Perceptions follow experience: Assessment of local crime risk

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Abstract

Life experiences can have a major impact on risk taking. We study how experiences affect perceptions of the prevalence of crime in the neighborhood as well as precautionary behaviors such as avoiding unsafe places in the neighborhood. We use time of exposure, defined as time since moving into the neighborhood, as a proxy for personal experience with crime in the neighborhood. We follow cohorts of movers for up to ten years after a move to another neighborhood. Our analysis is based on four successive waves of a large crime survey matched with household-level data for the complete history of moves between 1995 and 2011 for the population of the Netherlands. Even though they are all asked to judge the same crime rate, we find that recent movers perceive crime in the neighborhood to be less prevalent than comparable incumbent residents. In the years after the move, new residents adjust their risk perceptions upwards – even though the actual neighborhood crime risk is held constant. The adjustment is large and continues for many years. We find residents to also increase their precautionary behaviors in line with their evolving beliefs. The observed adjustment can at least in part be explained by the accumulation of victimization experiences in the years after a move.

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1. Introduction

Personal experience of adverse events is an important determinant of risk taking. Within a range of different contexts, including investment behavior, consumption behavior, and demand for insurance, risk taking has been shown to respond more strongly to actual experience of the event, and less strongly to information obtained without personal involvement.[1] One possible explanation for these findings focuses on risk perceptions. Personal experience is found to greatly affect risk perceptions, even when a new experience provides very little new statistical information given the history of past events. Apparently, the sensory impressions that come with living through an adverse event have a distinct effect on beliefs that is absent when learning in other ways (Malmendier 2016). Typically, individual risk perceptions are found to be adjusted sharply upwards in response to negative experiences, even when the objective risk remains unchanged, and to be adjusted downwards slowly in the absence of negative experiences.

In this paper, we build upon these previous findings by studying how time of exposure affects perceptions of local crime risk. Crime is a risk to which everybody is exposed, but potential victims' beliefs about crime risk have been subject to surprisingly little study.[2] We focus on perceptions of the prevalence of crime in someone's own neighborhood.[3] Each neighborhood resident has a judgment of the population base rate of crime, but judgments may vary with their

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[1] Homeowners are more likely to buy flood insurance after they have experienced a flood in their area (Kunreuther 1995, Gallagher 2014). This applies even when the actual risk of flooding remains unchanged and accurate descriptions of the risk are readily available. Likewise, individuals are more likely to take precautions against hurricanes in response to recent experiences with hurricanes (Meyer 2012); investors are less likely to own stocks if they have experienced periods of poor stock market returns such as the great depression (Malmendier and Nagel 2011); young fund managers are more likely to shift their investments towards stocks that presently show high returns than old fund managers (Greenwood and Nagel 2009); consumers become penny-pinching individuals once they have lived through times with great unemployment (Malmendier 2016); portfolio managers take less risks if they have personally experienced adverse investment outcomes (Chernenko et al. 2016); and individuals are more likely to buy long-term care insurance when their parents or in-laws become institutionalized in a nursing home, i.e. when they gain experience with long term care (Coe et al. 2015).

[2] Existing work in this area tends to focus on how victims interact with offenders given a set of correct beliefs, not how victims form their beliefs. That holds for Ehrlich's (1981) canonical model of victim-offender interaction, but also for related theoretical work by Mayhew et al. (1976), Clotfelter (1977, 1978), Cook (1986), Hui-Wen and Png (1994), Van Dijk (1994), Helsley and Strange (1999, 2005), Allen (2013) and Vasquez (2018). Empirical work into how people form beliefs about crime risk is rare, but see Jackson and Gray (2010). For a review of the literature on fear of crime, the negative emotional response to assessment of crime risk, see Henson and Reyns (2015).

[3] Our focus on perceptions of neighborhood crime risk rather than personal crime risk allows us to ignore the relationship between perceived risk and (often unobserved) precautionary measures. Perceptions of personal crime risk may affect an individual's level of precaution, which in turn may affect personal risk. Neighborhood crime risk is not affected by an individual's precautionary behavior.

experience with crime in the neighborhood. In our analysis, we use time of exposure, defined as time since moving into the neighborhood, as a proxy for personal experience with crime in the neighborhood. Moving into the neighborhood marks a distinct point in time at which time of exposure is zero. At that moment, residents' initial perceptions are not yet informed by personal experience. They have to rely on descriptions of local crime risk such as media reports, conversations with neighborhood residents, and publicly available crime statistics. Personal experience with crime in the neighborhood only starts to accumulate after the move. Thus, time of exposure can be seen as a proxy for a greater availability of experience for assessments of local crime risk. In addition to looking at risk perceptions, we also examine how time of exposure affects avoidance behaviors such as avoiding unsafe places in the neighborhood or not allowing children to go to some places in the neighborhood because of crime concerns.

Our empirical approach is based on following cohorts of movers. We examine how their perceptions of neighborhood crime risk and avoidance behaviors change with increasing time since the move date. In our analysis, we control for cohort fixed-effects for annual cohorts of movers and for underlying time trends at the neighborhood level based on the assumption that time trends are the same for incumbent residents and different cohorts of movers. Our empirical strategy is similar to Borjas (1995), who examines how immigrant wages evolve with time since immigration.

In addition to this source of indirect evidence on the importance of personal experience with crime for perceptions of crime risk, we also directly study how victimization of crime in the neighborhood affects perceptions. We estimate the effect of victimization on perceptions, and use these results to simulate the process of upward and downward adjustments in perceptions that occurs once people have moved into the neighborhood. We then compare our simulations to the observed temporal patterns in perceptions.[4]

An empirical analysis of risk perceptions that allows for learning by way of experiencing a fairly rare event like crime requires a very large sample size. We match extensive household-level administrative data for the complete population of the Netherlands ('Gemeentelijke

[4] Whether average perceptions of the population base rate are positively or negatively related to time of exposure is not a trivial question. It depends on how the discounting of past information compares to upward shocks in beliefs when misfortune strikes. For instance, Greenwood and Nagel (2009) find that fund managers with longer tenure behave as if their risk perceptions are higher than those of rookie fund managers. In contrast, if individuals do not experience the bad event for a long time, then greater weight is given to that realization, resulting in a downward adjustment in beliefs (Yechiam, Barron, and Erev 2003, Hertwig et al. 2004).

Basisadministratie') with survey data on crime. The administrative records provide the history of all places of residence of every individual for the period between 1995 and 2011. We match the administrative data with four waves of the Netherlands Crime Survey (IVM), a cross-sectional survey that is repeated annually. The IVM is one of the largest crime surveys in the world relative to size of population, providing us with a sample of about half a million respondents, one out of 25 of the Dutch population aged 15 or over. We show that the elicited beliefs about crime in the neighborhood have face validity: the perceived prevalence of a crime is strongly related to its actual rate of occurrence.

We find that recent movers perceive crime in the neighborhood to be less prevalent than comparable residents who have lived in the neighborhood for many years. This result does not depend on whether the move is from a relatively low-crime to a relatively high-crime area or vice versa. Hence, after the initial judgment of the frequency of crime incidents locally, which is of course higher for a neighborhood in a large city than for a neighborhood in a rural town, average perceptions are always lower shortly after the move than they are longer after the move – at least for the ten-year time window that we look at. The corollary of this result is that adjustment of perceptions after moving to a new neighborhood is a slow process. This positive relation between time of exposure and average perceptions holds across a range of different types of crime.

Taken over the ten-year period, changes in risk perceptions are large and statistically significant. For example, the observed adjustment in the perception that burglary is rare in the neighborhood over ten years is 14 percentage points, relative to a baseline of 43 percent. This is equivalent to 1.0 standard deviation of the distribution of the average perceived burglary risk across municipalities. In addition, our assertion that the survey questions reveal the beliefs that respondents truly hold is validated by the finding that changes in elicited beliefs with time since the move date are in line with changes in precautionary behavior. In other words, we not only find particular patterns in the beliefs that people report in the survey, but also that people act on those beliefs.

We interpret these results as saying that personal experience with crime conditions is a major determinant of perceptions of crime risk and risk taking behavior. Potential victims tend to learn the hard way, and this process is exceedingly slow. This interpretation of our findings is validated by the direct evidence from our additional analysis of how victimization affects perceptions. For this analysis, we exploit the subset of survey respondents who were approached more than once in the survey years 2008-2011. The longitudinal nature of this subsample allows us to difference out all fixed personal characteristics, including those that affect the risk of being victimized by crime. We find that perceptions of the prevalence of crime in the neighborhood are sharply adjusted upwards upon victimization and slowly adjusted downwards in the absence of victimization. Based on simulations, we demonstrate how the fairly rare incidence of crime victimization generates patterns in average perceived prevalence of crime of a cohort of movers that are similar to those observed in the data.

We contribute to the study of how personal experience affects beliefs and risk-taking behavior by taking the empirical study of this topic to a new area: perceptions of crime. We do this in a completely natural setting, using extensive household-level data for a large sample. We exploit a setting that allows us to, first, define a distinct point in time at which time of exposure is zero and, second, separate time of exposure from the mere passing of time. We provide detailed evidence for how spending time in a locality results in a steady upwards adjustment in average local risk perceptions of a population. This is a new finding. We show that potential victims' beliefs about the local prevalence of crime are dynamic and at least sometimes incorrect. Risk perceptions are dynamic because they change in response to exposure to local conditions. Risk perceptions are at least sometimes incorrect because they change with increasing time since the move date while the local crime risk is held constant.

Our findings have important policy implications. Victim-focused crime prevention policies such as burglary prevention advice are not uncommon, albeit often limited in scale and scope relative to offender-focused policies (Felson and Clarke 2010), but the *rationale* for such policies is often left implicit. The underlying question is why potential victims cannot fend for themselves. Given the common belief that the public is overly worried about crime, then why should we be concerned that victim precaution is at too *low* a level? One reason is that potential victims tend to learn the hard way, as we show in our paper. Beliefs are updated *in response to* rather than in anticipation of crime (cf. Van Dijk and Vollaard 2012). As such, victimization of crime is not simply the outcome of a calculated risk; it is a costly form of learning about the appropriate way of addressing the threat of crime.[5] Beliefs that do not accurately reflect the actual situation may

[5] This finding also helps to explain why the level of victim precaution is often found to be exceedingly low, with a sizeable share of all burglaries occurring in homes with windows or doors left open, for instance (Budd 1999).

be common in many domains of life, but they may be particularly costly within the context of crime. Think about having to experience a robbery first before taking proper precautions. If government intervention is able to affect the level of victim precaution without merely displacing crime, for instance by mandating burglar-resistant features in residential construction or anti-theft devices in cars (Vollaard and Van Ours 2011, Van Ours and Vollaard 2016), then this helps people to avoid large losses suffered during the time that it takes to gather better information about the crime risk. The evidence presented in this paper provides an alternative argument for government intervention in crime preventive behavior, next to the more commonly discussed externalities emanating from private victim precaution (Shavell 1991).

The remainder of the paper is structured as follows. The next section motivates and discusses the empirical strategy. Section 3 describes the data. In Section 4, we present estimation results on how crime risk perceptions evolve after a change of environment. In Section 5 we present results on how crime risk perceptions are affected by own victimization. Section 6 discusses alternative interpretations of our findings, and Section 7 concludes.

2. Learning about crime risk and empirical specification

Individuals learn about the risk of crime in their neighborhood in many ways. Broadly speaking, these sources of information can be grouped into two main categories: description and experience. Immediately after a move to a new neighborhood, perceptions are primarily based on descriptions of local crime risk, for example information from conversations with real estate agents and new neighbors, media reports, and official statistics. At the time of move, individuals typically have no personal experiences with crime in the new neighborhood. With increasing time since the move date, experiences with crime – personal victimization or observation of criminal events – become a more important source of information. Given previous evidence of how people learn from experience (Gallagher 2014), personal victimization rather than statistical information is likely to have the greatest impact on beliefs. Learning from own experience, however, is a slow process because crime events tend to be rare. For instance, on average a US household experiences burglary once every 50 years (Lauritsen and Rezey 2013) and a Dutch household once every 40 years (IVM 2011).

In a formal framework, we assume that at the time of moving individuals form an initial perception of local crime risk in the new neighborhood that we denote as p_0. In each period after the move individuals receive a signal about local crime risk that we denote as $s_1, s_2, .., s_T$

for periods 1...*T* after the move. Individuals' perception of crime risk in period *T* is determined as a weighted average of initial perceptions and the signals the individuals has received after the move.

$$y_i = w_0 p_0 + w_1 s_1 + w_2 s_2 + .. + w_T s_T \tag{1}$$

where w_0 is the weight given to p_0 and $w_1 ... w_T$ are the weights given to $s_1, s_2, .., s_T$. The weights $w_0 ... w_T$ sum up to one. We assume that p_0 is a random variable with mean μ_p, and $s_1, s_2, .., s_T$ are random variables with mean μ_s. Then, the expected value of an individual's perception of crime risk is given by $E(y_i) = w_0 \mu_p + (1 - w_0)\mu_s$. We further assume that the weight given to initial perceptions w_0 is a strictly decreasing function in time since move *T* with $w_0 = 1$ for $T = 0$ and $w_0 \to 0$ as $T \to \infty$. Thus $E(y_i) = \mu_p$ for $T = 0$ and $E(y_i) \to \mu_s$ as $T \to \infty$. μ_s depends on how the signals during periods when no crime event occurs compare to the signals if a crime event is experienced. In section 5, we present a more restrictive version of the framework above, in which signals about local crime risk depend exclusively on whether or not an individual was recently victimized.

There are reasons to believe that $\mu_p \neq \mu_s$. For instance, information from descriptions of crime may be less salient and emotionally loaded than information based on personal experience, leading to an upward adjustment in beliefs with a growing importance of personal experience (we discuss alternative explanations for why $\mu_p \neq \mu_s$ in Section 6). If the mean value of initial perceptions is lower than the mean value of signals, then we would expect that average perceptions of local crime risk increase during the years after a move.

Our empirical strategy is based on following cohorts of movers, and we examine how their perception of crime risk changes over successive survey years. In our estimation, we control for cohort fixed-effects for annual cohorts of movers, and for time trends in crime risk perception at the neighborhood level. Specifically, we estimate linear regression models of the following type:

$$y_i = \mathit{time\ here}_i \beta + \mathit{incumbent}_i \gamma + X_i^{'} \lambda + I_c{}' \mu + \alpha_{n,t} + \varepsilon_i \tag{2}$$

where outcome variable y_i measures perceptions of crime in the neighborhood; *i* indexes persons; $\mathit{time\ here}_i$ measures time since the move date to the current address for up to ten years ($\mathit{time\ here}_i$ is set to zero for incumbent residents); $\mathit{incumbent}_i$ is a binary indicator for persons who have lived at their current address for more than 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 address 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 represents a linear trend of how perceptions of crime change with time since the date of moving to the current neighborhood. Estimated coefficients for β can be interpreted as causal effects if the exogeneity assumption below holds:

$$E[\varepsilon_i \mid \textit{time here}_i, \text{mover}_i\, X_i, \text{I}_c, \alpha_{n,t}] = 0 \tag{3}$$

This assumption could be violated if unobserved determinants of risk perception in ε_i are correlated with explanatory variables. In the following, we discuss whether the exogeneity assumption is plausible within the context of our study. We discuss four possible violations of this assumption, and how we can address these violations: 1) differential trends in risk perception between movers and incumbent residents in the absence of the effect of time of exposure, 2) selective attrition, 3) the direct effect of time, and 4) a non-linear effect of time.

Differential trends between movers and incumbents

In our empirical strategy, we control for time trends in crime risk perception at the neighborhood level. A violation of the exogeneity assumption could be caused by different time trends in risk perceptions between movers and incumbent residents. 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 the move date 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 perceptions or about cohort effects. Regression equation (2) is based on the assumption that time trends are the same for incumbent residents and for different cohorts of movers in the same neighborhood. Formally, we assume:

$$\alpha_{n,t,\textit{incumbents}} = \alpha_{n,t,\text{cohort}\,1998} = \alpha_{n,t,\text{cohort}\,1999} = \ldots = \alpha_{n,t,\text{cohort}\,2011} \tag{4}$$

This assumption is similar to the assumption that for example Borjas (1995) uses in a 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 incumbent residents and different cohorts of movers in different ways.

We consider the assumption in equation (4) 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 town that subsequently followed a different time trend in crime. In order to minimize potential biases due to differential trends we control for trends at a very disaggregated geographical level, namely the neighborhood (for details, see Section 3). In alternative specifications we also control for time trends in crime risk perceptions at a geographical level higher than the neighborhood such as the municipality or national level. If estimation results for the effect of time since the move date do not differ much between these alternative specifications, then this suggests that our results are robust to the specific geographical level of the time trends.

As a robustness test, we use an alternative empirical approach that requires no assumptions about time trends. Specifically, we estimate regression equation (2) without cohort effects. Thus, we compare respondents who live in the same neighborhood in the same survey year, but who have lived there for different lengths of time. In place of assumption (4) this specification assumes that there are no systematic differences in risk perceptions between those who moved in different years. This assumption could be violated if those who moved for example during the great recession in 2009 are systematically different from those 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 (2), we can also test whether cohort fixed-effects are jointly significant.

Selective attrition

A second reason why the exogeneity assumption in equation (3) could be violated is selective attrition. During our study period, some respondents move away from their current address, and those who move away might be different from those who stay at their current address. Thus, time since the move date could be related to unobserved components of risk perception because of selective attrition. In our study, we address this problem by restricting the sample of movers to respondents who do not move between the date of the survey and the end of year 2011.[6] By restricting the sample of movers to those who will not move again during our study period, we make sure that movers in all survey years are drawn from the same population. In this way, we exclude any bias from selective attrition, in a similar fashion as Lubotsky (2007). The effects of attrition that took place before the start of our study period in the year 2008 are captured by the cohort fixed-effects.

Direct effect of time

A third possible source of violation of the exogeneity assumption is caused by time itself. In our study we use data over a period of four years. With increasing time since the move date, individuals become older. Age can affect risk perceptions. We address this issue 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.

Non-linear effect of time

Estimation equation (2) assumes a linear relationship between time since the move data and risk perceptions. We also show specifications that allow for a more flexible relationship between time since move and risk perceptions by using binary indicators for each year since move, and by showing specifications that fully interact cohort indicators with indicators for years since move.

3. Data

The source of data on perceptions of 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. If they do not respond, they 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

[6] For incumbent residents, we do not exclude future movers from the sample. Selective attrition for incumbent residents does not bias our results because the time since the move date variable for incumbent residents is zero, and does not vary between survey years.

largest, if not the largest, crime survey in the world. We pool the four waves of the survey for the years 2008, 2009, 2010, 2011.

Constructing the history of places of residence of respondents is facilitated by the fact that the sampling frame of the survey is the population register (Gemeentelijke Basisregistratie). In the population register, which is administered by municipalities, demographic details for each individual citizen of the Netherlands 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 examine movers who moved to a different neighborhood during the last 10 years before the survey. The earliest cohort moved in 1998; the latest cohort moved in 2011.

Part of the survey relates to 'neighborhood problems'. Respondents are asked about their perception of the prevalence of crimes in the neighborhood of residence based on a verbal assessment of likelihood. 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 and violent crime. The answer category 'frequently' is rarely chosen. For our main specification, the outcome variable is a binary indicator which is one if a respondent answers 'almost never' and zero otherwise. As a sensitivity analysis, we show that using all three answer categories (using ordered logit) produces qualitatively similar results (see the online appendix). In the baseline specification, we treat the answer "don't know" as missing. As a sensitivity analysis, we show that our results are robust if we control for "don't know" answers with a Heckman selection model.

Respondents may not answer questions about the neighborhood crime risk accurately and thoughtfully if the questions are not incentivized (Loughran et al. 2014) – even though untruthful reporting has been found to be less important for well-defined events that are relevant to respondents' lives (Manski 2004), such as crime. As we show in Figure 1, the responses have face validity: the perceived prevalence of a crime is related to its rate of occurrence. If the prevalence of victimization of crime is higher in a municipality, then fewer people think that it is rare, and vice versa. This holds for each of the four crime types. Although the time period we consider is too short to examine whether this also holds across time, this relationship has been shown elsewhere for similar data (Innes 2011). As a further check on the accuracy of the elicited beliefs, we also analyze avoidance behavior. Respondents are asked whether they avoid unsafe places in their neighborhood and whether they do not allow their children to go to some places in the neighborhood because of crime concerns. The outcome variable is a binary indicator which is one if a respondent answers ‘yes, frequently’ and zero otherwise.

[FIGURE 1]

Another challenge is the inter-personal comparability of the elicited beliefs. Different respondents may not interpret the verbal assessment of likelihood in the same way. In our analysis, we follow cohorts of movers over time. We compare beliefs across time rather than across individuals. Since we keep the composition of (the randomly selected samples of) the cohorts the same, it is as if we follow a representative individual over time. In this sense, our analysis does not rest on inter-personal comparisons of beliefs. That leaves the assertion that the responses are intra-personally comparable. A potential concern is a shift in reference point from the previous to the current place of residence. The survey questions do not provide an explicit reference point for the risk assessment. If a shift in reference point occurs, then its effect depends on how the crime rate in the previous place of residence compares to the current place of residence. In the empirical analysis, we test whether the change in perceptions varies between moves from relatively low-crime areas to relatively high-crime areas and vice versa. We also analyze avoidance behavior, which is likely to be at least partly driven by beliefs. If a change in avoidance behavior corresponds with the observed change in beliefs, then this makes it less likely that the change in beliefs is simply the result of a change in reference point.

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 a neighborhood provided by Netherlands Statistics. In 2011, the Netherlands had 2,572 neighborhoods. The average population of a neighborhood was 6,475. A small municipality like Ten Boer (population of 7,400) has two neighborhoods; a provincial capital like Groningen (population of 200,000) has 10 neighborhoods; a large city in the densely populated western part of the country like The Hague (population of 500,000) has 44 neighborhoods.

Our data include 550,760 respondents. In the sample used for the baseline estimation (column (1) in Table 2) we exclude 106,637 respondents because they respond “don’t know” on the question about perceived neighborhood risk; 1,688 respondents were excluded because they refuse to answer this question. We exclude 15,414 respondents who moved after the interview date and 908 respondents for whom the neighborhood of residence is unknown. This leaves an estimation sample of 425,593 respondents. As stated before, we test how robust our findings are to excluding the answer category "don't know" as a sensitivity analysis.

Table 1 presents the summary statistics. The first two columns relate to the subsample of 116,699 respondents who moved at least once in the last 10 years before the survey interview, the next two columns relate to the full estimation sample. Movers are on average more likely than the general population to be young, well-educated, to have paid work and live in an apartment. The differences are generally small. 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 violent crime about 80 percent hold this belief.

[TABLE 1]

4. Estimation results

4.1 Graphical evidence: cohort trends

As a first step, we graphically analyze the effect of time since the move date on perceptions of the neighborhood crime risk for different cohorts of movers. We estimate the following equation:

$$y_i = I_c T_t \beta + X_i^{'} \lambda + \alpha_{n,t} + \varepsilon_i \qquad (5)$$

$I_c T_t$ is an interaction of moving cohort and survey year, e.g. the 1998 moving cohort in the survey year 2008. The coefficient β represents how risk perceptions of specific moving cohorts in a specific survey year differ from risk perceptions of incumbent residents with the same observed characteristics in the same neighborhood and survey year.

[FIGURE 2]

The upper four graphs in Figure 2 show the estimation results for the four different crime types. The horizontal axes show the time since the last move in calendar years. The vertical axes show the percentage of movers who think that a crime is rare in the neighborhood relative to incumbent residents. The outcome variable in the upper left figure is a binary indicator for "bicycle theft occurs almost never in this neighborhood". We find that risk perceptions of recent movers are more positive than risk perceptions of incumbent residents. They are more likely to state that bicycle theft almost never happens. In the years after the move, risk perceptions tend to become more negative: close to all cohort curves slope downward. Ten years after the move, risk perceptions of movers are close to risk perceptions of incumbent residents, but they are still somewhat more likely to state that bicycle theft almost never happens. As the other three graphs for perceptions of crime risk show, perceived prevalence of burglary, theft from car, and violence in the neighborhood all follow a similar pattern.

The lower two graphs in Figure 2 show adjustment in avoidance behavior. The graph shows that avoidance behavior tends to increase with time since the move date, but the patterns are noisier than for risk perceptions.

4.2 Relation with the crime rate in the previous place of residence

Next, we investigate adjustment in beliefs by the nature of the change in the neighborhood crime risk resulting from a move. We distinguish four types of moves, depending on the level of crime in the previous and in the current neighborhood of residence: from safe to safe, from safe to risky, from risky to safe and from risky to risky. 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. Our estimation is based on the estimation equation below:

$$y_i = I_{timehere} I_{typemove} \beta + incumbent_i \gamma + X_i^{'} \lambda + I_c{}' \mu + \alpha_{n,t} + \varepsilon_i \quad (6)$$

$I_{timehere} I_{typemove}$ is an interaction of indicators for annual time since move categories and indicators for type of move. The estimation equation is similar to equation (2), but we substitute the linear term for time since the move date with a vector of binary indicators for annual time since move categories that are estimated separately for each type of move. Thus, β represents a set of binary indicators rather than one coefficient. We take those who moved less than 12 months ago as the reference group (in the graphs referred to as ‘recent movers’). We estimate the average trend across cohorts, i.e. the coefficients are estimated including cohort-fixed effects.

[FIGURE 3]

The upper four graphs in Figure 3 show the adjustment in perception of crime risk for the different types of moves. The adjustment is similar for the four types of moves, and this holds for each crime type. In other words, the risk adjustment is found to be independent of the crime rate in the previous place of residence relative to the new place of residence. In all cases, the adjustment is substantial. In 10 years’ time, the percentage of movers who think that bicycle theft is rare has declined by 8 percentage points (or by 17 percent given an average of 0.47, see Table 1). For burglary, the adjustment is 14 percentage points (30 percent), for theft from car it is 12 percentage points (18 percent), and for violence 10 percentage points (13 percent).

The lower two graphs in Figure 3 show that adjustment in avoidance behavior is in line with the observed changes in beliefs. The longer people live in a neighborhood, the more careful they become, regardless of the type of move. The adjustment is large, in both cases around 66 percent. This suggests that the changes in beliefs that we find are real in the sense that they go together with behavioral changes.

These results also suggest that the reference point that respondents use to answer questions about the neighborhood crime risk does not gradually shift from the previous to the current place of residence after having moved (see the discussion in Section 3). Such a shift would have been apparent in a different adjustment for different types of moves.

4.3 Parametric evidence

In Table 2, we test whether the observed change in perceived crime risk with time since the move date meets the standards of statistical significance. These results are based on the following estimation equation:

$$y_i = time\ here_i \times I_{typemove}\beta + incumbent_i\gamma + X_i^{'}\lambda + I_c{}'\mu + \alpha_{n,t} + \varepsilon_i \qquad (7)$$

This estimation equation is similar to equation (2), but estimates the effect of time since the last move separately by type of move. We distinguish four types of moves, depending on the crime rate in the current and previous place of residence. $time\ here_i \times I_{typemove}$ is an interaction variable between a linear variable for time since the last move and indicator variables for the type of move. β is a vector of four parameters.

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 the move date on risk perceptions that is statistically highly significant. Taking the specification with cohort-fixed effects and dividing the estimated coefficients by 1,000, multiplying by 12 (months to years) and by 9 (number of years covered in Figure 3), we obtain a decrease of about 8 percentage points. This is similar in size to what we found in Figure 3. The coefficients for the four types of moves are also roughly similar. The adjustment is large. The standard deviation of the perceived prevalence of bicycle theft in the neighborhood across municipalities is 12.4. This means that the adjustment over ten years is about 0.6 standard deviations.

Similarly, we find statistically significant effects of time since the move date on the perception of the risk of burglary, theft from car, and violent crime (columns 3-8). Again, the effects are similar in size to those we found in Figure 3. The perception of burglary risk and the perception of theft from car changed 1.0 standard deviation over ten years; perception of violent crime 1.5 standard deviations.[7] Finally, the changes in avoidance behavior with time since the move date in the specification with cohort-fixed effects are also found to be statistically significant at conventional levels, and comparable in size with the results shown in Figure 3 (columns 9-12).

[TABLE 2]

4.4 Heterogeneity

In Figure 4, we allow the effect of time since the move date on the perceived risk to vary between different groups of movers: home owners and renters, young and old, high and low levels of education, males and females, and infrequent and more frequent movers. The beliefs are estimated relative to people who moved less than one year ago (‘recent movers’).

[FIGURE 4]

In all cases, we find a similar change in perceived risk with time since the move date as reported previously. We only report estimates for perceived risk of bicycle theft; the results for the three other crime types are similar.

[FIGURE 5]

In Figure 5, 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 (in 2001, the Netherlands had 12 provinces and 418 municipalities). We find the adjustment in risk perceptions to be somewhat lower for moves within the same neighborhood compared to moves to a different neighborhood. The difference in adjustment after 10 years for moves within the neighborhood versus moves to a different province is statistically significant at the 1 percent level for all four crime types.

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[7] The standard deviation of the percent of respondents who think that burglary is rare in their neighborhood across municipalities is 12; it is also 12 for the perceived prevalence of theft from car; it is 7 for the perceived prevalence of violence.

5. Learning from personal experience

One explanation for what we find is that learning about the frequency of a rare, adverse event is based on personal experience. People only start to accumulate personal experience after the move. Learning based on personal experience can lead to an upward adjustment in risk perceptions at the population level if upward shocks in beliefs for persons who experience crime dominate the downward adjustment through discounting of past information. Then, the stock of crime-related experiences grows with increasing time of exposure, resulting in a progressively greater perceived risk.[8]

The data allow us to explore how well victimization – one element of experience – explains the observed adjustment in beliefs. While our data are based on a repeated cross-section of the Dutch adult population, a number of individuals have been included in the sample repeatedly – by chance rather than by design. We can identify repeat observations based on their unique identification number. In total, our estimation sample includes around 2,200 individuals with repeated observations.

The empirical approach is based on a version of the framework outlined in section 2 in which signals about local crime risk depend exclusively on whether or not an individual was recently victimized. We assume that individuals have not yet been victimized in the new neighborhood at the time of the move. Thus, the initial perception at the time of the move is $p_0 = 0$. In each period after the move individuals receive a signal $s_1, s_2, .., s_T$ which takes on the value β if the individual is victimized in the respective period, and 0 otherwise. In the periods after victimization, individuals gradually forget their victimization experience. The speed of forgetting is determined by parameter γ. Perceptions of local crime risk $y_{i,t}$ of individual *i* at time *t* are determined by:

$$y_{i,t} = \max(0, victimized_{i,t}\beta - time\ vict_{i,t}\gamma) \tag{8}$$

where $victimized_{i,t}$ is a binary indicator for individuals who have been victimized in the current place of residence, and $time\ vict_{i,t}$ is a variable for the length of time since the most recent victimization experience. According to this framework, risk perceptions depend on the stock of victimization experiences, akin to the availability heuristic. If expectations are accurate then own

[8] This interpretation also fits well with results from evolutionary biology (see Baumeister et al. 2001: 344-348): a bad event (in our context: victimization of crime) has a longer lasting and more intense consequence for impression formation than a good event (the realization that crime did not happen).

victimization should not affect perceptions of neighborhood crime risk. A single incidence of crime has a negligible impact on crime rates in the neighborhood.

In order to estimate the parameters β and γ of the framework above, we use linear models with individual fixed effects. Specifically, we estimate the following regression model:

$$y_{i,t} = victimized_{i,t}\beta + time\ vict_{i,t}\gamma + Z_{i,t}^{'}\lambda + I_t{}'\mu + \alpha_i + \varepsilon_{i,t} \qquad (9)$$

Where $Z_{i,t}$ is a vector of time-varying individual characteristics (age, age squared, household size, and labor force participation), I_t is a vector of indicators for years t, α_i are individual specific fixed-effects, and $\varepsilon_{i,t}$ are time varying error terms. β, γ, λ and μ are (vectors of) parameters. Variation in $victimized_{i,t}$ comes from respondents who were victimized between waves. $time\ vict_{i,t}$ changes with the time passed between surveys, as well as for respondents who have been victimized between survey waves.

Estimation results are shown in Table 3. These results show that risk perceptions strongly respond to victimization. As a response to becoming a victim of bicycle theft, beliefs that bicycle theft is rare in the neighborhood decrease by 15.2 percentage points. The corresponding decreases are 7.7 percentage points for burglary, 11.9 percentage points for theft from car, and 6.4 percentage points for violence. With the exception of burglary, all coefficients are statistically significant at the five percent level. The coefficients for time since victimization are all positive, which indicates that the effect of victimization diminishes over time. However, these coefficients are small compared to the effect of victimization and they are not statistically significant. For example, the coefficient for time since bicycle theft is equivalent to 2.2 percentage points. This implies that it would take around 7 years to offset the impact of a stolen bike on risk perceptions. The corresponding time until forgetting for other crime types is even longer.[9]

In Figure 6 we show simulations results about how risk perceptions evolve in a new risk environment. These simulations are based on the estimation coefficients shown in Table 3 and victimization rates shown in Table 1 under the assumption that risk perceptions respond exclusively to own victimization and that there are no other sources of information about local crime risk. We also assume that directly after a move individuals have no previous victimization

[9] The panel data contain only a small number of movers. Consequently, we cannot follow movers over time and see how their perceptions change at the time of move or look at perceptions of movers who were never victimized.

experiences in the new neighborhood. The patterns that emerge from these simulations are very similar to the patterns in the actual adjustment process shown in Figure 3. Individuals become on average gradually more pessimistic about crime risk in the new neighborhood. With increasing time since the move date more and more individuals accumulate experiences with victimization. These could be the underlying pattern that explains our main results.

Of course, these simulations omit many important factors that can influence risk perceptions. Risk perceptions do not only depend on own victimization experiences. Individuals might also learn for example from experiences of family members or neighbors, or also from failed burglary attempts. This can be one of the reasons why the size of the change in risk perceptions in the years after a move is smaller in the simulations than it is for actual movers. Thus, own victimization can only account for part of the adjustment in risk perceptions.

6. Other explanations

In the previous section, we discussed how the process of accumulating experiences with crime in the neighborhood can explain an upwards adjustment in risk perceptions after moving house. From this perspective, the initial risk assessment is relatively low because the stock of local experiences is relatively small shortly after a move, just like young investors who have not experienced a financial crisis may be more naïve with regards to financial risk than seasoned investors who did experience a crisis. Within the context of our paper, however, the initial risk assessment may also be relatively low for reasons other than a lack of experience. We discuss two alternative reasons below.[10]

6.1 Winner's curse

Individuals with over-optimistic beliefs about the neighborhood crime risk may be overrepresented among movers to that neighborhood. This idea is similar to the winner's curse in auctions: those who win an auction are likely to overpay. Movers may be attracted by house prices that to them seem relatively low, but in the views of incumbent residents of the neighborhood simply reflect broadly shared perceptions of the neighborhood crime rate. Over time, these movers come to realize that they had too positive a picture of the neighborhood crime

[10] An adjustment in beliefs after a move can also occur when people follow the anchoring and adjustment heuristic (Tversky and Kahneman 1974). The anchoring and adjustment heuristic posits that an individual's prior beliefs are determined by an anchor. In our case, that could be the level of crime in the previous neighborhood. Since we find that the upwards adjustment is independent from the crime level in the previous neighborhood (the 'anchor'), this explanation does not fit the observed pattern.

risk. The initial misperception and following adjustment result in a positive relation between time since the move date and perceived risk.

First of all, it should be noted that even when the winner's curse adds to the relatively low risk assessment at the time of move, the adjustment in beliefs over time may well be related to the mechanism of experience-based learning that we described above. After all, the observed adjustment takes many years, which is in line with directly or indirectly experiencing a low frequency-event like crime, and we find that it is at least partly driven by actual direct experience with crime. But this leaves the possibility that the winner's curse may be an important explanation of the initial low risk assessment, casting our findings in a very context-specific light.

Results reported in Section 4.4 allow us to gauge how important the winner's curse is. If the winners' curse is at work, then it should have less of an effect for people who have limited choice of where to live. After all, for this group, beliefs about neighborhood crime have little to no effect on the specific neighborhood they eventually move to. In the Netherlands, this holds for most renters. The reason is that almost 70 percent of renters live in rent-controlled homes provided by social housing foundations (one in three of all homes are in this sector). Due to the highly restricted supply of this type of housing, prospective tenants often need to compromise many of their wishes, including their preferred neighborhood of residence. We found similar patterns for the evolution of risk perceptions for owners and renters (see Figure 4). This is not in line with the winner's curse explanation.

6.2 Cognitive dissonance

Cognitive dissonance may result in a tendency to justify the decision to choose the new neighborhood by casting characteristics of this neighborhood – including the neighborhood crime risk – in too positive a light (see Akerlof and Dickens 1982; this tendency is also known as choice-supportive bias). If this tendency diminishes over time, then this may also explain the positive relation between time since the move date and perceived neighborhood crime risk.

First of all, whether cognitive dissonance leads to an upwards adjustment in perceived neighborhood crime risk with time of exposure is not clear: the belief that the neighborhood someone lives in is special or better than other neighborhoods can be enduring or even grow with time of exposure (the 'mere exposure'-hypothesis, see Harrison 1977). Even if we believe that cognitive dissonance fades over the years, then this source of the initial underestimation relative to later years does not contradict that people adjust their beliefs in response to experience either. But it is of concern, because it would again make our findings very context-specific. The similar findings for owners and renters also suggest that cognitive dissonance is not an important explanation for what we find. If someone has limited influence over the neighborhood of residence, then cognitive dissonance may be less important. The absence of any heterogeneity between owners and renters is not in line with this alternative explanation either.

7. Discussion

In summary, we find that after the initial adjustment at the time of move, perceptions of local crime risk are adjusted upwards with greater time of exposure to local conditions. Our results are independent of the specific motive to move[11], from differences in the capability of dealing with risk[12], from gender differences and, perhaps most surprisingly, from being in the position to learn from previous moves. The size of the adjustment in beliefs differs by distance of move. It is smaller for moves within the same neighborhood, and it is larger for moves to a different province.

An upwards adjustment in risk perceptions after moving house fits with theories of experience-based learning and with recently uncovered evidence in other areas such as investment behavior. At the level of the population, we find that after a complete reset of locally gained experiences, upward shocks in beliefs from experience dominate the more gradual downward adjustment through discounting of past information for many years. The stock of crime-related experiences seems to increase over time, resulting in a progressively greater perceived risk of crime.

More generally, if this is how potential victims' beliefs evolve, then perceptions of crime risk are primarily based on recent or particularly disturbing direct and indirect experiences with crime in their neighborhood rather than statistical information such as official crime statistics. This is consistent with the finding that adjustment in risk perceptions is lower for moves within the same neighborhood than for moves to a different neighborhood: the stock of experiences built up in the previous place of residence is partly relevant for nearby moves but not for moves further away. The exceedingly long duration of the adjustment process could be related to the infrequent

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[11] People younger than 30 often move for work or study; older people often out of a preference for a better home or neighborhood (WoON survey 2012).

[12] Given the results for educational attainment, which is related to cognitive ability (see Dohmen et al. 2010).

occurrence of victimization of crime: for most people, the stock of direct experiences expands only slowly.

Our results suggest that beliefs about local crime risks are at least sometimes incorrect. Beliefs are adjusted upwards with increasing time since the move date, even when local crime risk is constant. As a consequence, people exposed to the same risk environment can have very different perceptions of the risk. This has important implications for our understanding of the causes of crime. For crime to occur, a potential victim needs to offer an opportunity. We show that one key element in precautionary decision making, assessment of the crime risk, can be off for an extensive period of time. As discussed in the introduction, our paper opens avenues for an alternative way of lowering the cost of crime to society: targeting victim behavior rather than offender behavior.

Our findings do not contradict the popular belief that the public tends to overestimate the crime risk, and the finding that subjective probabilities are generally higher than objective probabilities within the context of crime risk (Quillian and Pager 2010, Dominitz and Manski 1997). We focus on how perceptions of crime risk evolve over time, not on the *levels* of perceived risk at a particular moment. Our qualitative measures of risk perception – based on statements that a type of crime occurs 'almost never' – would not allow us to do so. Our findings do contradict the commonly held view that perceptions of the crime rate do not go down when the crime rate falls. Perceptions are fed by real experiences, and perceptions are adjusted downwards with the discounting of past experiences.

This leaves the question whether risk perceptions become *less distorted* with greater time of exposure to the new environment. If we believe that the ability to draw upon a greater stock of direct and indirect experiences of crime makes people better informed about what goes on in their neighborhood, then movers' perceptions better reflect the true risk the longer they live in a neighborhood. We should note that under the above assumption about the value of gained experiences with crime, a convergence of beliefs only suggests less distortion, not that crime risk perceptions converge to the correct value. As stated above, beliefs of the incumbent residents may well be off – even though we find differences in crime risk perceptions to correspond with differences in actual victimization rates.

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Table 1. Summary statistics

	Sample of movers		Full sample	
	Mean	Standard Dev.	Mean	Standard Dev.
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
"Violent crime is rare in neighborhood"	0.762	0.426	0.796	0.403
Avoidance behavior				
"Frequently avoids unsafe places in neighborhood"	0.059	0.235	0.053	0.215
"Frequently doesn't allow children to go to some places in neighborhood because of crime concerns"	0.119	0.324	0.096	0.207
Personal characteristics				
Months since the move date	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
Victimization last 12 months				
Any crime	0.367	0.482	0.304	0.460
Bicycle theft	0.065	0.248	0.086	0.281
Burglary	0.020	0.143	0.025	0.157
Theft from car	0.023	0.151	0.031	0.174
Violent crime	0.065	0.247	0.087	0.282
Number of observations	116,699		425,593	

Notes. The sample of movers is restricted to respondents who have moved to a different neighborhood 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 the move date on risk perception and avoidance behavior, 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 (1)	With cohort FE (2)	Without cohort FE (3)	With cohort FE (4)	Without cohort FE (5)	With cohort FE (6)
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)
p-value cohort-FE=0		0.1059		0.0065		0.1104
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

Notes. Results show coefficients for linear regression as in Equation (7). Coefficients are multiplied by a factor of 1,000. A neighborhood is denoted as safe if the crime rate is below average. A neighborhood is denoted as risky if the 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) are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.

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

	"Violent crime is rare in neighborhood"		"Frequently avoids unsafe places in neighborhood"		"Frequently doesn't allow children to go to some places in neighborhood"	
	Without cohort FE (7)	With cohort FE (8)	Without cohort FE (9)	With cohort FE (10)	Without cohort FE (11)	With cohort FE (12)
Months since move × move from **safe to safe** neighborhood	-0.3803*** (0.0644)	-1.0049*** (0.1514)	0.1286*** (0.0391)	0.2865*** (0.0933)	0.3495*** (0.0730)	0.7415*** (0.1595)
Months since move × move from **risky to safe** neighborhood	-0.3399*** (0.0912)	-0.9647*** (0.1692)	0.0833* (0.0435)	0.2421** (0.0951)	0.2718*** (0.0834)	0.6618*** (0.1670)
Months since move × move from **safe to risky** neighborhood	-0.5114*** (0.1055)	-1.1116*** (0.1722)	0.0947 (0.0591)	0.2469** (0.0974)	0.4956*** (0.1248)	0.8754*** (0.1876)
Months since move × move from **risky to risky** neighborhood	-0.4590*** (0.0781)	-1.0643*** (0.1470)	0.0026 (0.0455)	0.1554* (0.0889)	0.1582* (0.0891)	0.5399*** (0.1620)
p-value cohort-FE=0		0.0038		0.0878		0.1029
Number of observations	410,675	410,675	338,664	338,664	192,678	192,678
R-Squared	0.022	0.022	0.018	0.018	0.019	0.019

Notes. Results show coefficients for linear regression as in Equation (7). Coefficients are multiplied by a factor of 1,000. A neighborhood is denoted as safe if the crime rate is below average. A neighborhood is denoted as risky if the 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) are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.

Table 3. Effect of own victimization on risk perceptions (fixed effect estimation)

	"Bicycle theft is rare in neighborhood" (1)	"Burglary is rare in neighborhood" (2)	"Theft from car is rare in neighborhood" (3)	"Violent crime is rare in neighborhood" (4)
Victimization in last 5 Years	-0.1517***	-0.0765*	-0.1186***	-0.0643**
	(0.027)	(0.042)	(0.028)	(0.026)
Years since last Victimization	0.0221*	0.0012	0.0030	0.0050
	(0.012)	(0.019)	(0.013)	(0.013)
Number of observations	4,479	5,371	4,607	4,691
R-Squared	0.023	0.014	0.013	0.006
Number of persons	2,285	2,681	2,295	2,341

Notes. Results show coefficients for linear regressions with individual-specific fixed effects as in Equation (9). Coefficients for age, age squared, household size, education, labor force participation, and survey year indicators are not shown. Robust standard errors (clustered at individual level) are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.

Figure 1. Actual and perceived prevalence of crime, by municipality and crime type

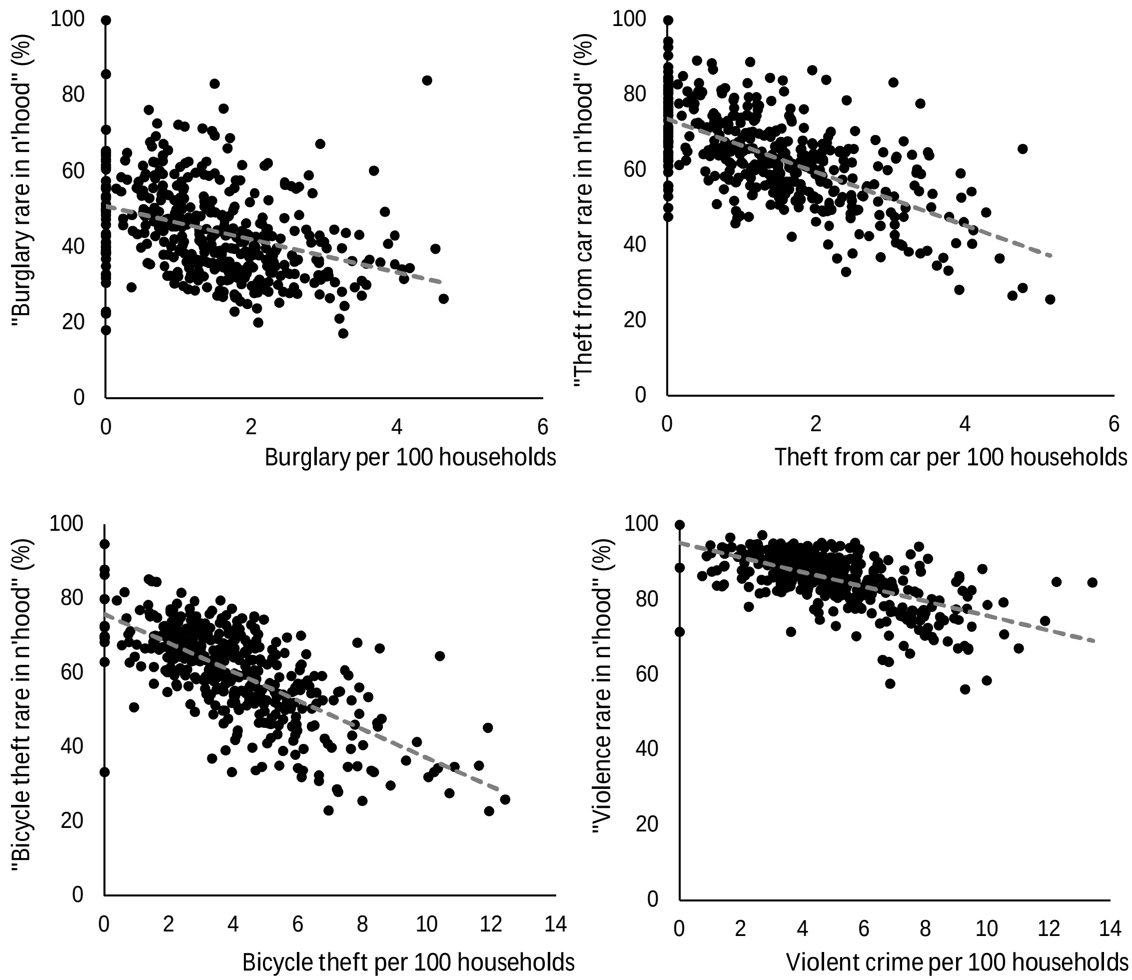
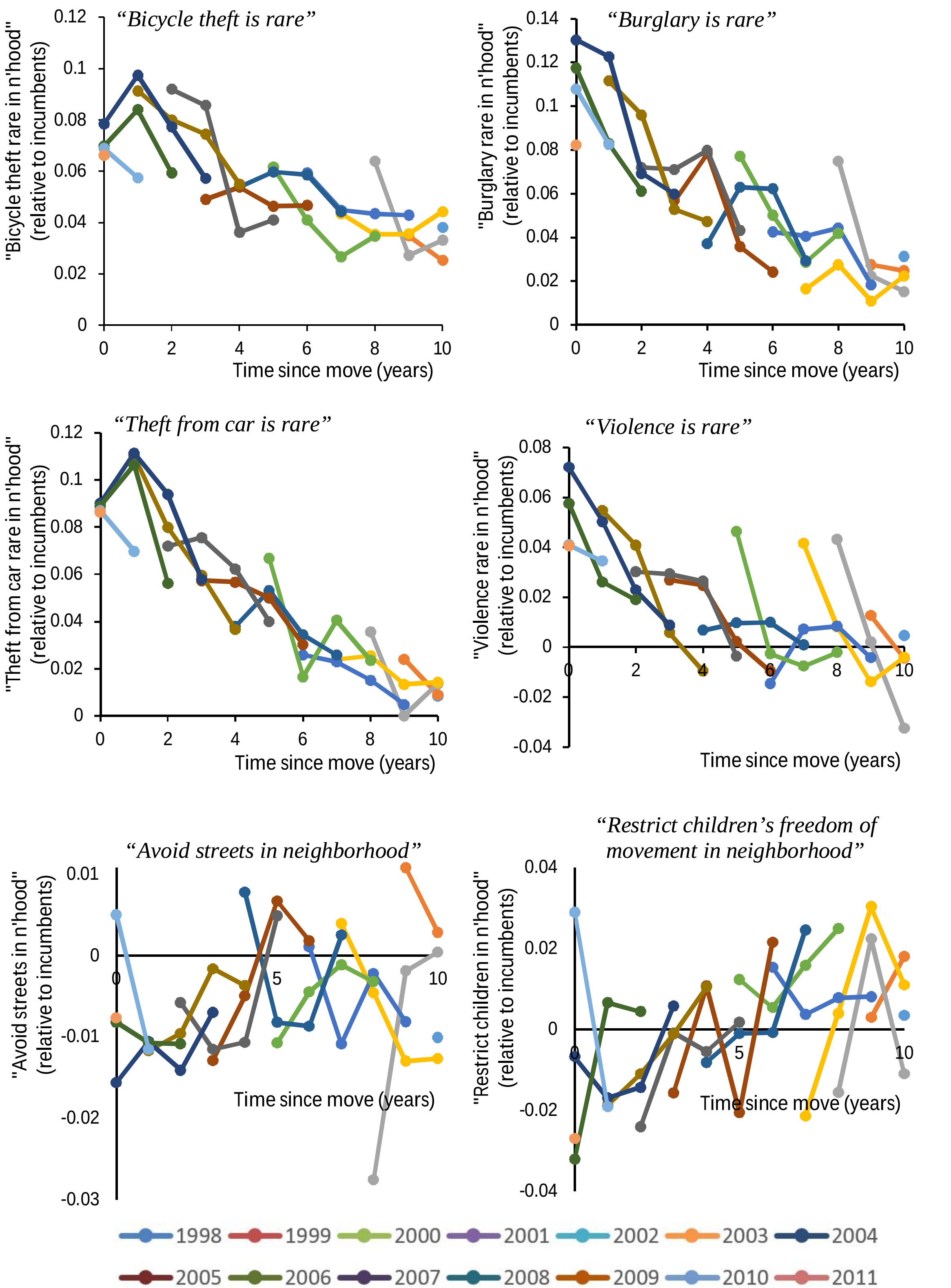
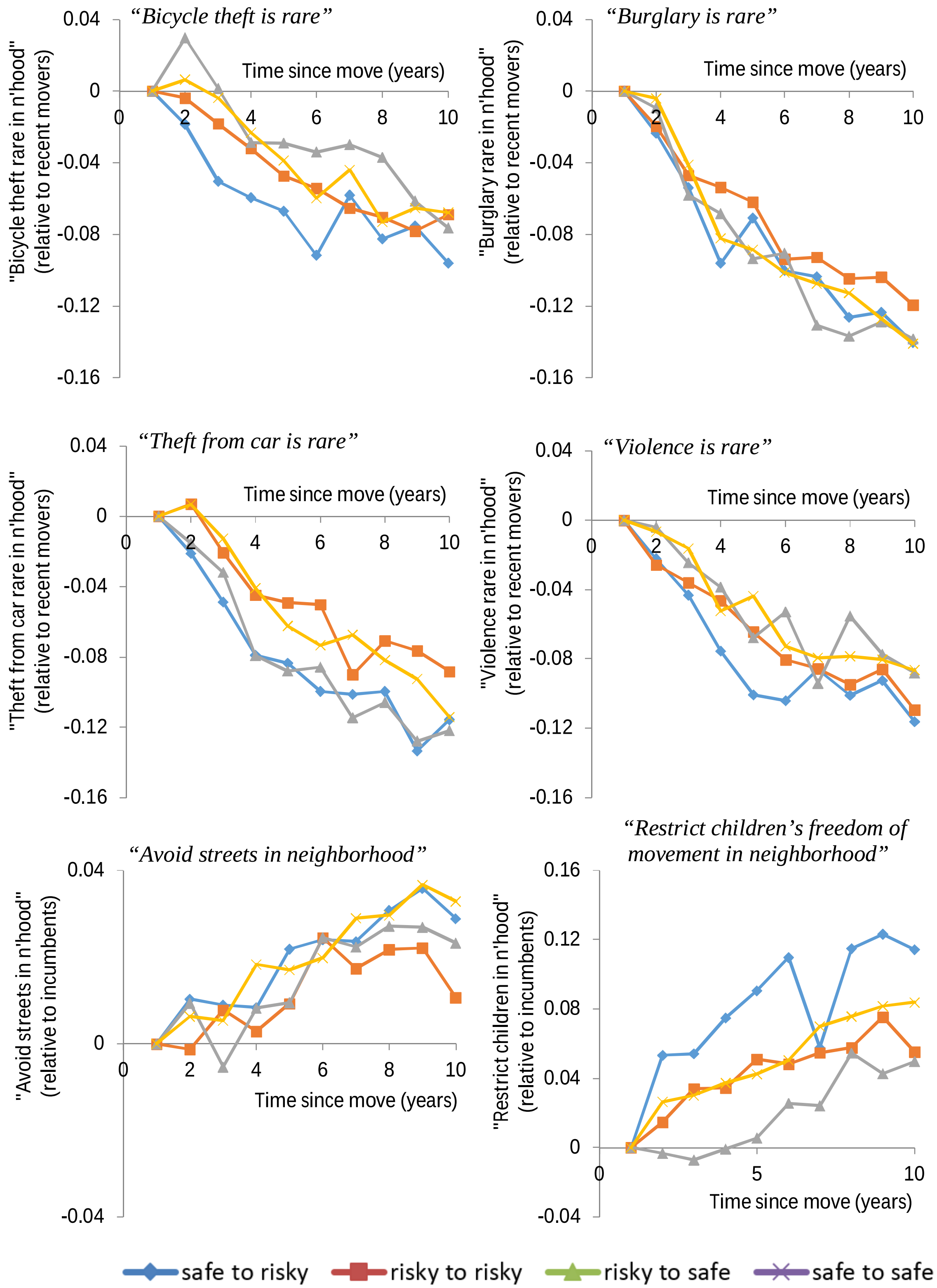


Figure 2. Perception of neighborhood risk and avoidance behavior in the neighborhood, individual cohort curves, relative to incumbent residents



Note. Figures plot coefficients from Equation (5). Based on survey data for calendar years 2008-2011.

Figure 3. Perception of neighborhood risk and avoidance behavior in the neighborhood, by type of move, relative to those who moved less than 1 year ago



Note. 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.

Figure 4. Perception of risk of bicycle theft in the neighborhood since the move date relative to those who moved less than one year ago, by home owner/renter, age at time of move, educational attainment, gender, number of moves in last 10 years

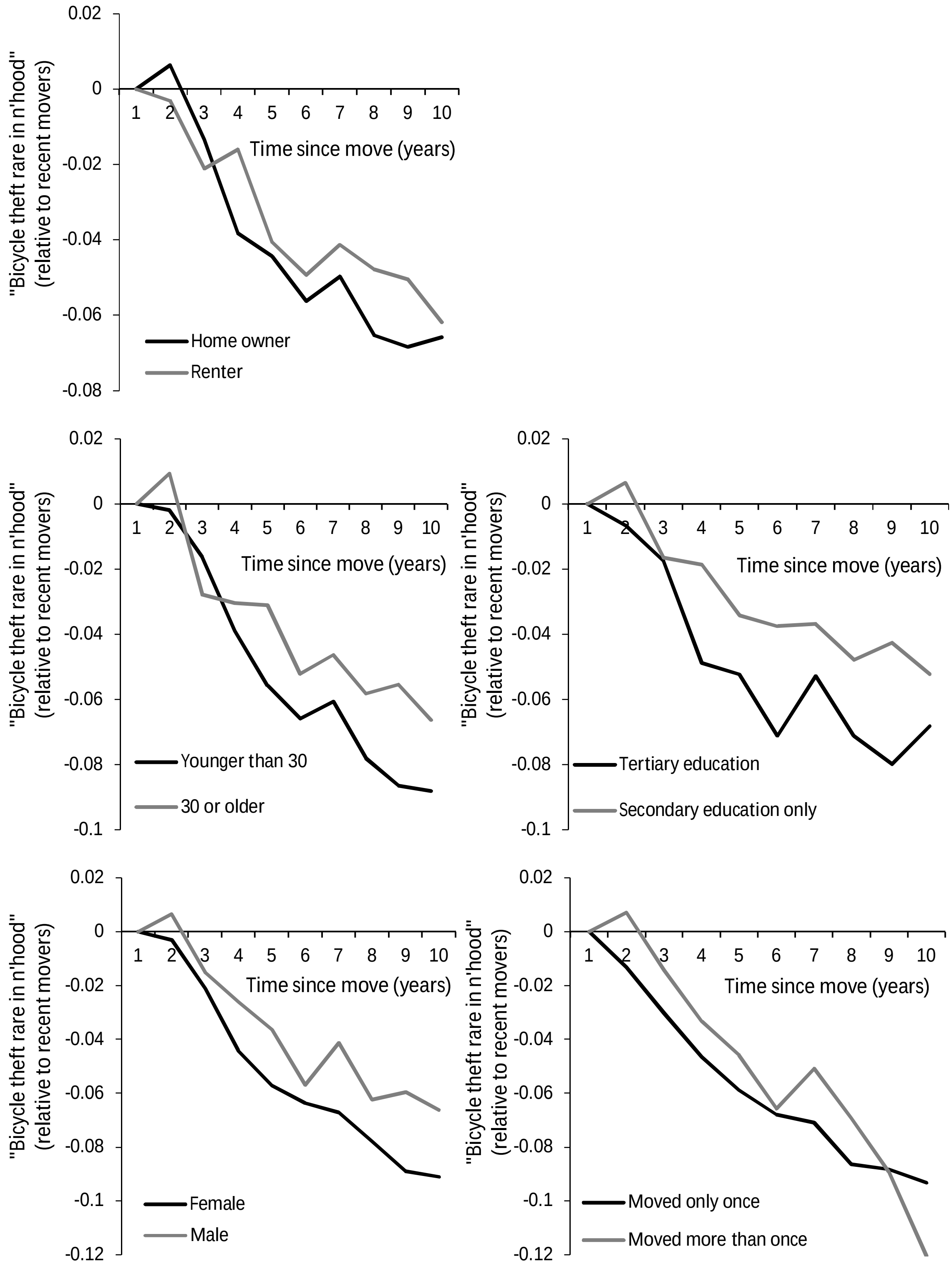


Figure 5 Perception of crime risk since the move date relative to those who moved less than one year ago, by distance of move and crime type

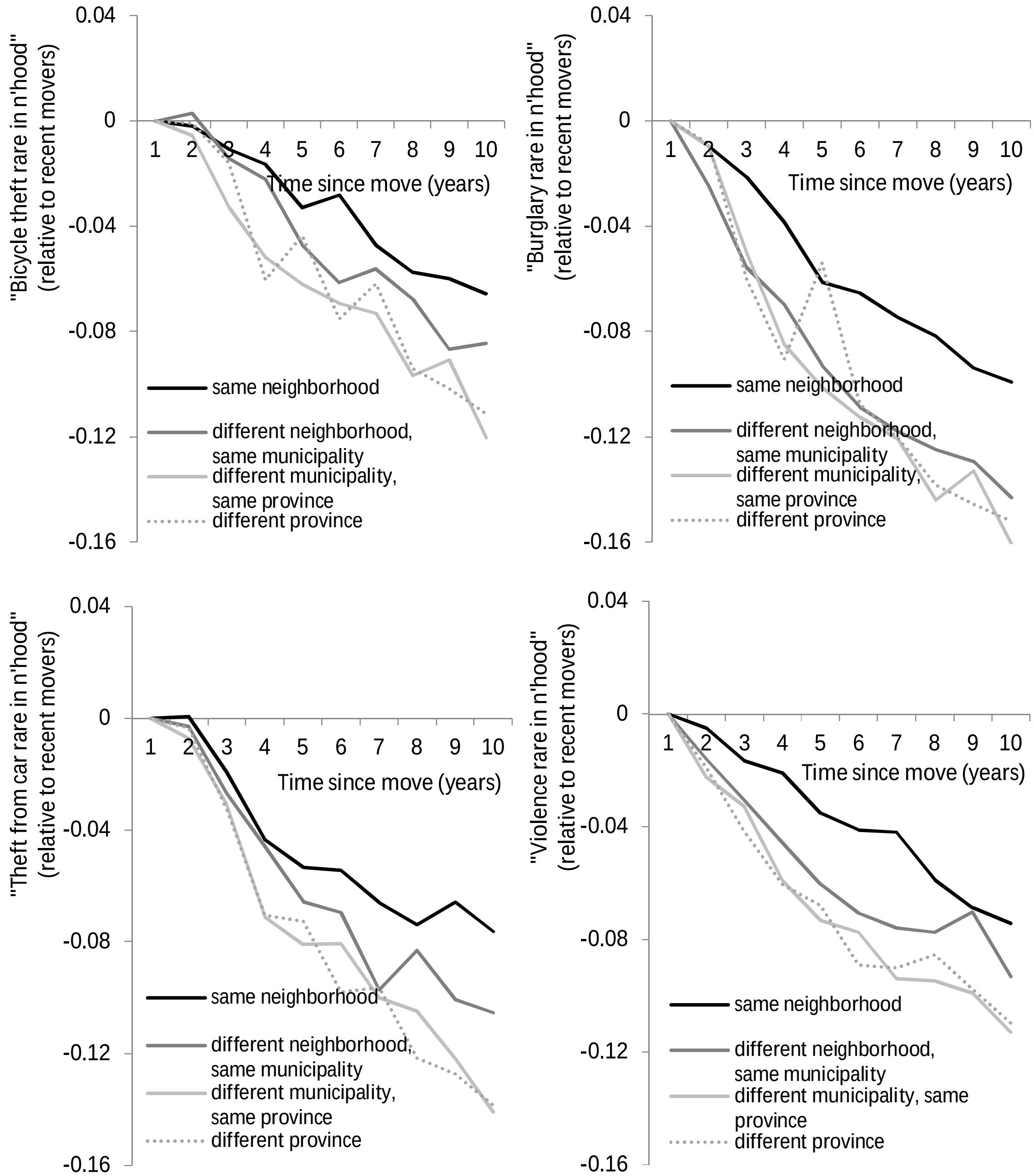
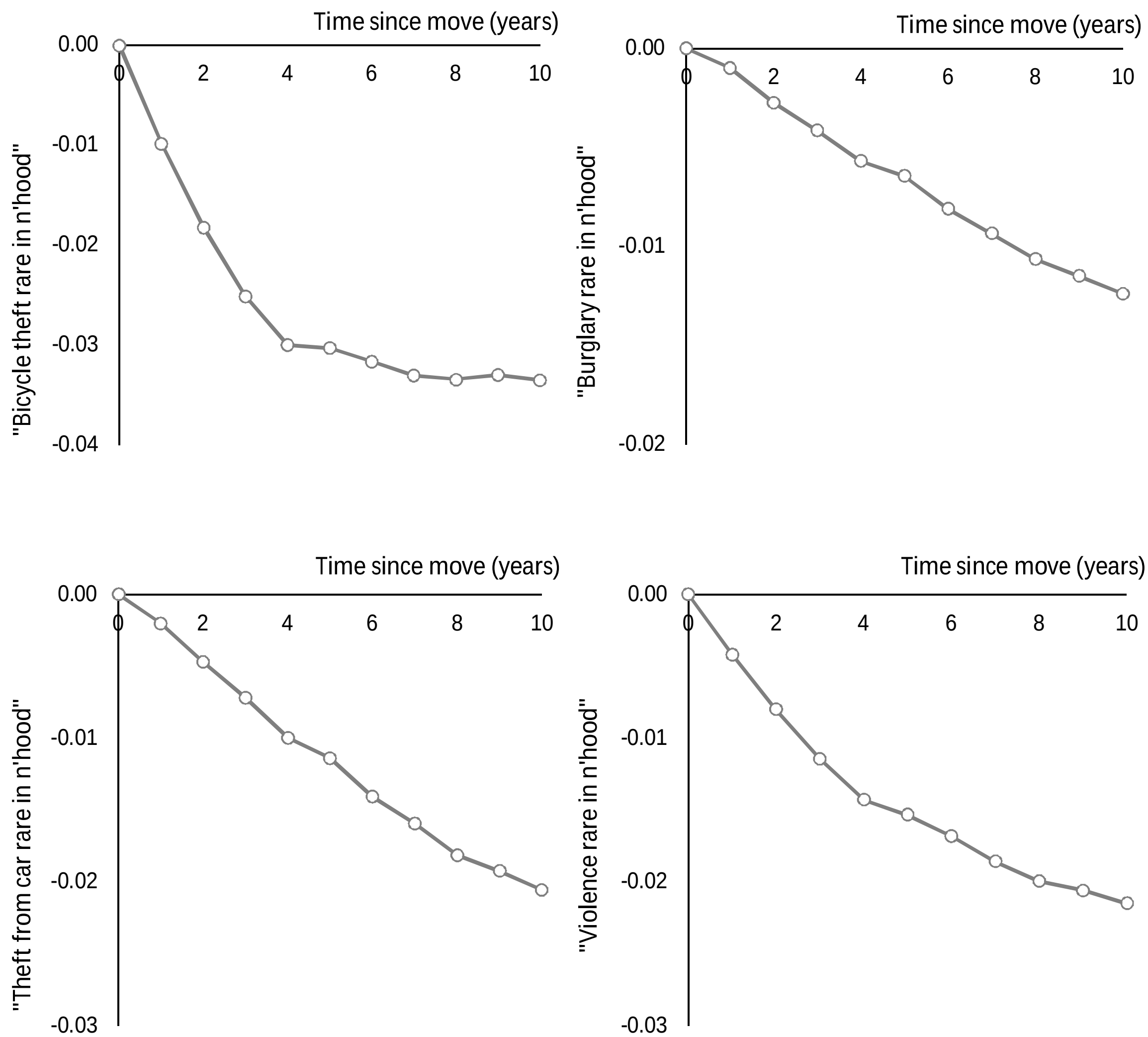


Figure 6 Simulations of changes in perceptions of crime risk in reaction to own victimization



Online Appendix: "Perception follows experience: Assessment of local crime risk"

Sensitivity to alternative assumptions and specifications

We conduct a number of tests to analyze the sensitivity of our results to alternative assumptions and alternative empirical specifications. As discussed in Section 2 of the main text, our empirical models rely on the assumption that time trends in the crime rate are the same for incumbent residents of a neighborhood and for those who moved into that neighborhood. A formal definition of this assumption is given in equation (4) in the main text. As a sensitivity test, we control for time trends in crime risk perceptions at geographical levels other than the neighborhood: the national level and the municipality level. The results for these two alternative specifications are shown in Table A1 and A2 in the Appendix. Results in both tables are very similar to the baseline specification in Table 2. Risk perceptions become strongly and statistically significantly more negative with increasing time since the move date, while avoidance behavior goes up. These results suggest that our results are robust to alternative specifications of time trends.

We reduced the responses to questions about crime perceptions from the three presented in the survey (frequently, occasionally, or almost never) to a binary indicator of whether a crime occurs almost never in the neighborhood. We use the binary indicator as an outcome variable in linear probability models. As a robustness check, we also estimate ordered logit models for all three outcome categories. We are not able to estimate ordered logit models with a complete set of neighborhood by year interaction variables due to an incidental parameter problem. Instead, we estimate a model with national time trends. Estimation results for ordered logit models are shown in Table A3. Coefficients from ordered logit models are not directly comparable with coefficients from linear regressions, given the use of three rather than two answer categories. Still, the estimation results from ordered logit models and from linear probability models point in the same direction. Crime risk perceptions decrease with increasing time since the move date, and this relationship is statistically significant.

A substantial fraction of respondents answered "don't know" to questions about the perceived crime risk in the neighborhood. So far, we excluded this response category. It could be that the share of respondents in this category is related to time since the move date, and should this be so, those who switch to (or from) an answer in another category may be different from those who have always remained in the "don't know" response category. In that case, our results may be biased. As a robustness check, we re-estimate our baseline specification including a Heckman selection model that takes sample selection caused by "don't know" answers into account. In the first stage, we estimate the probability of giving an answer other than “don’t know.” As an instrumental variable for giving a valid answer about crime risk perception, we use a binary indicator for responding “don’t know” on a different question in the survey: whether playgrounds are sufficiently available in the neighborhood. The model can only be estimated with a national time trend in the crime rate. Estimation results for Heckman selection models are shown in Table A4 in the Appendix. We find that “don’t know” answers about crime risk perception in the neighborhood strongly and significantly decrease with increasing time since the move date. Still, estimation results for crime risk perceptions are very similar to those based on a national rather than a neighborhood crime trend reported in Table A1 and also to the baseline specification in Table 2. Crime risk perceptions strongly and significantly decrease with increasing time since the move date.

The level of crime in a neighborhood is measured based on the frequency of victimization of crime in our sample. For neighborhoods with few observations, crime rates could be measured imprecisely, leading to an inaccurate classification of neighborhoods into having a crime rate that is above or below the national average. As a robustness check, we re-estimate our model while restricting the sample to respondents with at least 100 observations in both their current and previous neighborhood. Estimation results are shown in Table A5. Again, similar to the baseline specification, we do not find any substantial differences in the effect of time since the move date on risk perceptions by type of move. Thus, this finding cannot be explained by measurement error in the classification of neighborhoods into ‘risky’ or ‘safe’.

Table A1. Effect of time since the move date on risk perception and avoidance behavior, by level of crime in current and previous place of residence, time trends at national level

	"Bicycle theft is rare in neighborhood"		"Burglary is rare in neighborhood"		"Theft from car is rare in neighborhood"	
	Without cohort FE (1)	With cohort FE (2)	Without cohort FE (3)	With cohort FE (4)	Without cohort FE (5)	With cohort FE (6)
Months since move × move from **safe to safe** neighborhood	-0.6867*** (0.0945)	-0.8611*** (0.2111)	-0.8557*** (0.0933)	-1.4659*** (0.2058)	-1.0666*** (0.0914)	-1.4196*** (0.2071)
Months since move × move from **risky to safe** neighborhood	-0.7741*** (0.1078)	-0.9496*** (0.2124)	-0.8924*** (0.1005)	-1.5039*** (0.2105)	-1.0687*** (0.1209)	-1.4219*** (0.2302)
Months since move × move from **safe to risky** neighborhood	-0.3014*** (0.1031)	-0.4950** (0.2150)	-0.7271*** (0.1233)	-1.3271*** (0.2245)	-0.7369*** (0.1158)	-1.0815*** (0.2176)
Months since move × move from **risky to risky** neighborhood	-0.4442*** (0.0824)	-0.6388*** (0.2013)	-0.6183*** (0.0959)	-1.2229*** (0.2104)	-0.6671*** (0.0898)	-1.0160*** (0.2070)
p-value cohort-FE=0		0.3613		0.0227		0.4707
Number of observations	425,593	425,593	447,487	447,487	428,190	428,190
R-Squared	0.076	0.076	0.041	0.042	0.060	0.060

Notes. Results show coefficients for linear regression similar to equation (7). Coefficients are multiplied by a factor of 1,000. A neighborhood is denoted as safe if the crime rate is below average. A neighborhood is denoted as risky if the 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 year fixed effects are not shown. Robust standard errors are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.

Table A1. Effect of time since the move date on risk perception and avoidance behavior, by level of crime in current and previous place of residence, time trends at national level (continued)

	"Violent crime is rare in neighborhood"		"Frequently avoids unsafe places in neighborhood"		"Frequently doesn't allow children to go to some places in neighborhood"	
	Without cohort FE (7)	With cohort FE (8)	Without cohort FE (9)	With cohort FE (10)	Without cohort FE (11)	With cohort FE (12)
Months since move × move from **safe to safe** neighborhood	-0.5984*** (0.0671)	-1.2198*** (0.1652)	0.1726*** (0.0395)	0.3528*** (0.0931)	0.4294*** (0.0734)	0.8279*** (0.1607)
Months since move × move from **risky to safe** neighborhood	-0.5772*** (0.0886)	-1.1988*** (0.1765)	0.1266*** (0.0427)	0.3078*** (0.0943)	0.3635*** (0.0810)	0.7587*** (0.1646)
Months since move × move from **safe to risky** neighborhood	-0.5372*** (0.1148)	-1.1323*** (0.1961)	0.1050* (0.0602)	0.2804*** (0.0995)	0.4736*** (0.1246)	0.8589*** (0.1900)
Months since move × move from **risky to risky** neighborhood	-0.5162*** (0.0876)	-1.1156*** (0.1788)	0.0280 (0.0461)	0.2048** (0.0894)	0.1875** (0.0874)	0.5734*** (0.1623)
p-value cohort-FE=0		0.0111		0.0479		0.0923
Number of observations	410,675	410,675	388,664	388,664	192,678	192,678
R-Squared	0.073	0.073	0.027	0.027	0.035	0.038

Notes. Results show coefficients for linear regression similar to equation (7). Coefficients are multiplied by a factor of 1,000. A neighborhood is denoted as safe if the crime rate is below average. A neighborhood is denoted as risky if the 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 year fixed effects are not shown. Robust standard errors are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.

Table A2. Effect of time since the move date on risk perception and avoidance behavior, by level of crime in current and previous place of residence, time trends at municipality level

	"Bicycle theft is rare in neighborhood"		"Burglary is rare in neighborhood"		"Theft from car is rare in neighborhood"	
	Without cohort FE (1)	With cohort FE (2)	Without cohort FE (3)	With cohort FE (4)	Without cohort FE (5)	With cohort FE (6)
Months since move × move from **safe to safe** neighborhood	-0.5219*** (0.1017)	-0.8541*** (0.1983)	-0.8286*** (0.0908)	-1.4100*** (0.1843)	-0.9657*** (0.0878)	-1.3837*** (0.1960)
Months since move × move from **risky to safe** neighborhood	-0.6354*** (0.1012)	-0.9698*** (0.1761)	-0.8696*** (0.1042)	-1.4521*** (0.2022)	-0.9964*** (0.1309)	-1.4148*** (0.1972)
Months since move × move from **safe to risky** neighborhood	-0.2475** (0.1123)	-0.6082*** (0.2093)	-0.6686*** (0.1387)	-1.2470*** (0.2092)	-0.6952*** (0.1179)	-1.1176*** (0.1899)
Months since move × move from **risky to risky** neighborhood	-0.3489*** (0.0568)	-0.7104*** (0.1873)	-0.5960*** (0.1002)	-1.1772*** (0.2074)	-0.6327*** (0.0696)	-1.0588*** (0.1970)
p-value cohort-FE=0		0.0004		0.0168		0.0222
Number of observations	426,499	426,499	448,376	448,376	429,058	429,058
R-Squared	0.029	0.029	0.042	0.043	0.026	0.026

Notes. Results show coefficients for linear regression similar to equation (7). Coefficients are multiplied by a factor of 1,000. A neighborhood is denoted as safe if the crime rate is below average. A neighborhood is denoted as risky if the 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 municipality and year interactions are not shown. Robust standard errors (clustered at municipality level) are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.

Table A2. Effect of time since the move date on risk perception and avoidance behavior, by level of crime in current and previous place of residence, time trends at municipality level (continued)

	"Violent crime is rare in neighborhood"		"Frequently avoids unsafe places in neighborhood"		"Frequently doesn't allow children to go to some places in neighborhood"	
	Without cohort FE (7)	With cohort FE (8)	Without cohort FE (9)	With cohort FE (10)	Without cohort FE (11)	With cohort FE (12)
Months since move × move from **safe to safe** neighborhood	-0.4689*** (0.0638)	-1.0201*** (0.1572)	0.1382*** (0.0407)	0.2723*** (0.0940)	0.3923*** (0.0660)	0.8022*** (0.1716)
Months since move × move from **risky to safe** neighborhood	-0.4615*** (0.1072)	-1.0126*** (0.1872)	0.1023** (0.0460)	0.2369*** (0.0812)	0.3530*** (0.0832)	0.7580*** (0.1540)
Months since move × move from **safe to risky** neighborhood	-0.4540*** (0.1031)	-0.9835*** (0.1693)	0.0869 (0.0563)	0.2161** (0.0994)	0.4488*** (0.1303)	0.8461*** (0.2160)
Months since move × move from **risky to risky** neighborhood	-0.4434*** (0.0935)	-0.9755*** (0.1717)	0.0084 (0.0557)	0.1382 (0.1026)	0.1567* (0.0810)	0.5536*** (0.0801)
p-value cohort-FE=0		0.0290		0.0083		0.0393
Number of observations	411,499	411,499	389,373	389,374	192,978	192,978
R-Squared	0.034	0.034	0.020	0.020	0.024	0.024

Notes. Results show coefficients for linear regression similar to equation (7). Coefficients are multiplied by a factor of 1,000. A neighborhood is denoted as safe if the crime rate is below average. A neighborhood is denoted as risky if the 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 municipality and year interactions are not shown. Robust standard errors (clustered at municipality level) are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.

Table A3. Effect of time since the move date on risk perception and avoidance behavior, by level of crime in current and previous place of residence, ordered logit regressions

	"Bicycle theft is rare in neighborhood"		"Burglary is rare in neighborhood"		"Theft from car is rare in neighborhood"	
	Without cohort FE (1)	With cohort FE (2)	Without cohort FE (3)	With cohort FE (4)	Without cohort FE (5)	With cohort FE (6)
Months since move × move from **safe to safe** neighborhood	-3.3164*** (0.4309)	-5.0376*** (0.9251)	-3.4189*** (0.3916)	-6.7704*** (0.8918)	-4.9868*** (0.4272)	-6.9196*** (0.9477)
Months since move × move from **risky to safe** neighborhood	-3.3499*** (0.4621)	-5.0678*** (0.9077)	-3.4952*** (0.4156)	-6.8484*** (0.9173)	-4.7069*** (0.5217)	-6.6396*** (1.0155)
Months since move × move from **safe to risky** neighborhood	-0.5120 (0.4706)	-2.3578** (0.9515)	-2.9154*** (0.5230)	-6.2134*** (0.9853)	-2.7883*** (0.4757)	-4.6752*** (0.9488)
Months since move × move from **risky to risky** neighborhood	-1.4584*** (0.3692)	-3.3054*** (0.8849)	-2.7133*** (0.4583)	-6.0332*** (0.9576)	-2.7428*** (0.4131)	-4.6497*** (0.9367)
p-value cohort-FE=0		0.0463		0,0114		0.3332
Number of observations	425,593	425,593	447,487	447,487	428,190	428,190
Pseudo R-Squared	0.0481	0.0481	0.0185	0.0186	0.0384	0.0384

Notes. Results show coefficients for ordered logit regression. Coefficients are multiplied by a factor of 1,000. A neighborhood is denoted as safe if the crime rate is below average. A neighborhood is denoted as risky if the 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 year fixed effects are not shown. Robust standard errors are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.

Table A3. Effect of time since the move date on risk perception and avoidance behavior, by level of crime in current and previous place of residence, ordered logit regressions (continued)

	"Violent crime is rare in neighborhood"		"Frequently avoids unsafe places in neighborhood"		"Frequently doesn't allow children to go to some places in neighborhood"	
	Without cohort FE (7)	With cohort FE (8)	Without cohort FE (9)	With cohort FE (10)	Without cohort FE (11)	With cohort FE (12)
Months since move × move from **safe to safe** neighborhood	-4.0211*** (0.5758)	-7.7088*** (1.1150)	-3.5050*** (0.5522)	-4.6187*** (1.0360)	-3.9973*** (0.5747)	-5.6213*** (1.1461)
Months since move × move from **risky to safe** neighborhood	-3.5814*** (0.7199)	-7.2709*** (1.2074)	-2.2159*** (0.5731)	-3.3441*** (1.0632)	-4.5403*** (0.5987)	-6.1642*** (1.1818)
Months since move × move from **safe to risky** neighborhood	-3.4460*** (0.5690)	-6.9616*** (1.1554)	-2.9913*** (0.5474)	-4.1057*** (0.9791)	-3.8578*** (0.7422)	-5.4578*** (1.2022)
Months since move × move from **risky to risky** neighborhood	-3.2089*** (0.4060)	-6.7671*** (1.0654)	-1.601*** (0.4272)	-2.8123*** (0.9625)	-3.1107*** (0.5040)	-4.7046*** (1.1140)
p-value cohort-FE=0		0.0141		0.2068		0.1357
Number of observations	410,675	410,675	388,664	388,664	192,678	192,678
R-Squared	0.0626	0.0627	0.0530	0.0531	0.0439	0.0439

Notes. Results show coefficients for ordered logit regression. Coefficients are multiplied by a factor of 1,000. A neighborhood is denoted as safe if the crime rate is below average. A neighborhood is denoted as risky if the 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 year fixed effects are not shown. Robust standard errors are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.

Table A4. Effect of time since the move date on risk perception and avoidance behavior, by level of crime in current and previous place of residence, Heckman selection model for "don't know" answers

	"Bicycle theft is rare in neighborhood"		"Burglary is rare in neighborhood"		"Theft from car is rare in neighborhood"	
	1st stage estimation (1)	2nd stage estimation (2)	1st stage estimation (3)	2nd stage estimation (4)	1st stage estimation (5)	2nd stage estimation (6)
Months since move × move from **safe to safe** neighborhood	5.3552*** (0.3933)	-0.8227*** (0.1530)	5.3792*** (0.4228)	-1.3734*** (0.1472)	5.3111*** (0.4041)	-1.2645*** (0.1521)
Months since move × move from **risky to safe** neighborhood	5.1507*** (0.4075)	-0.8800*** (0.1593)	5.3078*** (0.4371)	-1.3953*** (0.1536)	5.2026*** (0.4186)	-1.2483*** (0.1586)
Months since move × move from **safe to risky** neighborhood	4.0142*** (0.4131)	-0.4629*** (0.1618)	5.1211*** (0.4361)	-1.2280*** (0.1600)	5.0893*** (0.4219)	-0.9152*** (0.1639)
Months since move × move from **risky to risky** neighborhood	3.8414*** (0.3738)	-0.6205*** (0.1457)	5.1106*** (0.3959)	-1.1216*** (0.1442)	4.7428*** (0.3820)	-0.8702*** (0.1473)
"Don't know" answer about availability of playgrounds	-0.4047*** (0.0073)		-0.3820*** (0.0078)		-0.4037*** (0.0074)	
Number of observations	526,740	526,740	526,668	526,668	526,137	526,137

Notes. Results show coefficients for Heckman selection model. Coefficients for months since the move date are multiplied by a factor of 1,000. A neighborhood is denoted as safe if the crime rate is below average. A neighborhood is denoted as risky if the 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 year fixed effects are not shown. Robust standard errors are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.

Table A4. Effect of time since the move date on risk perception and avoidance behavior, by level of crime in current and previous place of residence, Heckman selection model for "don't know" answers (continued)

	"Violent crime is rare in neighborhood"		"Frequently avoids unsafe places in neighborhood"		"Frequently doesn't allow children to go to some places in neighborhood"	
	1st stage estimation (7)	2nd stage estimation (8)	1st stage estimation (9)	2nd stage estimation (10)	1st stage estimation (11)	2nd stage estimation (12)
Months since move × move from **safe to safe** neighborhood	3.3967*** (0.3957)	-1.2729*** (0.1232)	0.6683 (0.7944)	0.3484*** (0.0719)	2.9217*** (0.7137)	0.9018*** (0.1337)
Months since move × move from **risky to safe** neighborhood	3.3815*** (0.4102)	-1.2326*** (0.1284)	1.4212* (0.8363)	0.3057*** (0.0748)	3.0410*** (0.7537)	0.8351*** (0.1389)
Months since move × move from **safe to risky** neighborhood	3.3085*** (0.4125)	-1.1922*** (0.1331)	-0.1047 (0.8568)	0.2735*** (0.0763)	3.0627*** (0.7873)	0.9391*** (0.1480)
Months since move × move from **risky to risky** neighborhood	3.4763*** (0.3731)	-1.1811*** (0.1199)	0.9064 (0.7729)	0.2075*** (0.0691)	3.4001*** (0.7112)	0.6517*** (0.1313)
"Don't know" answer about availability of playgrounds	-0.3721*** (0.0074)		-0.1964*** (0.0143)		-0.5541*** (0.0172)	
Number of observations	526,486	526,486	402,242	402,242	225,078	225,078

Notes. Results show coefficients for Heckman selection model. Coefficients for months since the move date are multiplied by a factor of 1,000. A neighborhood is denoted as safe if the crime rate is below average. A neighborhood is denoted as risky if the 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 year fixed effects are not shown. Robust standard errors are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.

Table A5. Effect of time since the move date on risk perception and avoidance behavior, by level of crime in current and previous place of residence, restrict sample to municipalities with 100+ observations

	"Bicycle theft is rare in neighborhood"		"Burglary is rare in neighborhood"		"Theft from car is rare in neighborhood"	
	Without cohort FE (1)	With cohort FE (2)	Without cohort FE (3)	With cohort FE (4)	Without cohort FE (5)	With cohort FE (6)
Months since move × move from **safe to safe** neighborhood	-0.4167*** (0.1319)	-0.8160*** (0.2128)	-0.8358*** (0.1149)	-1.5130*** (0.2001)	-0.8560*** (0.1139)	-1.3573*** (0.2006)
Months since move × move from **risky to safe** neighborhood	-0.5628*** (0.1200)	-0.9638*** (0.1987	-0.8303*** (0.1052)	-1.5079*** (0.1968)	-0.9093*** (0.1308)	-1.4111*** (0.2250)
Months since move × move from **safe to risky** neighborhood	-0.3036*** (0.1145)	-0.7247*** (0.1978)	-0.6617*** (0.1357)	-1.3363*** (0.2090)	-0.7126*** (0.1405)	-1.2101*** (0.2174)
Months since move × move from **risky to risky** neighborhood	-0.3762*** (0.0715)	-0.7998*** (0.1726)	-0.5568*** (0.0865)	-1.2358*** (0.1769)	-0.6448*** (0.0769)	-1.1478*** (0.1801)
p-value cohort-FE=0		0.1209		0.0029		0.0365
Number of observations	360,319	360,319	379,211	379,211	362,218	362,218
R-Squared	0.023	0.023	0.044	0.044	0.025	0.025

Notes. Results show coefficients for linear regression as in Equation (7). Coefficients are multiplied by a factor of 1,000. A neighborhood is denoted as safe if the crime rate is below average. A neighborhood is denoted as risky if the 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) are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.

Table A5. Effect of time since the move date on risk perception and avoidance behavior, by level of crime in current and previous place of residence, restrict sample to municipalities with 100+ observations (continued)

	"Violent crime is rare in neighborhood"		"Frequently avoids unsafe places in neighborhood"		"Frequently doesn't allow children to go to some places in neighborhood"	
	Without cohort FE (7)	With cohort FE (8)	Without cohort FE (9)	With cohort FE (10)	Without cohort FE (11)	With cohort FE (12)
Months since move × move from **safe to safe** neighborhood	-0.4041*** (0.0901)	-1.1023*** (0.1804)	0.1835*** (0.0521)	0.4039*** (0.1113)	0.2776*** (0.0997)	0.7329*** (0.1870)
Months since move × move from **risky to safe** neighborhood	-0.3233*** (0.1077)	-1.0205*** (0.1966)	0.0752 (0.0497)	0.2960*** (0.1103	0.2651*** (0.0951)	0.7204*** (0.1901)
Months since move × move from **safe to risky** neighborhood	-0.5558*** (0.1369)	-1.2333*** (0.2081)	0.1072 (0.0712)	0.3240*** (0.1134)	0.5112*** (0.1524)	0.9536*** (0.2216)
Months since move × move from **risky to risky** neighborhood	-0.4827*** (0.0811)	-1.1648*** (0.1670)	-0.0024 (0.0473)	0.2153** (0.1038)	0.2090** (0.0939)	0.6532*** (0.1764)
p-value cohort-FE=0		0.0086		0.1084		0.0426
Number of observations	346,040	346,040	327,533	327,533	161,156	161,156
R-Squared	0.023	0.023	0.018	0.018	0.019	0.019

Notes. Results show coefficients for linear regression as in Equation (7). Coefficients are multiplied by a factor of 1,000. A neighborhood is denoted as safe if the crime rate is below average. A neighborhood is denoted as risky if the 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) are given in parentheses. Statistical significance at *** 1% ** 5% * 10% level.