	0	1
Internet at Home	1192	0.641	0.480	0	1
Computers/Tablets	1192	0.608	0.488	0	1
Domestic Service	1192	0.138	0.345	0	1
Washing Machine	1192	0.372	0.484	0	1

Table 2: Frequencies of Investment Similarity Score Values

Investment Similarity Score Value	Frequency	%
0	3	0.01
1	67	0.27
2	161	0.64
3	348	1.39
4	834	3.34
5	2105	8.43
6	3945	15.79
7	5615	22.47
8	7063	28.27
9	4844	19.39
Total	24985	100

Notes. Unit of observation is pair of households in the same administrative neighborhood.

Table 3: Spatial Clustering of Burglary Protection Investment

	Investment Similarity Score				
	(1)	(2)	(3)	(4)	(5)
Close Neighbors	0.166***	0.161***	0.161***	0.156***	0.157***
(Same Cell)	(0.033)	(0.030)	(0.028)	(0.029)	(0.028)
NB Fixed Effects	Y	Y	Y	Y	Y
Demographic Controls		Y	Y	Y	Y
Economic Controls			Y	Y	Y
Dwelling Type Controls				Y	Y
Beliefs Controls					Y
Outcome mean	7.139	7.139	7.139	7.139	7.139
Observations	24985	24985	24985	24985	24985
R^2	0.135	0.136	0.141	0.143	0.1445

Notes. Unit of observation is pair of households belonging to the same administrative neighborhood. Outcome variable is investment similarity score defined as above. Dummies for demographic controls include: both interview household members above the median age, both female, both households with any member aged less than 18, both married, both couple households. Dummies for economic controls include: both house howlers, both primary schooling, both secondary schooling, both college graduates, both employees, both self-employed, both retired, both unemployed. Dummies for dwelling type controls include: both flats, both independent houses. Dummies for beliefs controls include: both interviewed household members consider the problem of crime in Buenos Aires very serious, both think crime has increased over the last year, both think crime has increased over the last 5 years. Bootstrapped SEs are computed using 200 repetitions. (* p-value< 0.1; ** p-value<0.05; *** p-value<0.01.)

Table 4: Spatial Clustering of Protection Investment: Robustness

	Investment Similarity Score					
	(1)	(2)	(3)	(4)	(5)	(6)
Close Neighbors	0.067***	0.166**	0.166***	0.105***	0.188***	0.188***
(Same Cell)	(0.021)	(0.079)	(0.021)	(0.030)	(0.033)	(0.032)
NB Fixed Effects	Y	Y	Y		Y	Y
Police District Fixed Effects				Y		
HHs Fixed Effects	Y					
Clustered SEs		Y				
Dyadic SEs			Y			
Outcome mean	7.139	7.139	7.139	7.139	7.139	7.139
Observations	24985	24985	24985	24985	24985	24985
R^2	0.697	0.135	0.135	0.149	0.135	0.135

Notes. Unit of observation is pair of households in the same administrative neighborhood. Outcome variable is investment similarity score defined as above. Column (5) and (6) provide results given an alternative definition of grid cell size, with edge equal to 350m and 400m respectively. Bootstrapped SEs are computed using 200 repetitions. Clustered SEs in Column (2) are clustered at the administrative neighborhood level. Dyadic SEs in Column (3) are from Fafchamps and Gubert (2007a,b). (* p-value< 0.1; ** p-value<0.05; *** p-value<0.01.)

Table 5: Neighbors' Information about Crime Episodes and Household Characteristics

	Neighbors Reporting Any Crime Suffered by Friends, Relatives, Acquaintances, Others (N^v_{150ib})												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Reports any crime	0.024												0.024
> 20 blocks away	(0.049)												(0.051)
Age		-0.001											0.000
		(0.001)											(0.002)
Female			0.049										-0.008
			(0.036)										(0.041)
Any HH member				0.003									0.019
Aged < 18				(0.040)									(0.047)
Married					-0.070*								-0.010
					(0.036)								(0.043)
House Owner						0.043							0.023
						(0.037)							(0.043)
College Degree							0.069*						-0.006
							(0.042)						(0.048)
Self-employed								-0.042					0.018
								(0.038)					(0.045)
Retired									-0.036				-0.076
									(0.046)				(0.069)
Unemployed										-0.033			-0.101
										(0.083)			(0.125)
House is a Flat											0.076*		0.057
											(0.039)		(0.045)
Beliefs on Crime												-0.041	-0.034
												(0.036)	(0.041)
N_{150ib}	0.104***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.064***	0.063***	0.062***	0.064***	0.102***
	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)
Constant	-0.058	-0.007	-0.069	-0.044	0.005	-0.080	-0.058	-0.024	-0.034	-0.042	-0.050	-0.020	-0.061
	(0.198)	(0.215)	(0.203)	(0.203)	(0.203)	(0.205)	(0.202)	(0.203)	(0.203)	(0.202)	(0.202)	(0.203)	(0.227)
F-test p-value													0.498
Observations	460	1185	1192	1192	1192	1192	1192	1192	1192	1192	1192	1192	457
R^2	0.381	0.256	0.258	0.257	0.259	0.258	0.259	0.258	0.257	0.257	0.259	0.258	0.390

Notes. Standard Errors in parenthesis. Unit of observation is individual household. Each column show the coefficient from a regression of the number of surveyed neighbors reporting information about at least one crime episode occurred sufficiently far away over the correspondent household characteristic, the total number of surveyed neighbors and the full set of administrative neighborhood fixed effects. In columns 1 and 13 a restricted sample of observations at distance of at most 310m between them to avoid the Nickell-Hurwicz bias problems described in the paper (Plümper and Neumayer 2010; Nickell 1981). $d = 150m$. (* p-value< 0.1; ** p-value<0.05; *** p-value<0.01.)

Table 6: Own and Neighbors' Protection Investment: OLS Results

	Protection Investment in the Same Technology				
	(1)	(2)	(3)	(4)	(5)
Neighbors' Investment in:					
Private Security	-0.049	-0.053	-0.054	-0.053	-0.052
	(0.050)	(0.046)	(0.045)	(0.044)	(0.042)
Special Door Locks	-0.032**	-0.034**	-0.037**	-0.037***	-0.038***
	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)
Bars	-0.009	-0.005	-0.005	-0.005	-0.005
	(0.024)	(0.025)	(0.024)	(0.024)	(0.023)
Armor plating	-0.032	-0.041	-0.043	-0.042	-0.044
	(0.033)	(0.031)	(0.030)	(0.030)	(0.030)
Alarm, monitored	-0.001	-0.001	-0.003	-0.003	-0.001
	(0.033)	(0.032)	(0.033)	(0.033)	(0.033)
Alarm, non-monitored	-0.066**	-0.076***	-0.077***	-0.077***	-0.080***
	(0.031)	(0.022)	(0.020)	(0.020)	(0.022)
CCTV Camera	0.003	-0.003	-0.000	-0.000	-0.007
	(0.035)	(0.036)	(0.037)	(0.037)	(0.037)
Outdoor lighting	-0.048	-0.051*	-0.049	-0.049	-0.051
	(0.029)	(0.030)	(0.031)	(0.031)	(0.032)
Permanently Stays at Home	-0.014	-0.012	-0.015	-0.013	-0.020
	(0.015)	(0.016)	(0.015)	(0.014)	(0.015)
Overall Investment Score (0-9)	0.006	-0.005	-0.010	-0.009	-0.010
	(0.030)	(0.029)	(0.028)	(0.028)	(0.028)
Any Crime Victim Within HH's Contacts	Y	Y	Y	Y	Y
N_{150ib}	Y	Y	Y	Y	Y
NB Fixed Effects	Y	Y	Y	Y	Y
Demographic Controls		Y	Y	Y	Y
Economic Controls			Y	Y	Y
Beliefs Controls				Y	Y
Dwelling Type Controls					Y
Observations	1192	1185	1185	1185	1185

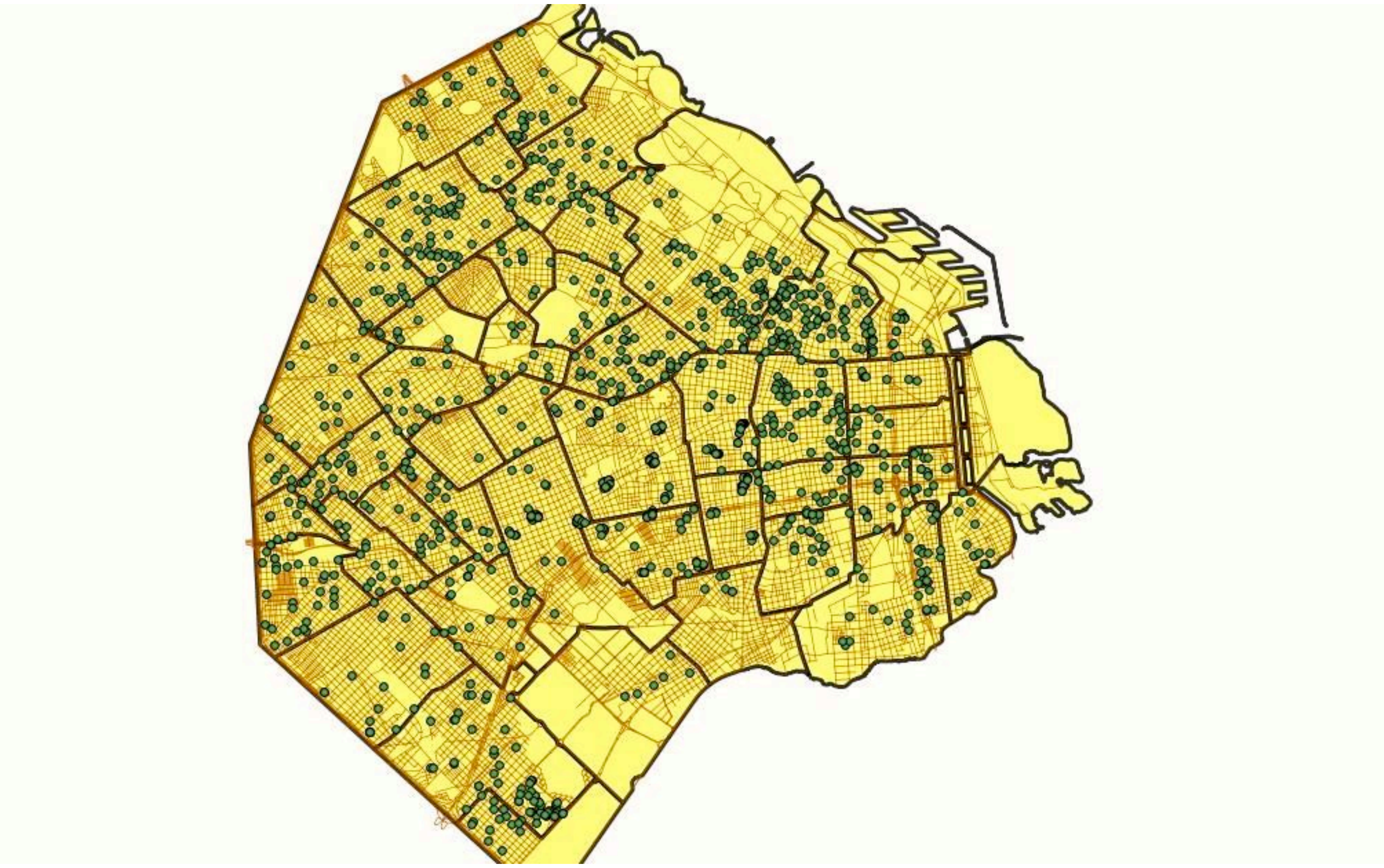
Notes. Standard Errors in parenthesis, clustered at the administrative neighborhood level. The table reports OLS estimates and SEs from the regressions of each row investment variable y over the correspondent number of surveyed neighbors who invest in the same technology, N^y_{150ib}. When considering the overall investment score, the cumulate investment of surveyed neighbors is considered. The total number of surveyed neighbors is controlled for in all specifications, together with the set of administrative neighborhood dummies and a dummy for whether the given household reports any crime suffered by friends, relatives, acquaintances or others occurred at least 20 blocks away. Demographic Controls include: age, age squared, dummies for female, whether there is any household member aged less than 18, married. Economic Controls include dummies for: house is owned, college degree, self-employed, retired, unemployed, durable goods ownership. Beliefs Controls include a dummy equal to one if interviewed household member thinks the problem of crime in the City is very serious. Dwelling Type Controls include dummy for whether house is a flat and distance from closest police station. $d = 150m$. (* p-value< 0.1; ** p-value<0.05; *** p-value<0.01.)

Table 7: The Effect of Neighbors' Protection Investment: IV Results

	Protection Investment in the Same Technology					
	(1)	(2)	(3)	(4)	(5)	(6)
Neighbors' Investment in:						
Special Door Locks	0.080	0.075	0.038	0.036	0.032	0.032
	(0.056)	(0.060)	(0.067)	(0.067)	(0.065)	(0.065)
1st Stage F-stat	46.51	47.06	48.44	48.16	47.47	47.47
Bars	0.006	0.004	-0.019	-0.020	-0.012	-0.012
	(0.056)	(0.061)	(0.072)	(0.073)	(0.073)	(0.057)
1st Stage F-stat	42.38	42.38	43.03	43.30	43.03	43.03
Alarm, monitored	0.198***	0.204***	0.183**	0.186***	0.189***	0.189**
	(0.075)	(0.077)	(0.072)	(0.072)	(0.073)	(0.088)
1st Stage F-stat	44.62	44.49	46.38	46.38	46.38	46.38
CCTV Camera	0.112**	0.104**	0.108***	0.113***	0.106***	0.106**
	(0.044)	(0.041)	(0.037)	(0.039)	(0.041)	(.047)
1st Stage F-stat	46.24	46.24	46.79	46.65	46.79	46.79
Outdoor lighting	-0.028	-0.024	-0.026	-0.027	-0.025	-0.025
	(0.076)	(0.074)	(0.076)	(0.075)	(0.074	(0.070))
1st Stage F-stat	48.30	48.30	49.14	49.84	50.13	50.13
Overall Investment Score (0-9)	0.069	0.067	0.047	0.052	0.050	0.050
	(0.064)	(0.067)	(0.073)	(0.073)	(0.071)	(0.061)
1st Stage F-stat	45.70	44.89	42.90	42.38	42.64	42.64
Any Crime Victim Within HH's Contacts	Y	Y	Y	Y	Y	Y
N_{150ib}	Y	Y	Y	Y	Y	Y
NB Fixed Effects	Y	Y	Y	Y	Y	Y
Demographic Controls		Y	Y	Y	Y	Y
Economic Controls			Y	Y	Y	Y
Beliefs Controls				Y	Y	Y
Dwelling Type Controls					Y	Y
Observations	1192	1185	1185	1185	1185	1185

Notes. Standard Errors in parenthesis, clustered at the administrative neighborhood level. The table reports IV estimates and SEs from the regressions of each row investment variable y over the correspondent number of surveyed neighbors who invest in the same technology, N^y_{150ib}. Instrument is the number of neighbors reporting any crime suffered by friends, relatives, acquaintances or others occurred at least 20 blocks away. When considering the overall investment score, the cumulate investment of surveyed neighbors is considered. *1st Stage F-stat* displays the value of the *F-statistics* for the test of significance of the instrument in the clustered first stage regression. The total number of surveyed neighbors is controlled for in all specifications, together with the set of administrative neighborhood dummies and a dummy for whether the given household reports itself any crime suffered by friends, relatives, acquaintances or others occurred at least 20 blocks away. Demographic Controls include: age, age squared, dummies for female, whether there is any household member aged less than 18, married. Economic Controls include dummies for: house is owned, college degree, self-employed, retired, unemployed, durable goods ownership. Beliefs Controls include a dummy equal to one if interviewed household member thinks the problem of crime in the City is very serious. Dwelling Type Controls include dummy for whether house is a flat and distance from closest police station. Column (6) reports GMM estimates allowing for non-zero correlation of residuals belonging to observations located within 150m one from the other (Conley 1999). $d = 150m$. (* p-value< 0.1; ** p-value<0.05; *** p-value<0.01.)

Figure 1: Buenos Aires City Map

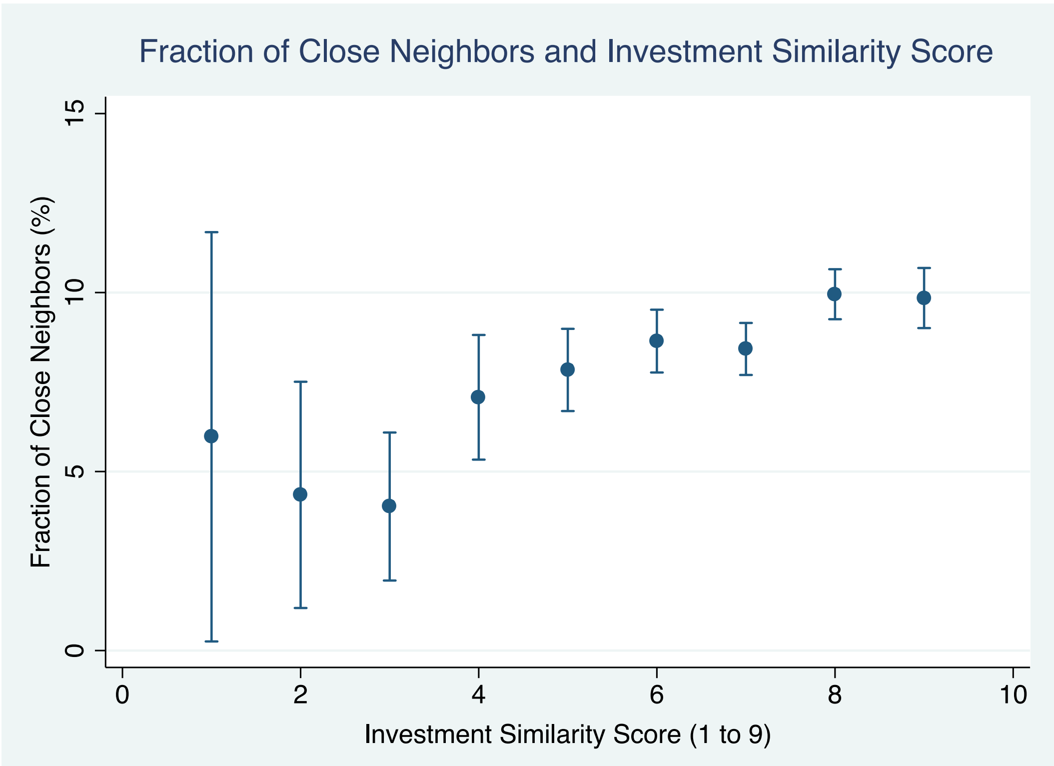


Notes. Map of the City of Buenos Aires with location of interviewed households.

Figure 2: Cell Grid and Administrative Neighborhoods' Boundaries

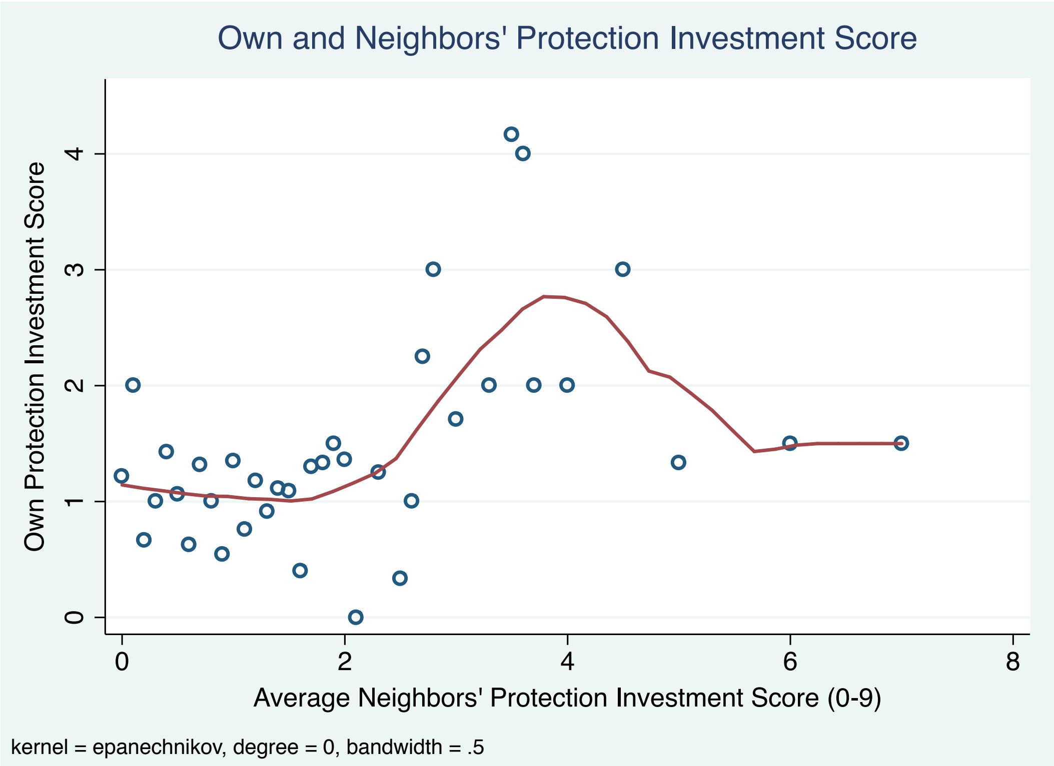
Notes. A detail of the Buenos Aires City map showing the *Recoleta* administrative neighborhood, households' location and the superimposed cell grid.

Figure 3: Neighbors and Investment Similarity Score



Notes. The figure plots the probability of two households in the sample of being close neighbors as estimated separately for each value of the protection investment similarity score for the pair, together with 95% confidence intervals.

Figure 4: Own and Neighbors' Protection Investment Score



Notes. The figure plots the smoothed average protection investment score of a given household per each bin of the average neighbors' protection investment score, with bin size being equal to 0.1.

A Appendix

A.1 Social Planner Problem

Consider the problem of a social planner willing to maximize the sum of payoffs of potential victims $W = \sum_i u_i$. In doing this, the social impact of i's choice of protecting himself on other potential victims is taken into account. The solution is given by

$$\left(\frac{\gamma_i}{\lambda}\right)^{\mu} L_i \geq K + \mu\gamma^{\mu}\lambda^{-1-\mu}\int_0^{\dot{L}} L_i h(L_i) dL_i \tag{14}$$

where the second term on the RHS defines the social cost of the individual investment choice, equal to the marginal increase in the potential loss of unprotected individuals as given by the increase in their victimization probability following the investment of i. Note that $\dot{L}$ is the loss correspondent to the individual whose investment choice is regarded as indifferent by the social planner. Following the same procedure as above we derive $\dot{L}$ and thus compute the equilibrium fraction of unprotected individuals as implicitly defined by

$$\lambda^* = H\left[K\left(\frac{\lambda^*}{\gamma}\right)^{\mu} + \frac{\mu}{\lambda^*}\int_0^{\dot{L}} L_i h(L_i) dL_i\right] \tag{15}$$

Comparing this equilibrium solution to the decentralized one we can see that, given the number of active criminals γ, the socially efficient equilibrium fraction of unprotected individuals is higher than the one reached by the decentralized equilibrium.

A.2 The Sign of Spillover Effects

Starting from equation (5), consider the probability for agent i to invest in protection, meaning to choose $a_i = 1$. This is given by

$$Pr(a_i = 1) = Pr\left[\left(\frac{\gamma}{\lambda}\right)^{\mu} L_i > K\right] = 1 - H\left[K\left(\frac{\lambda}{\gamma}\right)^{\mu}\right] \tag{16}$$

From which it follows

$$\frac{\partial Pr(a_i = 1)}{\partial \lambda} = -K\mu\left(\frac{\lambda}{\gamma}\right)^{\mu}\left[\frac{1}{\lambda} - \frac{1}{\gamma}\frac{\partial\gamma}{\partial\lambda}\right] h\left[K\left(\frac{\lambda}{\gamma}\right)^{\mu}\right] \tag{17}$$

The middle term on the RHS of the above equation captures the tension between the *diversion* and *deterrence* effect. In case the fraction of active criminals γ was unresponsive to the change in the fraction of unprotected individuals ($\partial\gamma/\partial\lambda = 0$), the diversion effect would prevail, and the above derivative would be negative. As a result, investment by others would correspond to a decrease in the fraction of unprotected individuals, and thus an increase in the individual likelihood to protect herself for agent i.

Using the equilibrium equation for γ, we can apply the implicit function theorem and derive

$$\frac{\partial\gamma}{\partial\lambda} = \frac{g\left[\left(\frac{\lambda}{\gamma}\right)^{1-\mu}(\hat{L}-R)\right]\left(\frac{\lambda}{\gamma}\right)^{1-\mu}\left[\frac{1-\mu}{\lambda}(\hat{L}-R)+\frac{\partial\hat{L}}{\partial\lambda}\right]}{1+g\left[\left(\frac{\lambda}{\gamma}\right)^{1-\mu}(\hat{L}-R)\right]\left(\frac{\lambda}{\gamma}\right)^{1-\mu}\frac{1-\mu}{\gamma}(\hat{L}-R)} \tag{18}$$

which is indeed positive provided that $\partial\hat{L}/\partial\lambda$ is negligible.