Learning about risk in a new environment*

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Abstract

We study how individuals learn about the crime risk in the neighborhood they live in. Specifically, we examine whether and how perceptions of crime risk change with time since move to a new neighborhood. Based on four successive waves of a large annual crime survey matched with administrative records on places of residence, we find large and statistically significant differences in how movers perceive crime risk according to time since move. The longer people live in the neighborhood, the higher their perceived prevalence of crime. Strikingly, the upwards adjustment in risk perceptions after the move is independent from the crime risk in the previous place of residence. One explanation for our findings is that judgment of the crime risk is primarily based on the ease in which experiences with crime in the new place of residence can be brought to mind. This stock of crime-related experiences in the new locality increases over time, resulting in a progressively greater perceived risk of crime.

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1. Introduction

Decisions to curb one's exposure to the threat from an act of theft or violence are often made under great uncertainty. It is challenging to deduce something about the nature of the crime danger from the – often prolific – descriptions of the risk, since the descriptions may not apply to the own situation. The danger from crime tends to vary greatly between places (Weisburd et al. 2012), individuals (Cohen and Felson 1979) and time of day (Felson and Poulsen 2003). Learning from own experience may not only be very costly, think about having to experience a robbery first before taking proper precautions, but also difficult because crime events tend to be rare. For instance, on average a US household experiences burglary once every 40 years, any type of violent crime once every 60 years, and motor vehicle theft once every 170 years (Truman and Planty 2012). For the same reason, direct observation of criminal events tends to be rare, rendering it another poor source of information about the risk.

How potential victims learn about the crime risk has been largely ignored in models of crime. If potential victims' actions play a role at all, as in Ehrlich's (1981, 1996) model of the market for offenses, then their behavior has been modeled under the assumption that all information relevant for making the right decision is known.[1] Potential victims are assumed to be able to act in anticipation of the crime risk. They invest in crime precaution up to the point where the marginal benefits of prevention are equal to the marginal benefits. In these static models, the crime rate is determined by a one shot interaction between potential offenders and potential victims. If potential victims have an imperfect understanding about the crime risk, however, then their level of precaution may well be off. The crime rate resulting from the interaction between imperfectly informed potential victims and offenders may be very different from the one in models with well-informed agents (see Lochner 2007 for a study into the behavior of imperfectly informed potential offenders). Most likely, the crime rate is going to be higher: evidence from crime surveys suggests that victimization of crime often comes as a surprise that people are unprepared for. Often precautions are taken in response to victimization rather than

[1] Even though crime is a risk everybody is exposed to, crime preventive behavior has seen little study (Cook and MacDonald 2011). Economists took some interest in crime preventive behavior in the late 1970s and the early 1980s (Clotfelter 1977; Ehrlich 1981; Cook 1986). This work resulted in models in which the crime rate was determined by the simultaneous actions of both offenders and victims. This line of research was largely discontinued, except for empirical work into the use of guns as private deterrent (for instance, Cook and Ludwig 2006; Acquisti and Tucker 2011) and car security (Ayres and Levitt 1998; Gonzalez-Navarro 2013; Van Ours and Vollaard 2013). Other work is focused on externalities emanating from precautionary measures, including Shavell (1991), Hui-Wen and Png (1994), Helsley and Strange (1999, 2005) and Di Tella, Galiani and Schargrodsky (2010). Within criminology, there is an extensive literature on fear of crime (for instance, Jackson 2011), which is primarily focused on measurement issues. [discuss Skogan and Maxfield (1981)]

in anticipation of the crime risk (Van Dijk and Vollaard 2012). This does not fit well with the traditional model of the market of offenses, where victimization should not result in a change in preventive behavior, because it does not provide new information to victims.

In this paper, we examine whether and how perceptions of crime risk change with time since move to a different neighborhood. Our empirical strategy is based on comparing persons who have lived in the same neighborhood for different periods of time. We follow cohorts of movers who have moved to a specific neighborhood in a specific year, and we examine how their perception of crime risk in their neighborhood changes over successive survey years. We control for underlying time trends at the neighborhood level based on the assumption that time trends in crime are the same for incumbent residents and different cohorts of movers.[2] We also control for selective attrition by excluding future movers from our sample.

We use micro-level survey data on perceptions of the crime risk in the neighborhood. The data are based on a representative sample of the population and allow us to study learning behavior over a long period of time, 10 years. Source of data is the Netherlands Crime Survey (IVM), a repeated cross section survey that is conducted annually. It is one of the largest crime surveys in the world relative to size of population. We merge four recent waves of the survey (2008-2011), providing us with a sample of 524,000 respondents, one out of 25 of the population aged 15 or higher. Uniquely, we are able to match the survey data with administrative records on the respondents' previous, current and future places of residence between 1995 and 2011. Given the cross-sectional nature of our data, we compare randomly selected samples of cohorts of individuals who made a move to a specific neighborhood in any of the years between 1998 and 2010. Exposure to the crime risk has been shown to be strongly affected by characteristics of the neighborhood someone lives in (Vollaard and Koning 2009: 342).

We find large differences in the beliefs of people according to time since move. With increasing time since move, residents become more pessimistic about crime risk in their neighborhood. Changes in risk perception are large and statistically significant. The adjustment of beliefs after moving to a new neighborhood is exceedingly slow. The adjustment process can take 10 years or longer. Strikingly, the upwards adjustment in perception of the neighborhood crime risk

[2] Our empirical strategy is similar to Borjas (1995) who examines how immigrant wages evolve with time since immigration based on the assumption that underlying time trends are the same for immigrant and native wages.

holds both for moves to neighborhoods with a higher crime risk than the previous place of residence and moves to neighborhoods with a lower crime risk.

Our findings are in stark contrast with the traditional assumption that potential victims adjust immediately and correctly to a change in the crime risk. The slow upward adjustment in the perceived crime risk indicate the presence of a judgment bias. Our results suggest that the majority of potential victims rely on the so-called availability heuristic to cope with changes in the local crime risk. A heuristic is a behavioral strategy that simplifies decision making (Gigerenzer and Gaissmaier 2011). When using the availability heuristic, the probability of an event is judged by the ease in which instances can be brought to mind (Tversky and Kahneman 1973). People who just moved into a neighborhood have few first-hand or second-hand experiences with crime in that locality. When they are asked about the local crime risk, few negative experiences with crime can be brought to mind, explaining the relatively low perceived risk. This stock of crime-related events in the new locality an individual draws upon increases over time, resulting in a progressively greater perceived risk of crime. This behavioral mechanism can explain the universal upward adjustment in risk perceptions after a move. The exceedingly long duration of the adjustment process could be related to the infrequent occurrence of victimization of crime but the data do not allow us to disentangle the channels by which risk perceptions are changed.

We are able to refute two alternative explanations for our findings. First, people may feel inclined to justify their decision to move house by viewing it in too positive a light, the so-called choice-supportive bias. We provide additional evidence that makes this explanation unlikely: we observe far less adjustment in risk perceptions for moves within a neighborhood than for moves outside a neighborhood. That fits with the availability heuristic, with the stock of experiences built up in the previous place of residence being partly relevant for nearby moves but not for moves further away, but not with the choice-supportive bias. Second, people with an overly positive perception of the crime risk in the new place of residence may be disproportionally represented among movers, similar to the winner's curse in auctions. Our findings are similar when we look at a group of movers that are highly restricted in selecting the location of their new home: renters of social housing. If the 'winner's curse' held, then it should have less of an effect for people who have limited choice of where to live, but that is not what we find.

The contribution of this article is threefold. First, we add to the literature on crime causation. We provide evidence for serious imperfections in the way potential victims perceive the crime risk. Adjustment of risk perceptions to changes in the crime rate is found to be anything but instantaneous, with a bias towards being too optimistic. Judgment of the crime risk can be off for many years – and substantially so. The traditional crime model with well-informed agents ignores this element in decision making. This judgment bias may well have consequences for precautions that people take, which in turn may result in a higher overall level of crime in society.

Second, we provide empirical evidence for why intervention in crime prevention could have a large pay off – beyond the traditional externality argument. People may not make the right preventive decisions at least temporarily simply because they do not have the necessary information. The time that it takes to gather better information may lead to large, avoidable losses. If government intervention is able to affect the level of crime prevention, then this may help people to prevent these losses. Our paper suggests a particular channel for intervening in victim behavior: feeding the stock of local experiences with crime.[3] Follow-up research should show what interventions can be designed and how effective they are in altering victim behavior.

Third, we contribute to the literature on risky choice. We present rare empirical evidence on risky choice in a natural setting. Most of the literature in this area is based on laboratory experiments. As has been argued in Hertwig et al. (2004), the usual framing of these experiments may not be representative of many situations in real life. In the laboratory, subjects tend to be provided with a description of risk, whereas this is often missing in practice. When people need to learn from experience, they often show the exact opposite behavior from what they do in laboratory experiments. Moreover, we study the behavior of a representative sample of the population rather than college students, the usual subject pool for a laboratory experiment, which enhances the external validity of our findings. Our paper is related to work in natural hazard mitigation, particularly in how people deal with flood risk (Gallagher 2013). Within this context, preventive behavior is also found to be in line with the availability heuristic. We add to this strand of the literature by studying how people play against another human being rather than nature. People have been shown to deal with risk differently when the threat is posed

[3] Another avenue for victim-oriented crime prevention policy is to mandate built-in security in products, which Vollaard and Van Ours (2011) and Van Ours and Vollaard (2013) show to have a large crime-reducing effect when applied to homes and cars.

by a stranger with bad intentions (Slovic et al. 1987). The crime setting is also different from the natural hazard context because of the great variation in risk across individuals and the multitude of preventive behaviors that people can choose from, including daily routines.

The remainder of the paper is structured as follows. The next section describes the data. Section 3 presents a model of learning about risk. Section 4 discusses the identification strategy. In Section 5, we present the estimation results. Section 6 concludes.

2. Data

Source of data on perception of the crime risk is the Netherlands Crime Survey (IVM). The IVM is an annual survey among some 200,000 randomly selected respondents in odd years and about 50,000 respondents in even years. Respondents are 15 years of age or older. The interviews are conducted from September 15 to December 31. Respondents are invited to participate in a letter. They can choose to complete the survey online or on paper. In case of no response, the respondents are asked to complete the survey in a telephone interview or, if that does not work out, in a face-to-face interview. Overall, the response rate is about 40 percent. The survey is based on a repeated cross section design. Relative to size of population (16 million), the IVM is one of the largest, if not the largest, crime survey in the world. The large sample size is the result of a particular structure of the survey. The default sample at the national level consists of some 20,000 respondents; municipalities have the option to pay for a larger sample within their area. The larger sample allows them to break down crime data to the local level or even the neighborhood level. In even years, some 5 to 10 percent of municipalities exercise this option, in odd years 50 to 60 percent. We pool the four waves of the survey for the years 2008, 2009, 2010, 2011, providing us with a sample of 550,444 respondents. Earlier waves of the national crime survey cannot be used because of comprehensive changes in sampling design and in the questionnaire in 2008. The survey was changed again after 2011, making later waves incomparable as well.

Constructing the history of places of residence of the respondents is facilitated by the fact that the sampling frame of the survey is the population register (Gemeentelijke Basisregistratie, GBA). In the population register, which is administered by the municipalities, demographic details for each and every individual citizen are recorded, including the history of places of residence, going back to 1995. We merge these records from the population register back on the survey data. We restrict the sample of movers to respondents who moved at least once during the last 10 years. The oldest cohort moved in 1998; the youngest cohort in 2011. Clearly, the worldwide economic crisis that started in 2008 did not leave movers unaffected. In the Netherlands, the effects were felt as of 2009. In the years 2000-2008 about 10 percent of the population moved house every year, this went down to about 9 percent in the years 2009-2011 (ABF Research 2013: 50). The number of moves declined under home owners in particular.

Part of the survey relates to 'neighborhood problems'. Respondents are asked about their perception of the prevalence of crimes in the neighborhood they live in. The exact question is: Can you indicate whether in your view [crime type] occurs frequently, occasionally or almost never in your neighborhood? We select the following crime types: bicycle theft, burglary, theft from car, street robbery and violent crimes.[4] In the questionnaire, no further definitions of these crime types are provided. It is up to the respondent to decide what falls under the heading of violent crimes, for instance. For our main specification, the outcome variable is a binary indicator which is one if a respondent answers 'almost never' and zero otherwise. In the sensitivity analysis, we show that using all three answer categories (using ordered logit) produces qualitatively similar results. In the empirical analysis, we distinguish four types of moves, dependent on the crime rate in the previous and new place of residence. The crime rate in the neighborhood can either be below or above the national average, with crime defined as overall victimization of property and violent crime.

In line with the survey questions about perception of the crime risk, the analysis is conducted at the level of the neighborhood. We use the definition of neighborhoods provided by Netherlands Statistics. In 2011, the Netherlands had 2,572 neighborhoods. The average number of population of a neighborhood was 6,475. A small municipality like Ten Boer (population of 7,400) had two neighborhoods; a provincial capital like Groningen (population of 200,000) 10 neighborhoods; a large city in the densely populated western part of the country like The Hague (population of 500,000) 44 neighborhoods. We do not know whether the formal definition of a neighborhood corresponds to the term used by the survey respondents. Colloquial use of the term neighborhood may relate to an even lower level of aggregation. The data do not allow us to conduct the analysis at a level lower than the neighborhood. Our results are only biased, however, when the crime trend during 2008-2011 differed between cohorts of people who

[4] We exclude crime types that do not occur at a clear frequency, including graffiti, littering, and dog fouling.

moved to the same (formally defined) neighborhood or between movers and the incumbent residents of the (formally defined) neighborhood. In the sensitivity analysis, we show our results to be robust to defining the crime trend at the level of the neighborhood, the municipality and the nation, suggesting that any possible bias from a mismatch between the respondents' concept of a neighborhood and the formal definition of a neighborhood is negligible.

Table 1 presents the summary statistics. The first two columns relate to the subsample of people who moved at least once in the last 10 years, the next two columns to the full sample of respondents. Movers are on average more likely to be younger, higher educated, to have paid work and live in an apartment. The differences are generally small, however, indicating that moving house is relatively common across the population. The last move of those who moved at least once in the last 10 years is on average about five years (58 months) ago. Some 40 to 50 percent of respondents believe that burglary, bicycle theft and theft from car occur rarely in their neighborhood, for street robbery and violent crimes about 80 to 90 percent hold this belief. At a general level, these statistics reflect that victimization of property crimes is much more prevalent than victimization of violent crimes (13 percent versus 5.5 percent). If we compare the perceived risk of different property crimes, however, then the subjective statements are not in line with objective victimization rates. For instance, victimization of bicycle theft is more prevalent than victimization of burglary (6 percent versus 2 percent), but the percentage of respondents who think that bicycle theft in the neighborhood is rare is higher than the percentage who think that burglary in the neighborhood is rare. This suggests that the perceived risk may also reflect the seriousness of the crime, with a serious crime like burglary resulting in greater perceived risk than a not-so-serious crime like bicycle theft. Slovic et al. (1987: 20) find a similar bias for causes of death, with the risk from dramatic and sensational causes being overestimated and the risk from unspectacular and common causes being underestimated.

[TABLE 1]

3. A model of learning about crime risk

Individuals learn about the risk of crime in their neighborhood in many ways, including own experiences, observation of criminal events, and description of experiences by others, including coverage in local news media and stories from friends and neighbors. Individuals do not necessarily know the true level of crime in their neighborhood, and learning about the risk of crime in a new environment is a gradual process. Over time, individuals will adjust their perceptions of crime risk as they obtain new information.

At the time of move to a different neighborhood, individuals form a prior distribution about the crime risk in the new place of residence. We assume that this prior distribution is a normal distribution with mean μ_p and variance σ_p^2. Later in this section we will discuss alternative theories how individuals form priors about the risk of crime in a new environment. At this point it suffices to state that the mean of the prior distribution is not necessarily equal to the true level of crime risk in the neighborhood which we define as θ.

After moving to a new municipality, individuals gradually obtain new information about the level of crime risk in the new environment. We assume that in every period $t = 1...T$ after the move, individuals receive a signal about the level of crime risk. For example, an individual will receive a high signal for a period in which she is victimized. We denote this signal as X_t, and we assume that it is normally distributed with mean μ_t and variance σ_0^2. If $\mu_t = \theta$ then the mean of the signals reflects the true level of crime risk. We assume that individuals know the variance of the signal, but they do not know the mean of the distribution. We further assume that signals are independently distributed across periods.

Individuals update their prior beliefs about the risk of crime based on the signals they have received to date. At the end of period t, individuals have received signals $X_1,...,X_t$. We denote the average value of these signals as $\overline{x}_t$. Posterior beliefs about θ at the end of period t are normally distributed with probability density function $f_t(\theta)$. The mean value μ_t of the posterior distribution is given by the formula below[5]:

$$\mu_t = \frac{t\sigma_0^2}{t\sigma_0^2 + \sigma_p^2}\overline{x}_t + \frac{\sigma_p^2}{t\sigma_0^2 + \sigma_p^2}\mu_p$$

[5] For a derivation see e.g. Wonnacott and Wonnacott (1985), p.599, theorem 19-23

This formula implies that as time since move progresses beliefs about crime risks depends more on the average value of the signals $\overline{x}_t$, and less on the mean of the prior distribution μ_p. For the case $\mu_p < \mu_t$ individuals' beliefs about crime risk are likely to increase with time since move. For the case $\mu_p > \mu_t$ individuals' beliefs about crime risk are likely to decrease with time since move.

So far, we have not discussed how the means of the prior distribution μ_p and the means of the signals μ_t are formed. In our study, we consider the following three theories how individuals form risk perceptions in a new environment:

1) Under rational expectations both the mean of the prior distribution μ_p and the mean of the signals μ_t should not systematically deviate from the true level of crime risk θ. On average, perceptions of crime should not change with time since move.
2) Behavioral economists suggest that individuals often base difficult decisions on judgmental heuristics which can lead to biases in risk perception. For example, the availability heuristic suggests that individuals judge an event to be likely or frequent if instances of the event are easy to imagine or recall (Slovic et al. 1987). Immediately after a move individuals might find it difficult to recall or imagine instances of crime in the new environment. With increasing time since move individuals will be exposed to more instances of crime in the neighborhood and to more crime-related stories about the neighborhood. These experiences can affect risk perception. Based on the availability heuristic we expect that the perceived prevalence of crime events will go up with time since move. A similar pattern could hold if individuals tend to select the neighborhood that they move to based on over-optimistic beliefs about crime risk (winner's curse), or if they justify a recent important decision they took with respect to moving to a new neighborhood with an over-optimistic view of the new neighborhood. Their way of reasoning could be: "I decided to move here, so the new neighborhood must be great."
3) Alternatively, the anchoring and adjustment heuristic suggests that individuals could form their prior expectations about crime risk in a new environment partly based on the crime risk in their previous place of residence. The anchoring and adjustment heuristic predicts that individuals who move from a municipality with lower crime risk than the new municipality should initially underestimate the crime risk after the move, and later

adjust their risk perception upward. In contrast, individuals who move from a municipality with higher crime risk than the new municipality should initially overestimate the crime risk after the move, and later adjust their risk perception downward.

These alternative theories provide different hypotheses about how risk perceptions evolve with increasing time since move to a new neighborhood. The aim of our study is to empirically test these alternative hypotheses.

4. Empirical specification

In our empirical analysis, we examine whether and how risk perceptions change with time since move to a different neighborhood. Our empirical strategy is based on comparing individuals who have lived in the same neighborhood for different lengths of time. We aim to estimate the effect of length of time spent in a neighborhood on the perception of crime risk in this neighborhood. For this purpose, we estimate regression models of the following type: [6]

$$y_i = time\ here_i \beta + mover_i \gamma + X_i^{'} \lambda + I_c{}' \mu + \alpha_{n,t} + \varepsilon_i \qquad (1)$$

where outcome variables y_i measure perceptions of crime in the neighborhood; i indexes persons; $time\ here_i$ measures time since move to the current neighborhood; $mover_i$ is a binary indicator for persons who have moved to the current neighborhood within the last ten years; X_i is a vector of individual characteristics; I_c is a vector of binary indicators for annual cohorts of movers, e.g. for persons who have moved to the current neighborhood in the year c; $\alpha_{n,t}$ is a vector of interaction terms of neighborhoods and survey years, i.e. for individuals who lived in neighborhood n in survey year t; β and γ are parameters; λ and μ are vectors of parameters; ε_i is an individual specific error term. We cluster the standard errors at the level of the neighborhood.

The main parameter of interest is β which measures a linear trend how perceptions of crime change with time since move to the current neighborhood. Estimation coefficients for β can be interpreted as causal effects if the exogeneity assumption below holds:

[6] Regression equation (1) abstracts from interaction effects that allow the effect of time since move to vary according to alternatively the crime rate in previous and current municipalities, the distance of move or individual characteristics of movers.

$$E[\varepsilon_i \,|\, \textit{time here}_i, \text{mover}_i\, X_i, \text{I}_c, \alpha_{n,t}] = 0 \tag{2}$$

This assumption could be violated if unobserved determinants of risk perception in ε_i are correlated with explanatory variables. In the following paragraphs we discuss whether the exogeneity assumption is plausible within the context of our study. Specifically, we discuss possible violations of this assumption, and how we can address these violations. We focus on three possible violations: 1) differential trends in risk perception between movers and incumbent residents, 2) the effects of selective attrition, and 3) the effect of age.

Let us first note that differences in unobserved characteristics between movers and non-movers cannot violate the exogeneity assumption. Our list of explanatory variables includes a variable for movers, and for estimating the effect of time since move we do not compare movers with non-movers.

A violation of the exogeneity assumption could be caused by different time trends in risk perceptions between movers and incumbents at the neighborhood level. Our estimation problem is akin to a classic problem in the empirical analysis of panel data and repeated cross-section data, namely how to disentangle the effects of age, cohorts and time. In our analysis, time since move takes the role of age, the year of move defines cohorts, and survey years define time. As is well known, age, time and cohort effects cannot be disentangled without further assumptions. In our example, we need to make assumptions either about time trends in risk perception or about cohort effects. Regression equation (1) is based on the assumption that time trends are the same for incumbents and for different cohorts of movers in the same neighborhood. Formally, we assume:

$$\alpha_{n,t,incumbents} = \alpha_{n,t,\text{cohort}\,1998} = \alpha_{n,t,\text{cohort}\,1999} = \ldots = \alpha_{n,t,\text{cohort}\,2011} \tag{3}$$

This assumption is similar to the assumption that for example Borjas (1995) uses in an influential study on immigrant wages where he assumes that underlying trends for immigrant wages are the same as underlying trends for the wages of natives. Our question on risk perception refers to the perceived frequency of crime in the neighborhood. Thus, we assume that changes in crime risk at the neighborhood level do not systematically affect incumbents and different cohorts of movers in different ways.

We consider the assumption in equation (3) to be generally plausible. However, there are specific situations for which this assumption could be violated, e.g. if movers of a specific moving cohort disproportionally moved into a newly built part of the neighborhood that subsequently followed a different time trend in crime. While we cannot control for different time trends at a regional level even smaller than neighborhoods, we can employ two robustness checks for the plausibility of assumption (3).

The first robustness check is to control for time trends in crime risk perception at a regional level higher than the neighborhood level. Instead of controlling for time trends at the neighborhood level, we control for time trends at the municipality level or at the national level only. If estimation results for the effect of time since move do not differ much between these alternative specifications, this suggests that the regional level of time trends might not be so important for influencing our estimation results.

The second robustness check is to replace assumptions about time trends by assumptions about cohort effects. Specifically, we estimate regression equation (1) without cohort effects. Thus, we compare persons who live in the same neighborhood in the same survey year, but who have lived there for different lengths of time. This specification assumes that there are no systematic differences in risk perceptions between persons who have moved in different years. This assumption could be violated if persons who moved for example during the great recession in 2009 are systematically different from persons who moved in 2007 before the great recession. However, if estimation results for specifications with and without cohort fixed-effects are similar this suggests that the respective biases might not be large (or they move in the same direction). Based on estimation equation (1) we can also test if cohort fixed-effects are jointly significant.

A second source of possible violation of the exogeneity assumption (2) is selective attrition. Not all persons who move into a new neighborhood will stay there for the next ten years, and those who move on early might be systematically different from those who stay longer. Thus, time since move could be related to unobserved components of risk perception because of selective attrition. In our study, we can address this problem by restricting the sample of movers to respondents who will not move again before the end of year 2011. Places of residence are obtained from administrative records which are merged with the survey data. By restricting the sample to persons who will not move away during our study period, we make sure that movers in all survey years are drawn from the same population, namely persons who have moved to a specific neighborhood in a specific year (their moving cohort), and who will not move away before the time of the last survey in 2011. If we look at cohorts of persons who have moved earlier than 2008, these cohorts will already be affected by attrition by the time of our first survey in the year 2008. However, the effects of this attrition before the start of the first survey will be captured by the cohort fixed-effects. By restricting the sample of movers in the above-mentioned way we exclude any bias from selective attrition.

A third possible source of violation of the exogeneity assumption is caused by time itself. With increasing time since move, individuals become older. Age can affect risk perceptions. We address this concern by including age and age squared as explanatory variables in the estimation equation as well as other personal characteristics including household size and labor force participation.

5. Estimation results

Graphical evidence

Figure 1 shows estimation results for the effect of time since move on the risk perception of five different crime types. The vertical axes show the percentage of movers who think that a crime is rare in the neighborhood relative to incumbent residents. The horizontal axes show the time since the last move in calendar years. The figures to the left show the estimated coefficients for the individual moving cohorts, i.e. these are estimated without the cohort-fixed effects. The figures to the right show the average trend across the cohorts, i.e. these coefficients are estimated including the cohort-fixed effects. Based on whether the crime risk in the previous and the new place of residence is above or below the national average, we distinguish four types of moves: from low-risk to low-risk; from high-risk to low-risk; from high-risk to high-risk and from low-risk to high-risk.

The outcome variable in Figure 1(a) is a binary indicator for "bicycle theft occurs almost never in this neighborhood". In the left figure, we find close to all cohort curves to be downward sloping. This suggests that the higher the time since move, the less likely people are to perceive prevalence of bicycle theft as rare – relative to the incumbent residents. The adjustment is substantial. In 10 years' time, the percentage of movers who think that bicycle theft is rare relative to the incumbent residents has declined by almost 20 percent.[7] In other words, people perceive the neighborhood prevalence of bicycle theft to be greater, the longer ago they moved. The right figure suggests that the adjustment in risk perception levels off towards the end of the 10-year period, but it is hard to tell for certain. The right figure also shows that the risk adjustment is essentially similar for the four types of moves, i.e. learning about the crime risk

[7] 0.12-0.04 divided by the average of 0.47, see the summary statistics.

is independent from the crime rate in the previous place of residence relative to the new place of residence.

The findings for the perceived prevalence of bicycle theft fit with the availability heuristic discussed in section 3. The longer people live in a place, the more experiences they have gathered about local crime events. If asked about the prevalence of a crime, then they draw upon these experiences. The greater the stock of experiences, the greater the perceived prevalence. Given the exceedingly slow adjustment process, movers are likely to underestimate the crime risk for many years. Clearly, the findings contradict the use of the anchoring-and-adjustment heuristic: we do not find the adjustment to differ depending on the crime risk in the previous place of residence relative to the new place of residence. At the end of this section, we discuss additional evidence that refutes two alternative explanations for our findings: cognitive dissonance and the 'winner's curse'.

Figure 1(b) shows the results for the perceived prevalence of burglary in the neighborhood. The findings are essentially similar to bicycle theft. The adjustment over the 10-year period after the move is somewhat larger: about 25 percent.[8] Again, we find no difference by type of move. The right graph does not provide the suggestion of leveling off as in the case of bicycle theft, i.e. the learning process seems to continue up until 10 years after the move. Again, these findings suggest that the process of gathering experiences in the new place of residence is important for understanding risk perceptions. Figure 1(c) for theft from car provides similar findings. The 10-year rate of adjustment in perceived prevalence of theft from car is very similar to that of bicycle theft, and slightly lower than that for burglary.

Perceived prevalence of street robbery and violence since time of move follows a similar pattern (Figures 1(d) and 1(e)). The 10-year rate of adjustment is much smaller than for the property crimes discussed above, however. It is around 10 percent rather than 20 percent. This either suggests that the judgment bias is relatively small for high-impact personal crimes like robbery and violence or that learning occurs relatively slowly for these crimes.

[FIGURE 1]

[8] (0.16-0.04) / 0.43

Statistical tests for average treatment effects

In Table 2, we test whether the observed change in perceived prevalence of crimes with time of move meets the standards of statistical significance. Time since last move enters as a linear variable. As in Figure 1, we distinguish four types of moves, depending on the crime rate in the current and previous place of residence.

The first two columns of Table 2 present the estimation results for the perceived prevalence of bicycle theft in the neighborhood. Whether including cohort-fixed effects or not, we find a negative effect of time since move on risk perceptions that is highly statistically significant. When dividing an estimated coefficient by 1,000, multiplying it by 12 (months to years) and by 9 (number of years covered in Figure 1), we get a percentage point decrease that is similar in size as in Figure 1 (a). The coefficients for the four types of moves are roughly similar. The results confirm what we found in Figure 1(a). Similarly, we find statistically significant effects of time since move on perception of the risk of burglary, theft from car, robbery and violent crime (Table 2, column 3-10). Again, the effects are similar in size to what we found in Figure 1.

[TABLE 2]

Heterogeneity

In Figure 2, we explore heterogeneity in the effect of time since move on the perceived risk. We allow the effect to differ by age group, educational attainment, gender, moving frequency, and being a home owner or renter. We only report estimates for perceived risk of bicycle theft; the results for the four other crime types are very similar. In all cases, we find a similar change in perceived risk with time since move (we do not interpret the intercept). In other words, the observed pattern is be universal across many dimensions.

[FIGURE 2]

In addition, in Figure 3, we allow the effect to differ by distance of move. We distinguish four types of moves: moves within the same neighborhood, moves to another neighborhood but within the same municipality, moves to another municipality but within the same province, and moves to a different province (the Netherlands had 12 provinces and 418 municipalities in 2011). We find the adjustment in risk perceptions to be substantially lower for moves within the same neighborhood compared to moves to a different neighborhood. These results are in line with the availability heuristic: the stock of experiences built up in the previous place of residence are partly relevant for nearby moves but not for moves further away.

[FIGURE 3]

Alternative explanations

Alternatively, the observed relation between risk perception and time since move could be explained by the presence of a choice-supportive bias and a type of 'winner's curse' for movers. In the first scenario, movers may have too rosy a picture of the new place of residence out of a tendency to justify their choice to move. That does not fit with the difference by distance of move that we discussed above. After all, it is not obvious why one would feel less inclined to justify a move to another neighborhood than a move to another neighborhood. As discussed, this additional evidence fits well with the hypothesis that people use the availability heuristic.

In the second scenario, people who underestimate the crime risk in the new place of residence may be overrepresented among movers. This is similar to the winner's curse in auctions. Again, additional evidence makes this explanation unlikely. Above, we distinguished home owners and renters. We found very similar patterns for both groups. Renters are very different from home owners, however, when it comes to the freedom of choice of the exact location of their new home. The reason is that almost 70 percent of renters live in social housing.[9] When they want to move, they are put on a waiting list with one of the social housing foundations. The waiting lists are often very long; it can take considerable time before one can be placed in a suitable home. Invariably, social renters need to compromise many of their wishes when they want to move within a reasonable time frame, including the preferred neighborhood, let alone the preferred street. If the 'winner's curse' held, then it should have less of an effect for people who have limited choice of where to live, but that is not what we find.

6. Conclusions

We study how potential victims learn about the crime risk, something that has been largely ignored in models of crime. We use a uniquely rich source of individual-level survey data on

[9] In the Netherlands, one out of three homes are in the social rented sector provided by social housing foundations.

perception of the neighborhood crime risk merged with administrative records of respondents' recent history of places of residence. We compare individuals who have lived in the same neighborhood for different periods of time. We provide evidence for serious imperfections in the way potential victims perceive the crime risk. We find that the longer people live in the neighborhood, the higher their perceived prevalence of crime. The adjustment is substantial, and seems to continue even after the 10-year window that we study. We find similar patterns for a range of different types of crime. One explanation for our findings is that most people use the availability heuristic when making a judgment of the crime risk. People seem to base perceptions of the crime risk on the ease in which negative experiences with crime in the new place of residence can be brought to mind. This stock of crime-related experiences increases over time, resulting in a progressively greater perceived risk of crime. That can explain the universal upward adjustment in risk perceptions in the years after a move, whether a move is to a more, less or equally risky location. Given our finding that judgment of the crime risk can be off for many years, people many not make the right preventive decisions simply because they do not have the necessary information. In turn, this may result in a higher level of crime in society than predicted by models of crime with fully informed potential victims.

References

ABF Research, 2013, *Wonen in ongewone tijden. De resultaten van het Woononderzoek Nederland 2012*, report commissioned by the Netherlands Department of the Interior (BZK), Delft.

Acquisti, Alessandro and Catherine Tucker, 2011, Guns, privacy, and crime, *unpublished manuscript*, Carnegie Mellon University/MIT Sloan School of Business.

Amodio, Francesco, 2013, Crime Protection Investment Spillovers: Theory and Evidence from the City of Buenos Aires, unpublished manuscript, Universitat Pompeu Fabra, Barcelona.

Ayres, Ian and Steven D. Levitt, 1998, Measuring positive externalities from unobservable victim precaution: an empirical analysis of Lojack, *Quarterly Journal of Economics*, 113 (1), 43-77.

Borjas, George (1995), Assimilation and changes in cohort quality revisited: what happened to immigrant earnings in the 1980s?, *Journal of Labor Economics*, 13 (2), 201-245.

Clotfelter, Charles T., 1977, Public Services, Private Substitutes, and the Demand for Protection against Crime, *American Economic Review*, 67 (5), 867-77.

Cook, Philip J., 1986, The demand and supply of criminal opportunities, *Crime and Justice*, 7, 1-27.

Cook, Philip J. and Jens Ludwig, 2006, The social cost of gun ownership, *Journal of Public Economics*, 90 (1), 379-391.

Cook, Philip J. and John MacDonald, 2011, Public safety through private action: an economic assessment of bids, *The Economic Journal*, 121, 445-62.

Cohen, Lawrence E. and Marcus Felson, 1979, Social change and crime trends: a routine activity approach, *American Sociological Review*, 44, 588-608.

Dijk, Jan J.M. van and Ben A. Vollaard, 2012, Self-limiting crime waves, in: Jan J.M. van Dijk, Andromachi Tseloni, Graham Farrell (eds.), *The International Crime Drop: New Directions in Research*, Palgrave MacMillan, New York, 250-267.

Di Tella, Rafael, Sebastian Galiani, and Ernesto Schargrodsky, 2010, Crime Inequality and Victim Behavior during a Crime Wave, in: Rafael Di Tella, Sebastian Edwards and Ernesto Schargrodsky (eds.), *The Economics of Crime: Lessons for and from Latin America*, University of Chicago Press, 175-206.

Ehrlich, Isaac, 1981, On the usefulness of controlling individuals: an economic analysis of rehabilitation, incapacitation and deterrence, *American Economic Review*, 71 (3), 307-322.

Felson, Marcus and Erika Poulsen, 2003, Simple indicators of crime by time of day, *International Journal of Forecasting*, 19, 595-601.

Gallagher, J., 2013, Learning about an infrequent event: evidence from flood insurance take-up in the US, *American Economic Journal: Applied Economics*, forthcoming.

Gigerenzer, G. and W. Gaissmaier, 2011, Heuristic decision making, *Annual Review of Psychology*, 62, 451-482.

Gonzalez-Navarro, M., 2013, Deterrence and geographical externalities in auto theft, *American Economic Journal: Applied Economics*, in press

Helsley, R.W. and W.C. Strange, 1999, Gated communities and the economic geography of crime, *Journal of Urban Economics*, 46 (1), 80-105.

Helsley, R.W. and W.C. Strange, 2005, Mixed markets and crime, *Journal of Public Economics*, 89, 1251-75.

Hertwig, R., G. Barron, E. Weber, I. Erev, 2004, Decisions From Experience and the Effect of Rare Events in Risky Choice, *Psychological Science*, 15(8), 534-539.

Hui-Wen, K. and I.P.L Png, 1994, Private security: deterrent or diversion?, *International Review of Law and Economics*, 14 (1), 87-101.

Jackson, J., 2011, Revisiting risk sensitivity in the fear of crime, *Journal of Research in Crime and Deliquency*, 48 (4), 513-537.

Jackson, J. and E. Gray, 2010, Functional fear and public insecurities about crime, *British Journal of Criminology*, 50, 1-22.

Meyer, R.J., 2012, Failing to learn from experience about catastrophes: the case of hurricane preparedness, *Journal of Risk and Uncertainty*, 45, 25-50.

Lochner, L., 2007, Individual Perceptions of the Criminal Justice System, *American Economic Review*, 97 (1), 444-460.

Ours, J.C. van, and B.A. Vollaard, 2012, The engine immobilizer: a non-starter for car thieves, working paper, Tilburg University.

Shavell, S., 1991, Individual precautions to prevent theft: private versus socially optimal behavior, *International Review of Law and Economics*, 11, 123-132.

Simonsohn, Uri and George Loewenstein, 2006, Mistake #37: the effect of previously encountered prices on current housing demand, *The Economic Journal*, 116, 175-199.

Skogan, W.G. and M.G. Maxfield, 1981, *Coping with crime. Individual and neighborhood reactions*, Sage, London.

Slovic, Paul, 1987, Perception of Risk, *Science*, 236(4799), 280-285.

Slovic, P., B. Fischhoff, and S. Lichtenstein, 1987, Behavioral decision theory perspectives on protective behavior, chapter 1 in: N.D. Weinstein (ed.), *Taking care. Understanding and encouraging self-protective behavior*, Cambridge University Press, Cambridge, 14-41.

Truman, J.L., and M. Planty, 2012, *Criminal victimization 2011*, NCJ 239437, Bureau of Justice Statistics, US Department of Justice, Washington D.C.

Tversky, A., and D. Kahneman, 1973, Availability: a heuristic for judging frequency and probability, *Cognitive Psychology*, 5, 207-232.

Tversky, A., and D. Kahneman, 1974, Judgment under uncertainty: heuristics and biases, *Science*, 185, 1124–1130.

Vollaard, Ben A. and Pierre Koning, 2009, The effect of police on crime, disorder and victim precaution. Evidence from a Dutch victimization survey, *International Review of Law and Economics*, 29 (4), 336-348.

Vollaard, Ben A. and Jan C. van Ours, 2011, Does regulation of built-in security reduce crime? Evidence from a natural experiment, *The Economic Journal*, 121, 485-504.

Weisburd, D., E.R. Groff, and S. Yang, 2012, *The criminology of place*, Oxford University Press, New York.

Wonnacott, Ronald, and Thomas Wonnacott, 1985, *Introductory Statistics*, 4th edition, Wiley & Sons, New York.

Table 1. Summary statistics

	Sample of movers		Full sample	
	Mean	Standard Dev.	Mean	Standard Dev.
Victimization last 12 months				
Any crime	0.367	0.482	0.304	0.460
Risk perception				
“Bicycle theft is rare in neighborhood”	0.472	0.499	0.481	0.500
“Burglary is rare in neighborhood”	0.431	0.495	0.393	0.488
“Theft from car is rare in neighborhood”	0.544	0.498	0.542	0.498
“Robbery is rare in neighborhood”	0.873	0.333	0.885	0.318
“Violent crime is rare in neighborhood”	0.762	0.426	0.796	0.403
Personal characteristics				
Months since move	58.197	35.613		
Moved at least twice in last 10 years	0.467	0.499		
Age	42.336	15.154	48.881	17.172
Female	0.521	0.500	0.529	0.499
Household size	2.651	1.256	2.712	1.240
Secondary education	0.362	0.481	0.370	0.483
Tertiary education	0.411	0.492	0.303	0.460
Education information missing	0.015	0.123	0.016	0.124
Paid work for more than 12 hours per week	0.676	0.468	0.553	0.497
Homeowner	0.688	0.463	0.704	0.457
Residence in detached house	0.139	0.346	0.186	0.389
Residence in townhouse	0.497	0.500	0.548	0.498
Residence in apartment	0.358	0.479	0.258	0.438

Table 1. Summary statistics (continued)

	Sample of movers		Full sample	
	Mean	Standard Dev.	Mean	Standard Dev.
Type of move by crime risk				
From safe to safe neighborhood	0.261	0.439	0.071	0.258
From risky to safe neighborhood	0.193	0.395	0.053	0.224
From safe to risky neighborhood	0.170	0.376	0.047	0.211
From risky to risky neighborhood	0.376	0.484	0.103	0.304
Type of move by distance				
Within same neighborhood			0.184	0.388
To different neighborhood in same municipality	0.484	0.500	0.133	0.339
To different municipality in same province	0.339	0.473	0.096	0.295
To different province	0.177	0.382	0.049	0.215
Number of observations	116,699		425,593	

Notes. Based on pooled cross section survey data for years 2008-2011, merged with registration records for places of residence since 1995. The sample of movers is restricted to respondents who have moved at least once in the last ten years. The sample size varies for different outcome variables. Sample statistics are for baseline estimation in Column (1) of Table 2.

Table 2. Effect of time since move on risk perception, by level of crime in current and previous place of residence

	"Bicycle theft is rare in neighborhood"		**"Burglary is rare in neighborhood"**		**"Theft from car is rare in neighborhood"**	
	Without cohort FE	With cohort FE	Without cohort FE	With cohort FE	Without cohort FE	With cohort FE
Months since move × move from **safe to safe** neighborhood	-0.4176*** (0.0933)	-0.7311*** (0.1754)	-0.7956*** (0.0889)	-1.3738*** (0.1692)	-0.8522*** (0.0861)	-1.2206*** (0.1688)
Months since move × move from **risky to safe** neighborhood	-0.4936*** (0.1031)	-0.8083*** (0.1772)	-0.8123*** (0.0949)	-1.3921*** (0.1713)	-0.8631*** (0.1132)	-1.2311*** (0.1937)
Months since move × move from **safe to risky** neighborhood	-0.3799*** (0.0975)	-0.7072*** (0.1747)	-0.6996*** (0.1180)	-1.2714*** (0.1823)	-0.7778*** (0.1140)	-1.1439*** (0.1890)
Months since move × move from **risky to risky** neighborhood	-0.3779*** (0.0705)	-0.7077*** (0.1572)	-0.5693*** (0.0831)	-1.1449*** (0.1583)	-0.6280*** (0.0749)	-0.9980*** (0.1596)
Number of observations	425,593	425,593	447,487	447,487	428,190	428,190
R-Squared	0.022	0.022	0.043	0.043	0.023	0.023

Table 2. Effect of time since move on risk perception, by level of crime in current and previous place of residence (continued)

	"Robbery is rare in neighborhood"		**"Violent crime is rare in neighborhood"**	
	Without cohort FE	With cohort FE	Without cohort FE	With cohort FE
Months since move × move from **safe to safe** neighborhood	-0.0934** (0.0470)	-0.3561*** (0.1153)	-0.3803*** (0.0644)	-1.0049*** (0.1514)
Months since move × move from **risky to safe** neighborhood	-0.0931 (0.0665)	-0.3571*** (0.1309)	-0.3399*** (0.0912)	-0.9647*** (0.1692)
Months since move × move from **safe to risky** neighborhood	-0.3752*** (0.0847)	-0.6249*** (0.1247)	-0.5114*** (0.1055)	-1.1116*** (0.1722)
Months since move × move from **risky to risky** neighborhood	-0.3617*** (0.0728)	-0.6142*** (0.1204)	-0.4590*** (0.0781)	-1.0643*** (0.1470)
Number of observations	404,696	404,696	410,675	410,675
R-Squared	0.021	0.021	0.022	0.022

Notes. Based on pooled cross section survey data for years 2008-2011, merged with registration records for places of residence since 1995. Results show coefficients for linear regression as in Equation (1). Coefficients are multiplied with a factor of 1,000. A municipality is denoted as safe if the property crime rate is below average. A municipality is denoted as risky if the property crime rate is above average. Coefficients for age, age squared, female, household size, education, labor force participation, home ownership, two or more moves during last 10 years, type of residence, for moves from a risky to a safe municipality, for moves from a safe to a risky municipality, for moves from a risky to a risky municipality, survey mode, cohort fixed effects, and fixed effects for neighborhood and year interactions are not shown. Robust standard errors (clustered at neighborhood level) between parentheses. Statistical significance at *** 1% ** 5% * 10% level. The sample of movers is restricted to respondents who do not move between the time of the survey and Dec 31, 2011.

Figure 1 (a) Perception that “bicycle theft in neighborhood is rare” since move

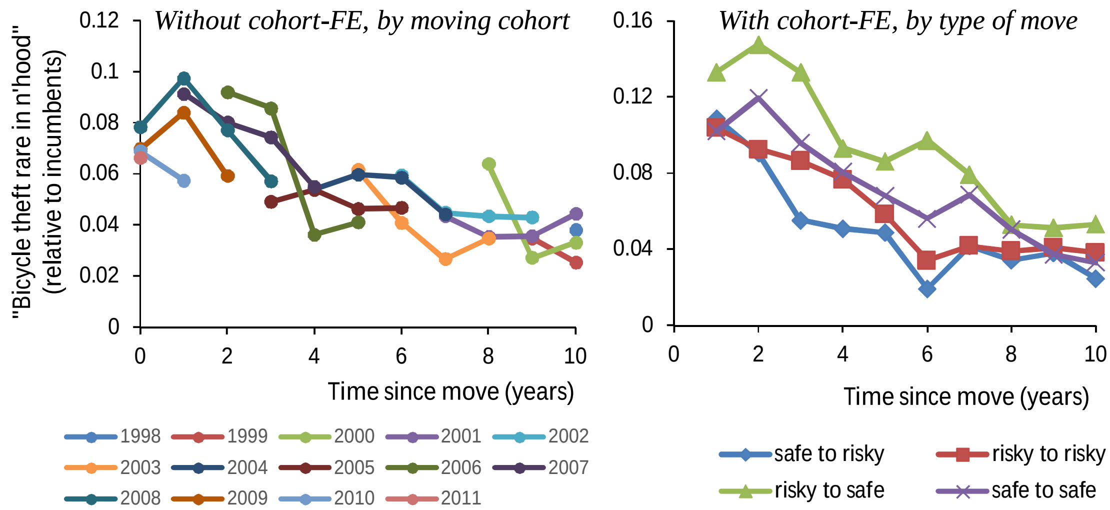


Figure 1 (b) Perception that “burglary in neighborhood is rare” since move

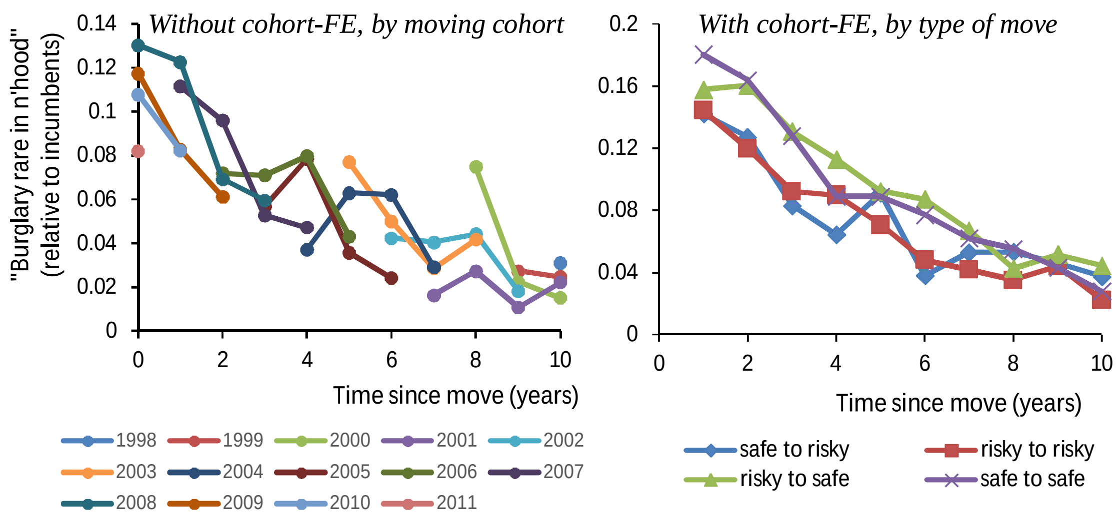


Figure 1 (c)Perception that “theft from car in neighborhood is rare” since move

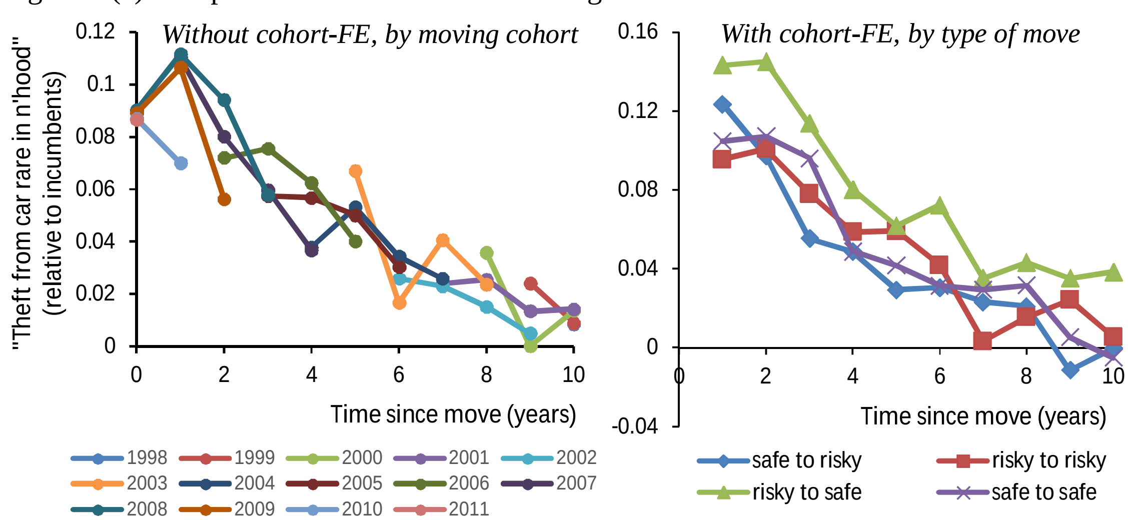


Figure 1 (d) Perception that “street robbery in neighborhood is rare” since move

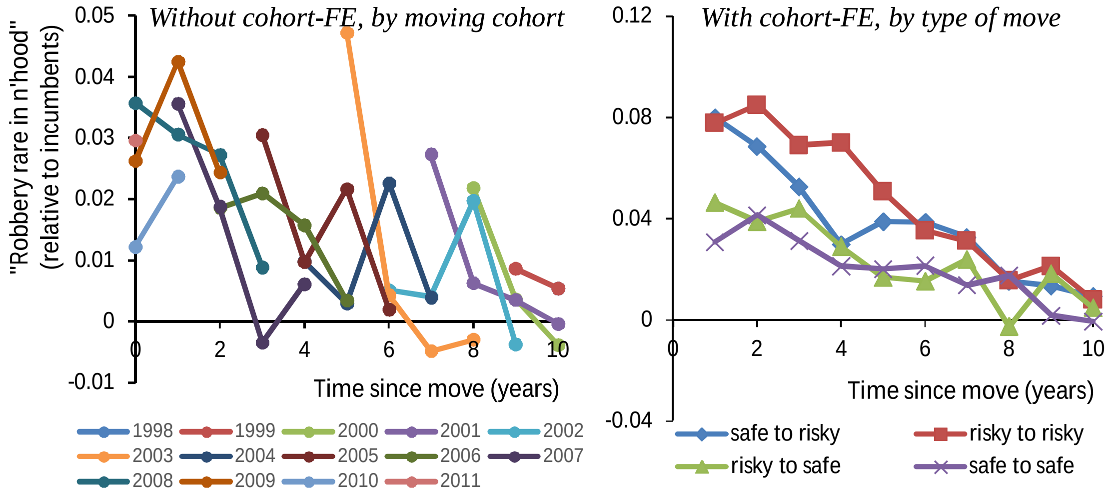
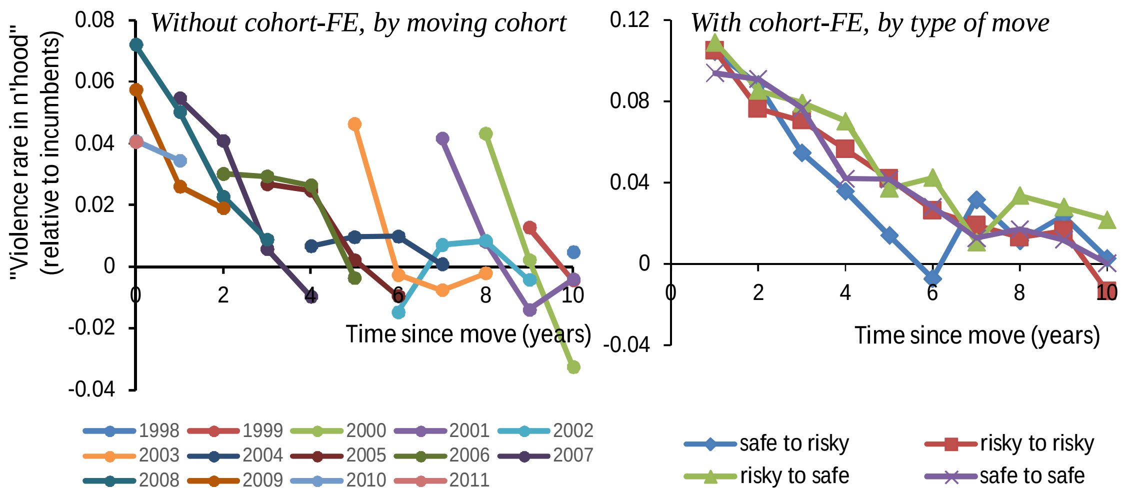


Figure 1 (e)Perception that “violence in neighborhood is rare” since move



Note. The figures plot coefficients from Equation (1). Based on survey data for calendar years 2008-2011. Safe neighborhoods have a rate of victimization of crime below the national average; risky neighborhoods have a rate of victimization of crime above the national average. Number of observations: x (1a, left); y (1a, right); z (1b, left); a (1b, right); b (1c, left); c (1c, right).

Figure 2 (a) Perception of crime risk since move, by age at time of move

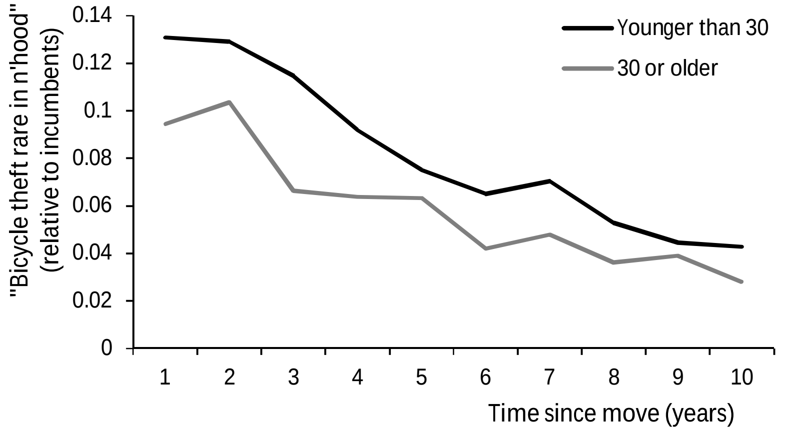


Figure 2 (b) Perception of crime risk since move, by educational attainment

Figure 2 (c) Perception of crime risk since move, by gender

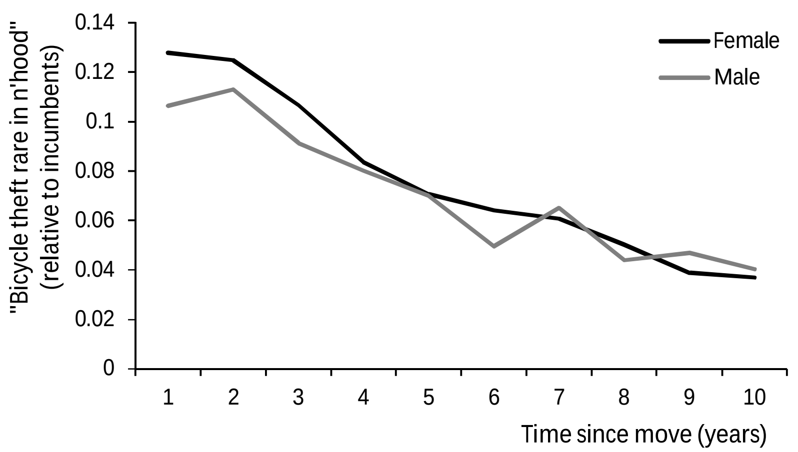


Figure 2 (d) Perception of crime risk since move, by number of moves in last 10 years

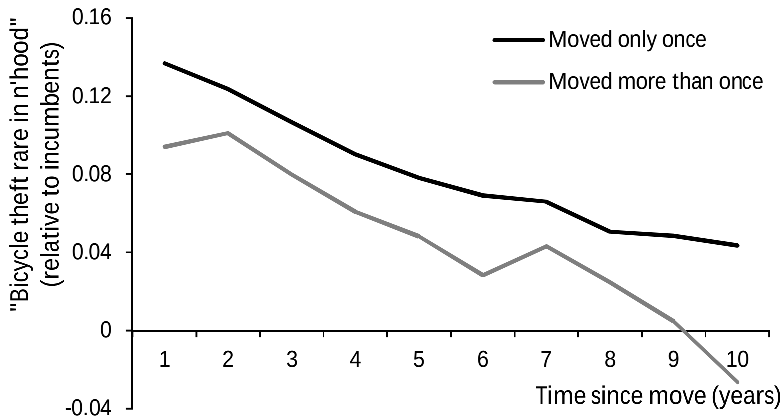


Figure 2 (e) Perception of crime risk since move, by home owner/renter

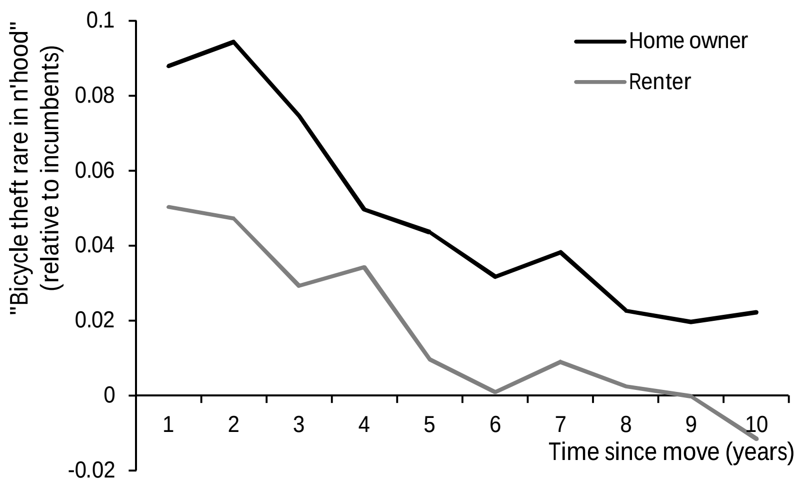


Figure 3 Perception of crime risk since move, by distance of move and crime type