CRIME-RELATED EXPERIENCES AND PERCEPTIONS*

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Abstract

We study how crime-related experiences relate to the crime-related perceptions individuals hold, spanning confidence towards institutions in the justice system, perceptions of their neighborhood, their own safety, fear of being victimized, and how crime impacts their quality of life. We combine 17 waves of the Crime Survey for England and Wales from 2001-18 to contrast two salient crime-related experiences: witnessing a crime and being a victim of crime. While there have been long run declines in rates of victimization, rates of witnessing crime have remained unchanged, due to a change in the composition of crime towards violent crime, that is witnessed at far higher rates than other crime types. We document that: (i) perceptions are negatively associated with either witnessing a crime or being a victim; witnessing crime has larger associations with confidence in the justice system, the police, and views of local neighborhoods, while victimization is more strongly associated with perceptions of personal safety, fear and quality of life; (ii) favorable post-victimization experiences in the justice system help restore confidence in institutions in the justice system, but have limited effects on perceptions of neighborhoods or well-being. We interpret and develop the results through the lens of the Bordalo *et al.* [2024] experience-based learning framework, emphasizing memory and the similarity of experiences to perceptions individuals form. At a second stage of analysis we consider implications for the unit social costs of crime if we account for experiences of witnesses. We show these costs rise by 25% relative to conventional methods that only account for costs to victims. Finally, we show that despite long run declines in victimization rates of 25% over our study period, the aggregate social costs of crime have risen by around 35% once costs to witnesses are accounted for. By accounting for witnesses as well as victims of crime, our analysis helps explain why, as in many countries, perceptions of crime levels have become unanchored from the actual incidence of crime, that has long been trending downwards. *JEL: D63, K42.*

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1 Introduction

Many individuals experience crime through being a victim of crime. In England and Wales, our study setting, in a nationally representative sample of adults from 2015-16, 12% reported being a victim of crime – corresponding to 5.8million individuals, or a victimization occurring every six seconds. However, crime-related experiences extend beyond direct victimization. In the same survey, 31% of individuals report actually witnessing a crime or other form of anti-social behavior. We compare and contrast how different crime-related experiences – either being a direct victim of crime or witnessing crime – shape crime-related perceptions. We consider a wide domain of perceptions individuals hold, spanning confidence towards institutions in the justice system, perceptions of their neighborhood, and more personal perceptions related to their own safety, fears of being victimized, and how crime impacts their quality of life.

Literatures in psychology and economics have documented how personal experiences can persistently shape individual beliefs and behavior [Malmendier 2021], and can exert greater influence on decisions than statistical information [Nisbett and Ross 1980]. We extend this work to understand the importance of distinguishing direct experiences of crime (victimization) and indirect experiences (witnessing) in shaping crime-related perceptions. We thus bridge to work in criminology where there has long been a distinction between direct victimization and indirect (*vicarious*) victimization [Tyler 1980]. We use our findings to reconsider the measurement of the social costs of crime once witnesses are accounted for, ultimately providing insights for why, as in many countries, perceptions of crime levels have become unanchored from the actual incidence of crime, that has long been trending downwards.[1]

Our analysis uses the Crime Survey for England and Wales (CSEW). This cross-sectional survey is fielded annually via face-to-face interviews to a representative sample of $40,000$ adults. We combine and harmonize 17 survey waves from 2001-02 to 2017-18. The survey provides detailed information on witnessing and victimization experiences of crime (measured over the 12 months preceding each survey) and crime-related perceptions. The question wording related to witnessing refers to events actually observed by the respondent (rather than learned from others or the media).

To motivate the importance of both crime-related experiences, we first present time series evidence on victimization rates and crime-related perceptions. As in other countries, victimization rates in England and Wales have declined steadily year-on-year, being 32% lower in 2017-18 than in 2003-04. Crime-related perceptions have improved, but far more modestly than declines in victimization: for example, perceptions of the effect of crime on quality of life are only 3% better in 2017-18 than in 2003-04.

To see what might lead to such a wedge between crime-related experiences and perceptions,

[1] That the incidence of crime has fallen in most Western countries is well documented [Pinker 2012]. Despite this, most individuals think crime is on the rise – a fact documented across countries including the US and UK [Mastrorocco and Minale 2018].

we document that in contrast to victimization rates, rates of witnessing crime have remained stable: they are exactly the same in 2017-18 as in 2003-04. Unpacking witness rates by crime types, we find that rates of witnessing violent crime have risen dramatically, being 30% higher in 2017-18 than in 2003-4. This is because: (i) the composition of crime has shifted towards violent crime; (ii) witnesses per violent crime are 10 times higher than for other crimes; (iii) witnesses per violent crime have risen over time. All this can combine to help explain why aggregate declines in victimization have not translated into corresponding improvements in perceptions of the justice system, neighborhoods, personal safety and how crime impacts quality of life. This underlines the importance of studying experiences of witnessing crime. Our analysis presents a first step in this direction, building on established work on the causes and consequences of victimization.[2]

Our core results on the association between crime-related experiences and crime-related perceptions are as follows.

First, both witnesses to crime and victims of crime report significantly lower perceptions across the board relative to non-victims. Viewed through the lens of experience-based learning frameworks [Malmendier *et al.* 2020a, b, Bordalo *et al.* 2023, 2024, 2025], both victimization and witnessing constitute salient crime-related experiences that meaningfully shape crime-related perceptions. Contrasting witnesses to victims, witnessing crime has larger associations than being a victim of crime for more aggregate perceptions such as confidence in the justice system, confidence in the police, and perceptions of problems in the neighborhood, while being a victim of crime has larger impacts than witnessing crime on more individual perceptions related to personal safety, fear of victimization, and quality of life.

Second, we find strong interactions between witnessing and victimization experiences (especially if they are more similar in terms of the crime type experienced), and dose responses to multiple incidents of the same type of experience. In contrast we find muted experience-information interactions using three proxies for information that individuals might have that help form priors for crime-related perceptions: (i) age; (ii) neighborhood crime rates; (iii) newspaper readership. More precisely, victimization-information interactions are generally weak for all three proxies, that reinforces how salient and traumatic such experiences are for individuals. In contrast, how experiences of witnessing crime translate into perceptions vary with information or priors for some domains, but in a way that such experiences typically worsen perceptions more among those that have worse perceptions to begin with (i.e. those in high crime neighborhoods or daily readers of

[2]There are long established literatures on the causes and consequences of victimization using victimization surveys that are available in many countries, but little of this work in economics has considered witnesses. Well established risk factors for victimization include demographics (gender, age, and race/ethnicity), socioeconomic characteristics (education, employment status, income), risky behaviors, precautionary behaviors and geographic exposure to high crime areas. More recent work has studied how immigration affects perceptions of crime (and crime itself), also using data on self-reported victimization [Ajzenman *at el.* 2023]. On the consequences of victimization, earlier work has considered impacts on feelings of safety and quality of life [Cohen 2008, Dustmann and Fasani 2016], as well as mental health and labor market outcomes [Frijters *et al.* 2011, Braakmann 2012, Cornaglia *et al.* 2014, Johnston *et al.* 2017, Bindler and Ketel 2022].

tabloids). Hence the experience of witnessing crime extenuates inequality in crime-related perceptions.

Third, we examine whether experience effects are malleable to (positive) experiences arising from institutional responses to victimization. Specifically, we exploit the richness of the CSEW data which records how the criminal justice system handled each case of victimization. We construct a categorical measure of post-victimization experience with the justice system, to estimate the perceptions gap between individuals experiencing the most favorable post-victimization experience (an offender being identifier and charged) and the least favorable experience (no offender being identified), conditional on reporting the crime to the police.

We find that favorable post-victimization experiences offset the initial negative impacts of victimization. The largest offsetting effects occur for confidence in the justice system and in the police, followed by offsetting effects on perceptions of being a future victim of crime. For example, the initial $.118\sigma$ fall in confidence in the justice system is more than offset by the $.149\sigma$ rise in confidence in the justice system following positive post-victimization experiences – leaving those that have experienced both events with higher confidence in the criminal justice than non-victims. Similarly, the initial $.121\sigma$ fall in confidence in the police is more than offset by the $.257\sigma$ rise in confidence following positive post-victimization experiences – leaving those with both experiences with higher confidence in the police than non-victims. In contrast, favorable post-victimization experiences appear to have little impact on improving perceptions of neighborhoods, personal safety and how crime affects quality of life.

The second stage of our analysis considers the consequences of these findings for accurately measuring the social costs of crime when taking account of: (i) costs extending beyond victims to witnesses; (ii) victims and witnesses being differentially affected by crime-related experiences; (iii) post-victimization outcomes in the justice system mitigating (or amplifying) victimization costs.

To do so, we take an established approach to measuring the social costs of crime in our study context and study period [Heeks *et al.* 2018]. For each crime type, their cost estimate can be decomposed into those arising from anticipation/avoidance behaviors, consequences of victimization, and other costs borne by victims and institutions in the justice system. Under a first (naive) approach, we assume witnesses bear the same unit cost as victims for those components of the Heeks *et al.* [2018] decomposition that our results on perceptions suggest could plausibly be affected for both victims and witnesses. For each crime type, we take the victim costs for these components and assign them to witnesses, while setting witness costs to zero for the remaining components. Under this approach the average unit social cost of crime rises by 59%. Across crime types, social costs are underestimated by between 26% and 69%, with the largest effect for violent crime. Our second approach relaxes the assumption that witnesses are affected by their experiences to the same extent as victims. Instead, we use our estimates of the association between crime-related experiences on crime-related perceptions to scale witness costs relative to victimization costs. The implied average unit social cost of crime still rises by 25% relative to

conventional methods, ranging from a 28% increase for violent crime, to a 14% increase for theft.

Hence standard approaches to calculating the social costs of crime substantially underestimate the true costs once we factor in crime-related experiences such as witnessing crime. This is a first order issue given the divergence between rates of crime victimization and rates of witnessing crime described earlier. *A fortiori*, the returns to crime-reducing interventions – especially those aiming to reduce violent crime – are far higher than previously recognized. Interventions considered not to be cost effective under conventional measures might prove to be cost effective once a wider set of impacts on witnesses are properly accounted for.

We then account for the third insight from our analysis: that favorable post-victimization outcomes can potentially mitigate some of the negative impacts of initial victimization on crime-related perceptions, and hence the costs of victimization. We explore the issue by adjusting victim unit costs to account for favorable post-victimization outcomes. We find the implied victim unit costs among those experiencing favorable post-victimization outcomes *rise* when these additional experiences are accounted for. The reason is that such experiences: (i) offset initial falls in confidence in the justice system and police, but these perceptions play no role in the social cost calculation based on the costs components in Heeks *et al.* [2018]; (ii) the key routes by which they influence social costs is through positive or negative changes in how crime affects quality of life, depending on the crime type. This last channel explains why victimization costs increase by 27-30% averaging across all crime types when favorable post-victimization outcomes are accounted for, but can rise or fall when considering particular crime type. Specifically, victimization costs decrease by 15-20% for those experiencing criminal damage, they remain unchanged for victims of burglary, and they rise for theft and victims of violent crime by 12% and 36% respectively.

These results have implications for the returns to investing into the justice system, or any channel through which the likelihood of favorable post-victimization outcomes increases. First, for some crime types – such as criminal damage – the returns to such investments are high because they substantially reduce victimization costs. For other crime types – most notably violent crime such as assaults – the results highlight the importance of investing in parts of the justice system that reduce negative impacts on perceived quality of life of victims, when their offenders are identified and charged (what we have referred to as a favorable outcome). Improving victim support might be one such avenue. By considering whether and how favorable post-victimization experiences in the justice system have mitigating impacts of the initial victimization, we start to open the black box of interactions between victimization and the criminal justice system, that has not been studied in the economics literature [Ketel *et al.* 2020].

Finally, a key purpose of measuring social costs by crime type is to make informed choices about the cost effectiveness of targeting resources to prevent crime. Given the changing composition of crime – that has seen a relative shift towards violent crime – trends in the aggregate social costs of crime might not be as pronounced downwards as would otherwise be implied by long run trends of falling victimization rates. We examine this by constructing annual estimates of the aggregate

social costs of crime taking into account witness costs from 2003-04 to 2014-15. We find that over this period: (i) victimization rates have fallen by 25%; (ii) using a standard methodology to measure the costs of crime arising from victims only (but that accounts for a changing composition of crime), the aggregate social costs of crime have still fallen – but by only 10% – reflecting the shift towards violent crime; (iii) when costs to witnesses are also accounted for, the aggregate social costs of crime have *risen* by 35%. If we consider these monetary costs of crime to victims and witnesses translating into utility losses, the result helps explain why individual perceptions of crime might be worsening over time, despite victimization rates falling – a puzzle that has long been considered across the social sciences [Garland 2001, Esberg and Mummolo 2018]. As a confirmation of this, we show that: (i) experiences of witnessing crime and being a victim of crime both increase the perception that national and local crime rates are rising; (ii) reinforcing the notion that witnessing might be key to understanding diverging trends between actual and perceived crime, witnessing crime has a significantly larger partial correlation than being a victim of crime with perceived changes in national crime rates ($p = .037$).

Our analysis contributes to two core literatures in economics.

First, we place witnesses centrally into the analysis of the economics of crime. Two prominent reviews of this literature, 25 years apart, mention the experience of witnessing crime zero times [Freeman 1999, Hjalmarsson *et al.* 2024]. This is despite the prevalence of such indirect experiences being as high as direct experiences of victimization, witnesses being impacted across a domain of perceptions, and this having implications for measuring the social costs of crime and thus evaluating crime-reducing interventions. At the same time, Hjalmarsson *et al.* [2024] argue that the economics of victimization lies at the frontier of crime research, and, 'despite this staggering statistic [on the estimated social cost of crime] little attention has historically been given to improving the measurement of these costs.' A feature of the wider literature has been a shift away from using survey data to using administrative records. While this has generated numerous insights, a limitation is that information on witnessing crime is generally unavailable from administrative data, either in our study setting or in most other countries.[3]

Second, we extend the empirical literature on experience-based learning, that has shown how experiences exert persistent effects on individual beliefs and behavior in a range of economic applications, including stock market participation, inflation expectations, consumption and home ownership. We extend these ideas to the context of crime-related experiences to: (i) examine the impacts of individual rather than aggregate experiences; (ii) contrast direct and indirect expe-

[3]The closest parallel to the study of witnesses is work examining effects of neighborhood exposure to violence or crime on educational outcomes [Ang 2021, Koppensteiner and Menezes 2021, Cabral *et al.* 2025]. Another strand of literature has explored indirect exposure of victimization, where exposure is measured through proximity to victims such as being a family member [Cohen 2005, Bindler and Ketel 2019, Bhuller *et al.* 2024], classmate [Monteiro and Rocha 2017], or neighbor [Cornaglia *et al.* 2014, Dustmann and Fasani 2016]. For both literatures, witnessing could be a key mechanism driving effects, but it is difficult to separate the effects of witnessing crime, becoming informed of the crime, or being affected through behavioral impacts on victims themselves.

riences; (iii) consider negative and positive experiences (within the same individual). We show how key ideas underlying experience-based learning especially those based on memory and retrieval [Bordalo *et al.* 2020, 2024, 2025] – such as the *similarity* of experiences and domains of perception, help interpret our findings.[4]

The paper is organized as follows. Section 2 discusses how the link between crime-related experiences and crime-related perceptions can be interpreted through the lens of experience-based learning models. Section 3 describes the data and presents novel evidence on characteristics of witnesses, including witness-age profiles. Section 4 presents our main results on how experiences of crime associate with perceptions, and the malleability of these effects due to post-victimization experiences in the justice system. Section 5 discusses implications for measuring the social cost of crime. Section 6 concludes by describing a future research agenda. The Appendix details the sample, variable definitions and data construction used in our analysis, further robustness checks, and the social cost of crime calculations.

2 Framework

We interpret any link between crime-related experiences and crime-related perceptions through the lens of experience-based learning [Bordalo *et al.* 2020, Malmendier *et al.* 2020a]. We focus on models based on memory and retrieval, drawing closely on the framework developed by Bordalo *et al.* [2024] because: (i) victimization and witnessing are highly salient crime-related experiences; (ii) these experiences enter individual's memory retrieval-simulation process when cued to form crime-related perceptions by in-person CSEW interviewers. To motivate the potential importance of direct experiences on the formation of crime-related perceptions, Table 1 shows evidence from the CSEW over our study period on the sources individuals report using to form their crime-related perceptions. Personal experiences play an important role, as do vicarious experiences of others, news sources, and the internet. While our focus is on direct experiences, our later analysis considers the roles of other sources.

The Bordalo *et al.* [2024] approach fits within the general framework of Bayesian learning, placing more structure on how individuals update their perceptions in light of new evidence. When an individual is cued to form a crime-related perception, they draw on both their experiences and information. We exposit the key features of the framework focusing on the retrieval from memory

[4]The term *experience effects* was coined in the context of individuals living through and experiencing realizations of aggregate macroeconomic or financial shocks, or political environments. Giuliano and Spilimbergo [2025] synthesize findings from across disciplines on how aggregate shocks such as recessions, inflation, and trade shocks, alongside noneconomic shocks like migrations, wars, terrorist attacks, pandemics, and natural disasters, shape beliefs, attitudes and behaviors. Malmendier and Shen [2024] study how consumption decisions are impacted by personal, local, or national experiences of unemployment. Using data from the PSID they find consumption spending is significantly and permanently lower for individuals who have experienced their own or someone else's unemployment, with the largest effect coming from a personal experience. They also document experience effects on beliefs about their own financial situation, savings behavior and wealth accumulation.

of experiences, and come back to discuss the role of information. Experiences can be domain or non-domain specific, so more or less related to the perception being formed. In our study context, domain specificity depends on: (i) the perception being considered, whether it relates to 'aggregate' beliefs towards the justice system, to the more personal or 'local' beliefs, reflecting views of individual safety, fear and well-being; (ii) the experience of witnessing a crime or being a victim of it; (iii) the type of crime experienced.[5]

The central idea in this framework, based on evidence from psychology and neuroscience, is that whatever experiences are retrieved from memory, they are used to simulate the perception based on their *similarity* to it. At the same time, experiences compete to be retrieved from memory, so that some domain specific experiences can be partially neglected because of a process of interference, even those that provide better material to simulate a perception with. This second feature diverges from standard learning models such as Bayesian updating, in which more informative experiences, i.e. those that are domain-specific, always receive greater weight in forming perceptions.[6]

Following Bordalo *et al.* [2024], we consider an individual forming a crime-related perception, $\pi \in [0,1]$, that can be the likelihood of an event (e.g. being a future victim of crime) or an assessment of the state of the world (e.g. confidence in the justice system). Individual experiences are stored in a database E, and individuals are cued to form perception π by the in-person CSEW interviewer. Experiences more similar to the cue in the database E are more likely to be retrieved, and they inhibit recall of less similar experiences. A symmetric function $S : E \times E \to [0,1]$ measures the similarity between experiences. Consider a set of experiences, A, that captures: (i) having experienced being a victim (e^v), and specific features of the victimization such as the type of crime, its location and so on (e^v_{type}, $e^v_{location}$, ..); (ii) all other experiences (including information) of the individual ($\Im$). Hence $A = \{e^v_{type}, e^v_{location}, .., \Im\}$. The similarity between sets of experiences A, $B \subset E$ is the average pairwise similarity of their elements:

$$S(A,B) = \sum_{e \in A} \sum_{e' \in B} S(e,e') \frac{1}{|A|} \frac{1}{|B|}. \tag{1}$$

$S(A,B)$ is symmetric and rises in the overlap in features between A and B. $S(e,\pi)$ is the similarity between experience e and perception π. This increases as e shares more features with π.

Assumption 1: *When forming perception π, the probability the individual recalls experience*

[5] Alternative approaches to experience-based learning include models of over-inference [Fuster *et al.* 2010, Augenblick *et al.* 2025], over-extrapolation [Barberis *et al.* 2015], scarring events altering individual reasoning [Kozlowski *et al.* 2020], and motivated reasoning [Thaler 2024].

[6] Bordalo *et al.* [2023, 2024, 2025] detail the evidence from psychology and neuroscience on simulation as a form of reasoning or thinking about the future by analogy, and how the recall of experiences is driven by similarity and interference.

$e \in E$, denoted $r(e)$, is proportional to its similarity to the event, $S(e, \pi)$:

$$r(e) = \frac{S(e, \pi)}{\sum_{e \in E} S(e, \pi)}. \tag{2}$$

The numerator implies experience $e \in E$ is sampled more frequently when it is more similar to π. The denominator captures interference: all experiences compete for retrieval, and may inhibit recollection of e, especially experiences that are more similar, frequent or recent, to the cue.

This establishes the experiences retrieved when cued to form perception π. The next step is simulation – the process of using the features of e to form perception π. The higher the number of features the two have in common, i.e. the higher their similarity, the stronger is the simulation

Assumption 2: *Based on the retrieved experience $e \in E$, the individual simulates π with probability $\sigma(e) \in [0, 1]$ that increases in similarity: $\sigma(e) \geq \sigma(e')$ if and only if $S(e, \pi) \geq S(e', \pi)$.*

Similarity between the experience and perception being cued to be recalled by CSEW interviewers thus plays two roles: it aids recall of an experience e (Assumption 1) and it aids simulation of the perception π (Assumption 2). Combining (1) and (2), when sampling from the database of experiences the individual recalls $e \in E$ with probability $r(e)$, and simulates π with $\sigma(e)$. Their simulation of perception π, averaged across all experiences, is:

$$\widehat{\pi}_E = \sum\nolimits_{e \in E} r(e)\sigma(e) = \frac{\sum_{e \in E} \sigma(e) S(e, \pi)}{\sum_{e \in E} S(e, \pi)}. \tag{3}$$

The framework makes precise that the impact of a given crime-related experience can vary across perceptions, depending on its similarity to the perception. For example, if victimization is more similar to personal or local perception domains related to personal well-being, such as safety, fear of victimization, or quality of life, then these perceptions will respond more strongly to experiences of victimization than to witnessing. Conversely, if witnessing is more similar to more aggregate perception domains, such as beliefs about the neighborhood or justice institutions, these perceptions will react more strongly to experiences of witnessing crime than to victimization. Our results can be interpreted within this mapping between experiences and a range of perceptions, what Bordalo *et al.* [2024] refer to as a similarity-based hierarchy of experience effects.

The information individuals have, say from news or social networks, can be considered as another experience $\Im$ in their database E. Our later empirical analysis considers how various sources of information that individual have, interact with crime-related experiences, as both compete for retrieval when cued to form crime-related perceptions.[7]

[7] We diverge from Bordalo *et al.* [2024] in that in their model, when combining the use of information (statistics) and experiences, individuals have an average assessment of π given by $\widehat{\pi} = (1 - \theta)\pi + \theta\widehat{\pi}_E$ where with probability $1 - \theta$ the individual samples the statistical truth π, and reports its value, and with probability θ, she samples experiences and uses them to simulate the target perception, and θ captures the reliance on experiences.

3 Data and Descriptives

3.1 Crime Survey of England and Wales

Our analysis uses the Crime Survey for England and Wales (CSEW). This cross-sectional survey is fielded annually via face-to-face interviews to around 40,000 adults aged 16 and older, and is representative of the population in England and Wales. The survey provides detailed information on experiences of crime, perceptions of institutions of the justice system, neighborhoods, individual safety and quality of life. The data is ideally suited to our research questions for four reasons.

First, it provides information on witnessing crime – something not typically recorded in administrative data. This allows us to make inroads in understanding the importance of this experience relative to direct experiences of victimization. Second, the CSEW samples victims and non-victims, with a module specifically administered to victims in the 12 months preceding the survey. This recall period balances a trade-off between biased recall of events occurring long ago, against the salience of recent experiences. Recency bias leads to more recent experiences being more likely to be retrieved from memory when individuals are cued to form perceptions. Third, it captures victimization incidents that are never reported to the police, and is therefore unaffected by changes in police recording practices. The CSEW suggests only 43% of offenses are reported to the police, with variation by crime type and the perceived severity of the crime. Hence this data provides a more comprehensive picture than administrative data on victimization experiences. Finally, it gathers information on post-victimization outcomes in the justice system such as whether the crime was reported, actions taken by the police and whether an offender was identified or charged. We can thus explicitly distinguish between positive and negative experiences, to understand whether they differentially enter the retrieval-simulation process.

We combine 17 survey waves from 2001-02 to 2017-18, covering 684,581 individual respondents. This period is chosen to ensure consistent availability of our key variables and to avoid changes to the survey design following the COVID-19 pandemic. The Data Appendix details the sample, variable definitions and data construction used in our analysis.

3.2 Key Variables

3.2.1 Crime-related Experiences

Witnesses In the majority of survey waves (2003-04 to 2007-08, 2011-12 to 2014-15, and 2017-18) the CSEW provides information on whether respondents have experienced witnessing a crime or forms of anti-social behavior (ASB), in the preceding 12 months. The question wording related to witnessing refers to events actually observed by the respondent (rather than learned from the media or other sources). Anti-social behaviors include potential crimes such as vandalism, threatening or violent behavior, or drug crimes. For our main analysis we combine both experiences

as they correspond to witnessing illicit behavior of others, that some respondents might classify as having witnessed a crime, and others classify as having witnessed ASB. For expositional ease, we refer to both experiences as having witnessed crime.

Victims Each survey wave asks respondents whether they have been a victim of crime in the preceding 12 months. Information is recorded for multiple victimizations over this period. For each victimization, the data records the month of occurrence, the type of crime, whether it was reported to the police, and information on subsequent case handling, such as whether an offender was found or charged. We restrict our analysis to those reporting a single victimization within the reference period. In our overall sample, 64% of victims experience a single incident. By focusing on single incident victims, we isolate how perceptions evolve following a one-off experience of victimization and avoid confounding effects from multiple incidents occurring at different time horizons. The fact that single incidents are as good as randomly timed relative to the survey date enables us to study the persistence of such experiences on crime-related perceptions.[8]

To ensure comparability with the experience of witnessing a crime, our main analysis focuses on respondents who report witnessing a single crime type within the reference period, corresponding to 55% of all witnesses. We later separately examine how interactions between the two types of experience associate with perceptions, as well as dose responses to multiple experiences of victimization and witnessing crime.

Post-victimization The CSEW records how the criminal justice system handled each case of victimization, in the period from victimization up until survey date, so potentially up to 12 months since the incident. Among single-incident victims, 43% report the incident to the police, 10% have an offender identified, and 4% have an offender both identified and charged. We use this to understand whether such post-victimization experiences shift individual perceptions, and the extent to which, within the same person, positive experiences post-victimization offset negative impacts across perception domains from the original negative victimization experience.

3.2.2 Crime-related Perceptions

The domains of perceptions we consider range from 'aggregate' beliefs towards the justice system and police, to the more personal or 'local' beliefs, reflecting views of the individual's own safety, fears and well-being. We consider this breadth of domains to link to the feature of the memory-

[8]Figure A1 shows the distribution of months since last victimization by the number of incidents. Panel A highlights that for individuals with a single victimization incident the distribution of months since last victimization is uniform, so such experiences are as good as randomly distributed across the 12 months preceding interview. As interviews take place uniformly through the month, the incidence of victimizations in the actual month of the survey (month = 1) are exactly half those of other months. In contrast, Panel B shows the distribution for multiple-incident victims is mechanically skewed toward more recent months because the data refers to the *last* victimization incident.

based framework – that the impact of crime-related experiences can vary across crime-related perceptions, depending on their similarity to the perception being formed. The four domains of perceptions considered are as follows.

Institutions: We consider two measures of perceptions of confidence in institutions in the justice system: respondents' confidence in the effectiveness of the criminal justice system, and their confidence in the police.

Local Neighborhoods: We construct an index of the perception respondents' hold about their neighborhood, based on seven survey items asking the extent to which various problems occur in their local area: noisy neighbors, teenagers loitering, littering, vandalism, drug use or dealing, public drunkenness, and abandoned cars. These problems span crime- and non-crime domains. The survey makes clear local is within 15 minutes walk of their home.

Own Safety: We consider two perceptions: how safe respondents feel when walking alone after dark, and by constructing an index of worrying about specific types of victimization – being burgled, mugged, or attacked.

Quality of Life: Respondents are asked to rate the effect of crime on their quality of life.

The questions measuring these perceptions use Likert-scale responses. To facilitate comparability across domains, after constructing each perception measure, we standardize the outcomes within our working sample. We thus relate crime-related experiences to effect size associations with each perception. We sign each perception so that positive values indicate better outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life.

As detailed in the Appendix, perceptions related to individuals' neighborhood, safety and quality of life are elicited before questions on victimization. The CSEW later asks about perceptions of institutions of the justice system. The last part of the survey asks respondents about other experiences, including witnessing crime. This ordering ensures that some perception measures used in our analysis are collected prior to respondents being prompted to recall specific crime-related experiences related to victimization, and all perception measures are asked prior to collecting information on witnessing crime. This ordering ameliorates concerns about anchoring or priming effects of experiences on perceptions.[9]

3.3 Descriptive Evidence

Perceptions and Characteristics by Experience Given our initial focus on single incident victims and witnesses to a single crime, our working sample covers 271,403 individuals: 29% report

[9] Criminologists often distinguish between confidence, trust and legitimacy of the police [Bradford *et al.* 2025]. We focus on a measure of confidence as this is consistently available across survey waves. As detailed in the Appendix, the wording of the perceptions questions specify the institutions, geographies or nature of concern being asked about – ameliorating concerns over subjective interpretation and researcher discretion.

having witnessed a crime in the 12 months preceding the survey; 13% report having been a victim of a crime. So the incidence of victimization is less than half that of witnessing, underlining the importance of considering both crime-related experiences. The sample divides into four mutually exclusive groups: 172,063 (63%) are non-victims and non-witnesses, 63,812 (24%) are witnesses and non-victims, 21,248 (8%) are victims and non-witnesses, and 14,280 (5%) are victims and witnesses. This variation allows us to separately identify the impact of each experience.

Table 2 presents descriptives on perceptions by experiences of crime. Along each margin, non-victims with no crime-related experience (Column 1) have more positive beliefs than those with recent crime-related experiences – they report significantly higher confidence in the justice system and police, fewer problems in their neighborhood, they are less worried about being victimized, and their quality of life is less impacted by crime. Comparing only witnesses to only victims (Columns 2 and 3), witnesses have more positive perceptions than victims on nearly all margins, except confidence in the police, in which the two groups do not differ. Perception gaps between witnesses and victims (Columns 2 and 3) tend to be smaller than those between witnesses and non victims (Columns 1 and 2).

The final set of comparisons are made within small geographies – in England and Wales these are known as Lower Layer Super Output Areas (LSOAs), comprising 400 to 1200 households (a resident population between 1000 and 3000) – so far smaller than US census tracts. Comparing within-LSOA perception gaps between non-victims and witnesses or victims, we see the magnitudes of differences are often comparable to the raw differences in perceptions across groups, suggesting geographic variation in crime rates across LSOAs does not help explain the variation in perceptions. Comparing only witnesses to only victims (Columns 2 and 3): (i) witnesses maintain higher confidence in the justice system, the police, and view their neighborhood to be better; (ii) for more local domains of crime-related perceptions related to individual safety, worry, or quality of life, witnesses and victims do not have significantly different perceptions.

To understand how these perception gaps might relate to observables, Panel A of Figure 1 shows characteristics of each group, where the histogram shows characteristics of non-victims and non-witnesses. As expected, witnesses and victims are more likely to be male, reside in urban areas and to not be married than non-victims/non-witnesses. Witnesses are closer in characteristics to victims than to non-victims on most margins, with differences in observables between these groups being small. One exception is age where witnesses are older than victims. To see this more clearly, Panel B shows victimization- and witnessing-age profiles. The victimization-age profile is in line with what has been much documented in the literature. The witnessing-age profile is far less established: we see that at any given age, individuals are more likely to witness a crime than be a victim of it, but this gap narrows with age.[10]

[10]Sociologists and criminologists have long studied correlates of criminal victimization [Hale 1996, Bindler *et al.* 2020]. Much of this focuses on risk factors for violent crime and sex offense victimization, given the higher costs associated with such crimes. For England and Wales, Jansson [2008] used the CSEW to compare risk factors for

Time Series of Perceptions, Victimization and Witnessing Panel A of Figure 2 shows the time series of each domain of crime-related perception, normalizing each to 100 in 2003-4. Perceptions have improved over time. For example, since 2008-09 confidence in the justice system has risen and by the end of our sample period it is 13% higher than in 2003-04. Confidence in the police has also steadily risen, being 9% higher in 2017-18 than in 2003-04. Perceptions of neighborhoods have also steadily improved, as have perceptions of personal safety and the effect of crime on quality of life, being 8% and 3% higher (respectively) in 2017-18 than in 2003-04.

Panel B shows that victimization rates have declined steadily year-on-year, being 32% lower in 2017-18 than in 2003-04. Hence the fall in victimization rates is far larger than any improvements in crime-related perceptions over the same period. To see what might lead to this wedge, we see that, in contrast to victimization rates, rates of experiencing witnessing crime have remained stable: they are exactly the same in 2017-18 as in 2003-04. Panel C further unpacks witness rates into those for: (i) non-violent crime; (ii) violent crime (assaults and threats). While rates of witnessing non-violent crime follow the steady decline in victimization rates, rates of witnessing violent crime have risen dramatically, being 20-40% higher from 2010-11 than they were in 2003-4. Increasing rates of experiencing witnessing violent crime can either be due to: (i) the composition of crime shifting towards violent crime; (ii) witnesses per violent crime rising.

To check explanation (i), Panel D shows rates of victimization by crime type. Violent crime has made up a larger share of all crimes over time: in 2003-4 they constituted 10% of all crimes, and by 2017-18 they constituted 20%.

To check explanation (ii), Panel A of Table 3 shows witnessing rates, victimization rates and their ratio, aggregating across all crimes. In most years, the share of adults that report witnessing a crime is the same or higher than the share reporting a victimization. Over time, the fall in victimization rates coupled with the constancy of witness rates means that while in 2003-4 the ratio of witnesses per victim was .920, this has risen to 1.21 by 2014-15.[11]

Panel B breaks this down by crime type. Two points are of note. First, the ratio of witnesses to victims for violent crime is far higher than for other crime types – in 2003-4 it is 4.69, while the ratio is less than one for all other crime types. Second, over time the ratio of witnesses to victims for violent crime has risen, from 4.69 in 2003-4 to 5.92 by 2014-15, a 26% rise. This is in contrast to other crimes where the ratio has either fallen over time (criminal damage), remained largely constant (burglary), or risen less dramatically (theft).[12]

violent crime victimization 25 years apart (1981 vs. 2005/6). In both survey rounds, individuals who are male, relatively younger and/or are single, face higher risks. Analyses of US national crime victimization surveys also highlight an increased risk of violent crime victimization for males, younger individuals, minorities (blacks and Hispanics), single individuals, low-income households, and city dwellers, and higher risks of property crime for those who are young, single, city dwellers, and/or of higher income [Zawitz *et al.* 1993]. The victimization- and witnessing-age profiles are very similar if we consider multiple victims and witnesses.

[11] Panel A focuses on witnesses and does not include those witnessing ASB because the type of behavior or crime observed is not available in all years. The aggregate rate of witnessing/ASB follows similar flat time trends (as shown in Panel B of Figure 1).

[12] We can rule out that some other trends might be driving the wedge between rates of experiencing victimization

To summarize, the experience of witnessing crime has become relatively more common than the experience of being a victim of crime. This is because of a change in the composition of crime towards more violent crime, witnesses per violent crime are far higher than for other crime types, and trending upwards over time. All this can combine to explain why aggregate long run declines in victimization have not translated into corresponding improvements in perceptions of the justice system, neighborhoods, and personal safety and well-being.

4 Results

4.1 Experiences

Our focus is on comparing witnesses and victims, to shed light on whether exposure to crime, even without experiencing direct harm, correlates to perceptions. We estimate the following specification:

$$y_{i(t)} = \gamma_0 + \gamma_1 Witness_{i(t)} + \gamma_2 Victim_{i(t)} + X'_{i(t)}\theta + \phi_P + \omega_m + \omega_t + \varepsilon_{i(t)}. \quad (4)$$

where $y_{i(t)}$ is the perception of respondent i surveyed in wave t. $Witness_{i(t)}$ is a dummy equal to one if individual i witnessed a crime. $Victim_{i(t)}$ is a dummy equal to one if individual i was a victim. $X'_{i(t)}$ is a vector of individual covariates that pick up many of the characteristics well-established to correlate to victimization – including age (and its square) and education levels, the observables for which there are the most pronounced differences across witnesses and victims. We control for police force area (ϕ_P), month of interview (ω_m), and survey wave fixed effects (ω_t) to account for time-invariant differences across areas, common temporal shocks given seasonality in crime types, and time trends in crime. We assume that within police force area, month and year of interview, perceptions of respondents are independently formed and compute heteroskedasticity-robust standard errors. All estimations apply survey weights.[13]

Panel A of Table 4 shows the estimates, and these are graphically summarized in Panel A of Figure 3, along with their 95% confidence intervals. All perceptions are standardized, so we measure the partial correlations (γ_1, γ_2) in effect sizes.

We find both experiences – being a witness or victim of crime – reduce positive crime-related perceptions across the board ($\widehat{\gamma}_1 < 0$, $\widehat{\gamma}_2 < 0$). Viewed through the lens of the framework, the results confirm that both victimization and witnessing constitute salient crime-related experiences

and witnessing crime, such as changes in the location of crime between rural and urban areas as these patterns show up in both areas. We can also compare these numbers to another context: Johnston *et al.* [2017] use the HILDA panel survey from Australia, that collects information on socioeconomic outcomes and major life events. Using a sample of 18,534 individuals over 2002-12 they document 1.5% of individuals report being victims of physical violence in the 12 months preceding the survey – very similar to the rates reported in Panel B of Table 3.

[13]The individual covariates included in $X_{i(t)}$ are gender, age, age squared, education, ethnicity, marital status, household composition, housing type, social class, and whether they reside in an urban or rural location.

that enter the retrieval-simulation process and meaningfully shape crime-related perceptions. In the set-up of the framework, there is a strong similarity between each experience and perception (π) considered: $S(witness, \pi) >> 0$, $S(victim, \pi) >> 0$.

However, the relative strength of association between each crime-related experience and crime-related perceptions depends on the domain of perception. For more aggregate domains of perception, such as confidence in institutions related to the justice system and views of the neighborhood, the association with being a witness is significantly larger than with being a victim ($|\widehat{\gamma}_1| > |\widehat{\gamma}_2|$). For example, confidence in the criminal justice system is $.152\sigma$ lower for witnesses, and $.099\sigma$ lower for victims ($p = .000$); confidence in the police is $.150\sigma$ lower for witnesses, and $.121\sigma$ lower for victims ($p = .000$); perceived problems in the neighborhood are $.423\sigma$ lower for witnesses, and $.258\sigma$ lower for victims ($p = .000$). In contrast, for more local domains of perception related to individual well-being, the association with being a witness is significantly smaller than with being a victim ($|\widehat{\gamma}_1| < |\widehat{\gamma}_2|$). For example, worrying about being a future victim of crime is $.128\sigma$ lower for witnesses, and $.167\sigma$ lower for victims ($p = .000$); the perceived effect of crime on quality of life is $.198\sigma$ lower for witnesses, and $.354\sigma$ lower for victims ($p = .000$). Both experiences have similar associations with feeling safe walking alone at night ($p = .576$).[14]

Viewed through the lens of the framework, the heterogeneous effects of each experience across outcomes aligns with a similarity-based hierarchy of different experiences. The framework makes clear this heterogeneity can be down to two reasons: (i) witnessing experiences are more likely to be recalled when aggregate domains of perception ($\overline{\pi}$) are cued to be simulated: $r(witness) > r(victim)$, and/or: (ii) such experiences create better material for simulation because they are more similar to those perceptions: $\sigma(witness) \geq \sigma(victim')$ because $S(witness, \overline{\pi}) \geq S(victim, \overline{\pi})$. The opposite argument holds for more local perceptions related to individual well-being ($\underline{\pi}$): $S(witness, \underline{\pi}) \leq S(victim, \underline{\pi})$.[15]

Given well documented associations between crime victimization, gender and urban/rural residence [Ketel *et al.* 2020], we benchmark the partial correlations of both crime-related experiences to other covariates controlled for in (4). Table A1 shows that for example in terms of confidence in the criminal justice system or in the police, the partial correlations with both crime-related experiences are far larger than with being male or residing in a rural area. On more personal margins of perception, the partial correlations with crime-related experiences are around a quarter of the gender dummy in terms of feeling safe to walk alone in the dark, or around a third of the gender dummy in terms of being worried to be a victim of crime. Finally, in terms of the effect of crime

[14]The result that crime-related experiences shift beliefs about future victimization suggests individuals do not view such experiences as being idiosyncratic and serially uncorrelated over time.

[15]Such aggregate domains of perception related to confidence in institutions of the justice system have long been argued to be important to understand why individuals obey the law – because they believe the system is legitimate rather than the fear of punishment [Tyler 2006]. This echoes similar issues with regards to tax compliance, where tax morale norms are often argued as key driver of behavior rather than expected enforcement or punishment. The fact that witnessing crime has a stronger association with such perceptions than being a victim of crime underlines the potential importance of such experiences for a wider set of behaviors.

on perceived quality of life, the partial correlations with both crime-related experiences are larger in absolute value that for all other covariates.

4.2 Robustness

Our research design does not pin down a causal relationship between crime-related experiences and perceptions. The primary econometric concern is that there are omitted unobservables, correlated to experiences and that have a direct impact on perceptions. A nascent literature identifies causal impacts of victimization, exploiting age discontinuities (at young ages) in risk factors such as access to alcohol [Chalfin *et al.* 2023, Bindler *et al.* 2024] others in the household being exposed to emotional cues [Card and Dahl 2011], or event study designs comparing current to future victims [Dustmann and Mertz 2024]. None of these designs are appropriate in our setting, nor do they extend to experiences of witnessing crime.

Nevertheless, our results suggest a simple concern based on a single unobserved characteristic – say the latent risk of having a crime-related experience – cannot easily explain the pattern of findings if we assume such unobservables are more strongly correlated to victimization than witnessing. This is because the witness-victim perceptions gap is significantly positive for aggregate domains of perception related to institutions and neighborhoods, but significantly negative for local domains of perception related to personal well-being. We formalize this intuition in the Appendix, where we also show that when the experiences are correlated and the latent risk factor is more strongly correlated to victimization than witnessing, biases are smaller when the covariance between witnessing and the latent risk factor is smaller.

Nevertheless, we probe the data further to help underpin the idea that the observed patterns are not merely driven by omitted variables. As detailed in the Appendix (Table A2), we do so by: (i) estimating bounds for the coefficients of interest accounting for selection on unobservables – across perception domains and for both experiences, these bounds remain away from zero; (ii) using three strategies to examine whether geographic variation in crime confounds the results; (iii) showing robustness to varying the definition of witnessing crime (Figure A2).

We also examine the stability of the results by respondent gender or the type of crime experienced. Figure A3 summarizes results by gender, where Panel B reports p-values for the equality of impacts across genders on the same perception-experience combination. While we find no gender differential in perceptions related to justice institutions, there are differences in the association between experiences and perceptions related to neighborhoods and personal well-being. Specifically, women are more impacted by witnessing crime in terms of perceiving problems in their neighborhood ($.456\sigma$ vs. $.401\sigma$, $p = .003$); both experiences have a significantly greater impact on womens' perception of feeling safe to walk alone after dark; witnessing crime has a larger impact on the fear of future victimization for men ($.130\sigma$ vs. $.110\sigma$, $p = .068$).

On crime types, Figure A4 shows both experiences have similar associations to each perception.

Two implications follow. First, worrying about being a future victim of crime – that is constructed from concerns over three specific types of victimization (being burgled, mugged, or attacked) – increases even if an individual has witnessed or been a victim of other types of crime. In the terminology of the framework, crime types are similar when thinking about future victimization. Second, the impacts on witnesses of anti-social behavior – that is technically not necessarily a crime – are still very similar to witnessing crimes. Relative to crime types, witnessing anti-social behavior has large effects on perceptions related to justice institutions and the neighborhood. This reinforces a notion long-discussed in criminology as the 'broken windows' theory, that minor bad behaviors should be tackled not only because they can escalate into serious crime, but because they have intrinsic welfare impacts on others.[16]

We next consider how crime-related experiences impact perceptions using the discrete distribution of each outcome rather than continuous normalized outcomes (Figure A5). Across perception domains, downward shifts are driven by those who would otherwise express the most positive beliefs, and these patterns are similar for both crime-related experiences.

Finally, given the large shifts in crime-related perceptions associated with crime-related experiences, it is natural to ask whether such effects persist. We examine the issue for victims of crime because the month of the incident is recorded, as well as the month of interview (the exact month of witnessing crime is not recorded). The results are detailed in the Appendix where we find: (i) the drop in perceptions is persistent, so there is no recovery in perceptions from the initial victimization experience; (ii) the persistence of effects across perceptions is largely common to both genders and across violent and non-violent crimes.

4.3 Interactions of Experiences

We use three approaches to understand how experiences interact with each other when forming perceptions.

We first consider that individuals can be both witnesses and victims of crime, so allow for an interaction between direct and indirect experiences in shaping individual perceptions, that has not been much considered in earlier work [Malmendier 2021, Bordalo *et al.* 2024, 2025]. We estimate the following specification:

$$y_{i(t)} = \gamma_0 + \gamma_1 Witness_{i(t)} + \gamma_2 Victim_{i(t)} + \gamma_3 \left[Witness_{i(t)} \times Victim_{i(t)}\right] + X'_{i(t)}\theta + \phi_P + \omega_m + \omega_t + \varepsilon_{i(t)}. \tag{5}$$

Panel B of Table 4 shows the estimates, and these are graphically summarized in Panel B of Figure 3 that shows $\widehat{\gamma}_1$, $\widehat{\gamma}_2$, $\widehat{\gamma}_1 + \widehat{\gamma}_2$ and separates out the interaction term, $\widehat{\gamma}_3$.

[16] We also examined the associations of each crime-related experience on perceptions by gender-crime type interactions. We find some differences across gender most notably that women are more negatively affected in terms of their perception of their neighborhood and worrying about being a future victim of crime when they witness violent crime.

Across perception domains, we find a positive interaction of both crime-related experiences: namely, the worsening perceptions of those that are both witnesses and victims tend to be slightly lower than the sum of individual effects on only witnesses and only victims. In nearly all cases the offsetting effect is around an eighth of the sum of the levels effect of being a witness or a victim. The only exception to this is in terms of perceptions of the police, for which the interaction of crime-related experiences is zero. Two implications follow.

First, these results run counter to the econometric concern that the results are fully driven by omitted variables. This cannot easily explain the pattern of findings because the interaction of both experiences offsets their individual association with perceptions rather than extenuating them, as might be expected if unobserved traits correlate to having each experience and crime-related perceptions. Second, the offsetting interaction effect between victimization and witnessing experiences is interpretable within the framework in that these experiences do not crowd out one another in memory retrieval when forming perceptions. The diminishing effect of the combined experiences relative to the sum of the individual experiences is in line with the different sources of domain relevant information having additive effects, albeit at a diminishing rate.

For those with both experiences, we can take this one step further by considering the similarity between the witnessing and victimization experience, namely whether the individual witnessed and was a victim of the same crime type, or not. We do so through suitably modifying the specification in (5). The results in Table 5 shows the similarity of experiences matters in how much they offset the combined effects of individual experiences. More precisely, when witnessing and victimization experiences are dissimilar, their offsetting effect is generally smaller than when they relate to different crime types (or ASB, that can only be witnessed). Indeed, for perceptions related to the justice system, police, the neighborhood, and quality of life, the offsetting effects of having both experiences only exist if those experiences relate to similar crime types.

Finally, we examine dose responses to experiences, so whether and how the association between crime-related perceptions varies for those with multiple experiences. We extend the sample to include those that either witness, or are victims of, multiple crimes in the 12 months preceding each survey. The specification is as in (4) but where we add interactions between each experience and whether it has occurred multiple times for the individual. The results are in Table A6 where we find strong dose responses for witnesses and victims: those with multiple experiences of either type have significantly lower perceptions across all six domains. In nearly all cases, the magnitudes are near double those for single experiences.

4.4 Interactions with Information

The framework makes clear that the information individuals possess captures the accumulation of experiences or having more established priors for crime-related perceptions. Information thus both has a direct association with perceptions, and can mediate the effects of recent experiences.

We examine the experience-information interaction by assessing how our baseline results vary along three margins: (i) the age of individuals; (ii) the crime rate in their LSOA; (iii) newspaper readership – where we saw earlier in Table 1 that such sources of information play an important role in the formation of crime-related perceptions. Tables A7 to A9 show the results.

First, the associations between victimization and crime-related perceptions do not vary much between age groups (16-25, 26-45, 45+). Across the six perceptions, for 11 out of 12 age range comparisons, we do not find significant differences on the partial correlation of victimization across age groups, as shown in Table A7. In sharp contrast, the associations between witnessing and perceptions show rising gradients by age, so older individuals are significantly more impacted by witnessing crime than younger individuals for all perceptions. Despite both victimization-age and witnessing-age profiles having similar trajectories (albeit with levels differences), an experience-age gradient for perceptions only exists for witnessing crime, not being a victim of it.

We next repeat the analysis but split the sample into terciles of crime rates in the LSOA (as measured in 2011, the first year in which LSOAs are identified in the CSEW). Panel A of Table A8 establishes that most perception domains worsen among those residing in higher crime neighborhoods. Panels B to D show that, splitting the sample into crime rate terciles, the association between victimization and crime-related perceptions do not vary much with the neighborhood crime rate. However, there are again more pronounced gradients with regards with witnessing for perceptions of neighborhoods, feeling safe and worrying about victimization. In each case, the negative partial correlation with witnessing crime is larger in high-crime areas – despite these individuals having worse perceptions to begin with. In other words, the inequality in perceptions between high and low crime areas become even more pronounced for individuals witnessing crime.

Finally, we consider differences by newspaper readership. Panel A of Table A9 establishes that, relative to those that report reading no national daily newspaper, those that read tabloid newspapers have worse perceptions on most domains, while those who read broadsheets have better perceptions on all domains, all else equal. Panels B to D show that, splitting the sample into newspaper readership groups, the association between either crime-related experience and crime-related perceptions do not vary much across groups – despite these groups having differing levels of perceptions to begin with.

While in the previous section we documented strong interactions between witnessing and victimization experiences (especially if they are more similar), and dose responses to multiple incidents of the same type of experience, we find more muted experience-information interactions. Victimization-information interactions are generally weak for all three proxies of information, while there are stronger witnessing-information gradients for two of the three proxies. This suggests how experiences of victimization translate into perceptions is not so sensitive to the information or priors individuals have for crime-related perceptions – reinforcing how salient and traumatic such experiences are for individuals. In contrast, how experiences of witnessing crime translate into perceptions vary with information or priors for some domains, but in a way that such experiences

typically worsen perceptions more among those that have worse perceptions to begin with (i.e. those in high crime neighborhoods or daily readers of tabloids). Hence the experience of witnessing crime extenuates inequality in crime-related perceptions.

4.5 Post Victimization Experiences

Our main result documents that adverse crime-related experiences are negatively associated with crime-related perceptions. Although such experience effects might be long-lasting, they are not immutable because new experiences exert new influences. To shed light on this we consider a second source of (positive) experiences arising from institutional responses to victimization. To do so, we exploit the richness of the CSEW data which records information on how the criminal justice system handled each case of victimization. In our working sample, 43% of victims have their crime recorded by the police, 10% had an offender identified, and 4% had an offender both identified and charged. We use this information to construct a categorical measure of post-victimization experience with the criminal justice system:

$$post_victim_{i(t)} = \begin{cases} 0 & \text{not reported} \\ 1 & \text{reported, offender not found} \\ 2 & \text{reported, offender found but not charged} \\ 3 & \text{reported, offender found and charged.} \end{cases} \tag{6}$$

This ranges from victims deciding to have no engagement with the system (0) to the most favorable outcome in which victims report the crime and an offender is charged (3). We estimate the following specification in the sample of victims, where those who did not report the incident to the police ($post_victim_i = 0$) are the omitted category:

$$\begin{aligned} y_{i(t)} \quad = \quad & \delta_1 \mathbf{1}\{post_victim_{i(t)} = 1\} + \delta_2 \mathbf{1}\{post_victim_{i(t)} = 2\} + \delta_3 \mathbf{1}\{post_victim_{i(t)} = 3\} + \\ & + \gamma Month_victim_{i(t)} + X'_{i(t)}\theta + \phi_P + \omega_t + \omega_m + \mu severity_{i(t)} + \varepsilon_{i(t)}. \end{aligned} \tag{7}$$

All terms are as previously defined. In addition, we include fixed effects for crime type (ω_m) and self-reported crime severity ($severity_{i(t)}$), based on an indicator ranging from 1 to 20, to account for crime-specific characteristics that may influence respondent's reporting behavior or police effort. $\delta_3 - \delta_1$ captures the perceptions gap between individuals experiencing the most favorable and least favorable post-victimization outcomes, conditional on the victimization and reporting the crime to the police.

Figure 4 plots $\widehat{\delta}_3 - \widehat{\delta}_1$ for each perception. We see that within-individual favorable experiences offset the earlier documented negatives impacts of the initial victimization for half the domains of perception. The largest offsetting effects occur for perceptions of the justice system itself, followed

by offsetting effects on perceptions of being a future victim of crime. To gauge the magnitude of these effects, the initial $.118\sigma$ fall in confidence in the justice system is more than offset by the $.149\sigma$ rise in confidence in the justice system following positive post-victimization experiences – leaving those that have experienced both events with higher confidence in the criminal justice than non-victims. Similarly, the initial $.121\sigma$ fall in confidence in the police is more than offset by the $.257\sigma$ rise in confidence following positive post-victimization experiences – leaving those that have experienced both events with higher confidence in the police than non-victims. Finally, the initial $.192\sigma$ increase in worry of being a victim of crime is halved by the $.103\sigma$ fall in worry following favorable post-victimization experiences. By contrast, favorable post-victimization experiences appear to have little impact on improving perceptions of neighborhoods, personal safety and how crime affects quality of life.

The results suggest that positive experiences can partially mitigate the consequences of earlier negative experiences. More precisely, effective institutional responses to crime may restore trust in justice institutions but have limited effects on more personal perceptions. It is natural that signals about the quality of the justice system lead to an updating of perceptions about institutions more than they affect perceptions in other domains, such as neighborhoods. However, the asymmetry of impacts of positive and negative experiences is of note, especially given the distinction between these types of experience have not been the focus of earlier work on experience-based learning. More specifically, positive experiences lead to updated perceptions in the same domain but not to other domains. This is in contrast to the earlier results, where negative experiences lead to updating across all perception domains. This leaves open the possibility that memory retrieval-simulation processes for forming perceptions depend on whether positive or negative experiences are drawn from the database E, a feature that goes beyond existing models.

Finally, these results further help rule out that unobserved characteristics that are correlated to both victimization and crime-related perceptions are likely driving our core results because favorable post-victimization experiences, in some cases, offset the negative association between victimization and crime-related perceptions and in some cases, leaving reported perceptions of victims similar to those of non-victims.

Robustness All the results on post-victimization experiences are predicated on individuals reporting the crime: our key parameter, $\delta_3 - \delta_1$, captures the perceptions gap between individuals experiencing the most favorable and least favorable post-victimization outcomes, conditional on the victimization and reporting the crime to the police. The recovery on some perception margins might reflect those that have greater latent confidence in the justice system and police to begin with, and so positive post-victimization experiences aid their recovery more so than for others. To assess this issue, we split the sample by mode of reporting to distinguish (i) incidents reported by the respondent or a household member, and (ii) known to the police via other channels. Figure

A10 shows the results are largely similar across these reporting groups.[17]

We also examine whether the impact of post-victimization experiences differ by gender and type of crime. Figure A11 summarizes results by gender. On no margin of perceptions can we reject impacts statistically differ by gender, but we do note that in terms of quality of life the impacts on women are more negative than on men. Figure A12 summarizes results by crime type. Positive post-victimization experiences all tend to restore confidence in the justice system and the police, irrespective of the crime type. Such positive experiences also generally lead to individuals feeling safer and worrying less about being a future victim of crime. However for two domains – perceived problems in the neighborhood and quality of life – positive post-victimization experiences can have impacts of either sign, depending on the crime type.

5 Implications for the Social Costs of Crime

Our results have implications for measuring the social cost of crime. The key insights are that: (i) these costs extend beyond victims to witnesses; (ii) victims and witnesses may be differentially affected by crime-related experiences; (iii) post-victimization outcomes in the justice system can mitigate (or amplify) victimization costs. In this section, we show the consequences of these three insights for social costs of crime. In each case, we describe the intuition behind the approach and results, while the relevant derivations are described further in the Appendix.

5.1 Accounting for Witnesses

We build on an established approach to measuring the social costs of crime in our study context and study period: Heeks *et al.* [2018] provide a comprehensive set of estimates of unit social costs, by crime type, for England in 2015/16. For each crime type, their total cost estimate can be decomposed into costs arising from anticipation/avoidance behaviors, consequences of victimization, and other response costs borne by victims and institutions in the justice system.[18]

Our first innovation is to extend their framework to incorporate costs of being a witness to crime. Denoting V^k as the victim unit cost for crime category k and W^k the corresponding unit

[17] Those who self-report are more likely to view the crime as having been more severe: on a 20-point scale of severity, the median (mean) is four (five). 59.4% of individuals report if the perceived severity is greater than four, and this falls to 29.7% if the perceived severity is less than or equal to four. We include fixed effects for self-reported crime severity to account for crime-specific characteristics that may influence reporting behavior.

[18] A long established literature across disciplines has estimated social costs of crime, based either on willingness-to-pay approaches to measure avoidance of victimization [Ludwig and Cook 2001, Cohen *et al.* 2004], hedonic evaluations of exposure to crime based on house prices [Rosen 1974], or tracing the range of costs stemming from victimization. As Dolan *et al.* [2005] describe, some costs are relatively straightforward to quantify in monetary terms: (i) realized direct costs, i.e. resources diverted from other uses as a result of crime, such as medical care or restoring property; (ii) realized indirect costs – such as earnings and productivity losses; (iii) anticipatory costs – resources spent to avoid being a victim of crime, such as installing alarms. Other costs are harder to measure – e.g. the pain, psychological distress, and a decrease in quality of life that victims experience.

cost borne by witnesses, the unit social cost of crime for each crime category k becomes:

$$\text{Unit Social Cost}^k = V^k + W^k. \tag{8}$$

To operationalize this we first map the detailed crime types of Heeks *et al.* [2018] into four categories available in the CSEW for both victims and witnesses: violent crime, burglary, theft, and criminal damage. For each crime type, we aggregate the unit costs taking the V^k's based on a finer categorization of crime types in Heeks *et al.*, as given. We set out two approaches to translate victim-based costs into witness-based costs.

Approach 1 Our first approach (naively) assumes witnesses bear the same unit cost as victims for those components of the Heeks *et al.* decomposition that our results on crime-related perceptions suggest could plausibly be affected for both victims *and* witnesses: defensive expenditures, physical and emotional harm, and lost output. For each crime type, we take the victim unit costs for these components and assign them to witnesses, while setting witness costs to zero for the remaining components (such as costs incurred by the criminal justice system, health services, insurance administration and victim support services). This delivers an adjusted unit social cost of crime in which witness costs mirror victim costs for a restricted set of cost items.

Approach 2 Our second approach relaxes the assumption that witnesses are affected by their experiences to the same extent as victims. Instead, we use our estimates of the impact of crime-related experiences on crime-related perceptions to determine the scaling of W^k relative to V^k. To do so we map the cost components that witnesses bear as in the first approach, to one or more perception outcomes that relate most closely to these costs: perceived safety when walking alone in the dark, worrying about victimization, and impacts of crime on quality of life. For each crime type and cost component, we use the estimates of witness and victim experiences on these perceptions from specification (5) to construct a multiplier of W^k relative to V^k. This multiplier is the ratio of the witnessing effect to the victimization effect. This scales victim unit costs into witness unit costs, allowing witnesses to be more or less affected than victims depending on the evidence. Given the multiple perceptions considered, we use the different estimates to construct lower and upper bounds for this multiplier.[19]

[19] A third approach would be to extend the methodology of Heeks *et al.* [2018] in two ways. First, to also include the costs associated with each perception we consider – such as a loss of confidence in the criminal justice system or the police. However to do so requires placing a monetary value on these changes in perception. Second, given the existing decomposition of costs in Heeks *et al.* [2018], to estimate impacts on labor market outcomes or avoidance responses arising from the experience of witnessing crime [Braakmann 2012, Bindler and Ketel 2022]. Given data limitations and our focus, we leave such extensions for future work.

5.2 Results

Table 6 summarizes findings using each approach, showing the proportionate change in unit social costs of crime relative to the established method of Heeks *et al.* when averaging across all crime types, and considering crime types separately. Column 1 shows that under the first approach, the average unit social cost of crime rises by 59% – highlighting the extent to which social costs are otherwise underestimated if only victims are accounted for. Across crime types, this underestimate varies between 26% and 69%, with the largest effect for violent crime and the smallest for criminal damage. Columns 2 and 3 show that under the second approach, that accounts for witness-adjusted costs, the implied average unit social cost of crime still rise relative to conventional methods. The implied increase is on average around 25% when taking the lower bound multiplier (Column 2), and the lower-bound increase ranges from 28% for violent crime, to 14% for theft.[20]

Two implications follow. First, standard approaches to calculating the social costs of crime that only consider victims substantially underestimate the true costs once we factor in crime-related experiences such as witnessing crime. This is a first order issue given the divergence between rates of crime victimization and rates of witnessing crime. As Figure 2 showed, while victimization rates have steadily declined over time, witnessing rates have remained stable over the last two decades, as the composition of crime has changed towards violent crime, that is witnessed to a greater extent than other crime types. *A fortiori* the returns to crime-reducing interventions – especially those aiming to reduce violent crime – are far higher than previously recognized. Interventions considered not to be cost effective under conventional measures might prove to be cost effective once the wider impacts on witnesses are accounted for.

Second, a key purpose of measuring social costs by crime type is to make informed choices about the cost effectiveness of targeting resources to prevent specific crime types. Given the changing composition of crime highlighted earlier – that has seen a relative shift towards violent crime – trends in the aggregate social costs of crime might not be as pronounced downwards as would otherwise be implied by long run trends of falling victimization rates. To see this in more detail we construct annual estimates of the aggregate social costs of crime taking into account witness costs as estimated under our second approach.[21]

The result is shown in Figure 5, where each series is normalized to 100 in 2003-4. As a point

[20] Intuitively, these changes in social costs are smaller than under the first approach because the second approach uses the estimates of witnessing on localized perceptions, that are smaller than for victims.

[21] To construct aggregate social costs, we first compute the average unit social costs for victimization and witnessing for each year – victim unit costs are based on the item-level cost components reported in Heeks *et al.* for 2015-16 aggregated into our four crime categories, while witness unit costs are taken from our estimates under our second approach. We then apply crime-type shares by year derived from the CSEW. As our analysis is restricted to single-incident victims and single-incident witnesses, we compute these annual crime counts and population counts using our main estimation sample. To obtain them, we rescale CSEW sampling weights within each year to account for observations dropped during sample construction, including individuals with multiple victimizations. This ensures the relative prevalence of each crime category reflects the population used in our analysis (and is consistent with the construction of the multipliers). We then convert unit costs into aggregate social costs by multiplying them by the estimated number of victims and witnesses in each year.

of comparison, we show the time series for victimization rates: as described earlier, this has fallen steadily over time, being 25% lower in 2014-15 than in 2003-04. The second series is from Heeks *et al.* that shows aggregate social costs of crime — based only on victims – have fallen by 10% over the same period. This change is proportionately smaller than for victimization rates because the composition of crime has tilted towards violent crime that has a higher unit social cost. The third series then includes costs to witnesses, for survey years in which witnessing crime is recorded in the CSEW. We see that: (i) in the early years from 2003-4 to 2007-8 the aggregate social cost of crime remains largely unchanged; (ii) in the latter years, from 2011-12 to 2014-15 the aggregate social costs of crime have risen by around 35%.

In short, once we account for costs borne by witnesses, aggregate social costs of crime have risen substantially over time despite sustained falls in victimization rates. If we consider these monetary costs of crime to victims and witnesses translating into utility losses, the result sheds light on why individual perceptions of crime might be worsening over time, despite victimization rates falling – a puzzle that has long been considered across the social sciences and often put down to individuals misperceiving levels of crime [Garland 2001, Esberg and Mummolo 2018].[22]

As further support for this, we consider how crime-related experiences associate with perceptions of changes in crime rates in recent years: (i) nationally; (ii) in the local area. We do so by estimating a specification analogous to (4) but where the outcomes relate to perceptions of recent changes in crime rates. Each outcome is normalized so the coefficients can be read as effect sizes. The results are in Panel A of Table 7 where we see: (i) both experiences increase the perception that national and local crime rates are rising; (ii) crime-related experiences have larger effect size associations with changes in local crime rates than changes in national crime rates; (iii) reinforcing the notion that witnessing might be key to understanding diverging trends between actual and perceived crime, witnessing crime has a significantly larger partial correlation than being a victim of crime with perceived changes in national crime rates ($p = .037$). Panel B repeats the analysis by crime type, where we see that: (i) witnessing or being a victim of different crime types have very similar associations with perceived changes in national crime rates; (ii) crime types matter for how witnessing and victimization experiences translate into perceived changes in local area crime rates.

5.3 Accounting for Post Victimization Experiences

We return to the third insight from our analysis: that favorable post-victimization outcomes in the justice system can potentially mitigate some of the negative impacts of initial victimization on crime-related perceptions, and hence the costs of victimization. We explore the issue by adjusting

[22] Esberg and Mummolo [2018] study the disconnect between actual and perceived levels of crime in the US. They find the extent of misperceptions does not correlate with levels or changes in local crime rates. Rather, individuals revise their beliefs when presented with accurate crime statistics, but this effect is attenuated when statistics are embedded in a typical crime news article.

victim unit costs V_k to account for favorable post-victimization outcomes – namely the offender being identified and charged. We use the same mapping between cost components and perception outcomes as before, but apply adjustments only to victims (so ignoring witnesses). For each relevant cost component, we compute a post-victimization multiplier that quantifies the share of the initial adverse victimization effect that is offset (or reinforced) by a favorable post-victimization experience. To do so, we combine estimates of victimization effects from (5) with estimates of post-victimization effects from (7). In this exercise: (i) we focus on point estimates given the small sample of individuals that actually experience a favorable post-victimization outcome within 12 months of the original incident, so we view this exercise as mostly illustrative; (ii) we set multipliers to zero when costs are fully recovered, that is, when post-victimization outcomes more than offset the negative victimization effects; (iii) multipliers may be larger than one, increasing victimization costs, if post-victimization perception impacts are negative following favorable experiences. As before, we report lower and upper bounds based on alternative perception outcomes.

The results are in Table 6. Columns 4 and 5 consider the implied victim unit costs V_k among those experiencing favorable post-victimization outcomes. These *rise* when these additional experiences are accounted for. The reason is that, as shown in Figure 4, such experiences: (i) have little impact on improving perceptions of neighborhoods, and while they do offset initial falls in confidence in the justice system and police, these perceptions play no role in the social cost calculation based on the costs components in Heeks *et al.* [2018]; (ii) they only influence social costs through changes in worrying about being a victim of crime and how crime affects quality of life. Driven by this last channel, victimization costs increase by 27-30% averaging across all crime types. However, considering crime types separately, taking into account favorable post-victimization experiences has different implications for victimization costs: for criminal damage these are estimated to fall by 15-20%, they remain largely unchanged from conventional estimates for burglary, they rise for theft by 12-23% and most notably, they rise by 36-40% for victims of violent crime. These falls/rises mirror the falls/rises of favorable post-victimization outcomes on perceived quality of life across crime types.

Columns 5 and 6 consider the unit victimization costs averaged over all victims – not just those that actually experience favorable post-victimization outcomes. As only a small share of victims experience such outcomes in the 12 month window since victimization, when we weight by their prevalence, reductions in average victimization costs are small – although for violent crime they still rise by 5%.

These results have implications for the returns to investing into the criminal justice system – or any channel through which the likelihood of victims experiencing favorable post-victimization outcomes increases. First, for some crime types – such as criminal damage – the returns to investing are potentially high because they substantially reduce victimization costs. For other crime types – most notably violent crime – the results highlight the importance of investing in parts of the justice system that reduce the negative impacts on victims of offenders being identified

and charged (what we have referred to as a favorable outcome). Improving the extent or nature of victim support might be one such avenue. While it is well established that experiencing violent crime impacts long-term mental health, including anxiety, depression and post-traumatic stress [Cornaglia *et al.* 2014, Bindler and Ketel 2022], what our analysis leaves unanswered is whether the process of engaging with the justice system has similar impacts on victims, even if the outcome leads offenders to be identified and charged.[23]

6 Conclusion

We study how crime-related experiences impact crime-related perceptions. We document that: (i) across perceptions, beliefs are negatively impacted by either witnessing a crime or being a victim; (ii) witnessing crime has larger impacts on more aggregate domains of perception related to institutions and neighborhoods, while being a victim of crime has larger impacts on more localized domains of perceptions related to personal safety, fear and quality of life; (iii) favorable post-victimization experiences help restore confidence in justice institutions, but have limited effects on perceptions of neighborhoods or personal well-being. These results can be interpreted through the lens of experience-based learning models based on memory and retrieval. We show two major implications of accounting for impacts on witnesses for the social costs crime: (i) the unit social cost of crime rises by 25% relative to conventional methods; (ii) the total social costs of crime have risen by around 35%, despite sustained falls in victimization rates – that helps explain why individual perceptions of crime might be worsening over time, despite victimization rates falling – a puzzle that has long been considered across the social sciences.

Our analysis opens up multiple areas for future work. We describe four we find most promising.

First, much of our analysis can be replicated using victimization surveys from other countries. A constraint remains that such surveys are often repeated cross sections rather than panels – limiting the use of alternative research designs. One direction is to use panel surveys, whose focus is not crime but that still collect data on a limited set of crime-related experiences and perceptions. An example is the Australian HILDA survey, that collects information on socioeconomic outcomes and major life events including victimization [Johnston *et al.* 2017]. Larger sample sizes from other contexts might also allow for a more high powered examination of gender-crime type interactions that our results hint at being important for how experiences translate into perceptions, and would bridge towards a growing literature on the causes and consequences of gender-based violent crime

[23] Comparing across the various scenarios in Table 6 can also be instructive for thinking about where returns to investing in the criminal justice system matter most – *ex ante* in preventing crime-related experiences from occurring, or *ex post* in generating favorable post-victimization outcomes. On the one hand, the results confirm the simple intuition that given the infrequency of favorable post-victimization outcomes in the 12-month horizon we are able to consider, it is always preferable to reduce the likelihood of crime-related experiences occurring in the first place. On the other hand, under a thought experiment of all victims eventually receiving a favorable post-victimization experience (so comparing Columns 2 and 4) the results imply the returns to investing in *ex ante* prevention is generally higher for most crime types, but the opposite is true for violent crime.

[Adams *et al.* 2024]. Moreover, our analysis has been focused on adult respondents, but in some years, the CSEW releases datasets for a youth sample (aged 11-15). Understanding how crime-related experiences shape perceptions earlier in life is important given age-victimization profiles show young people are more likely to be victimized [Bindler *et al.* 2024], we document hat witness-age profiles show young people are more likely to witness crime (Figure 1), and that experience-based learning can be more pronounced in impressionable early years.[24]

Second, a wider set of experiences should be considered in the economics of crime literature beyond victimization. We thus bridge to work in criminology where there has long been a distinction between direct victimization and indirect (*vicarious*) victimization [Tyler 1980, Hale 1996], where the latter includes witnessing a crime in person, but also learning that a close other was victimized, or hearing about crime through media. This is important for at least two reasons. First, distinguishing the mediating effect of these specific indirect experiences can help advance an establish strand of literature on how exposure to crime and violence – say through families, neighbors, coworkers or classmates – propagates across individuals. Second, the increased aggregate social costs of crime we document taking into account witnessing effects might still underestimate the true social costs if other crime-related experiences – such as learning about crime through media – has increased over time as well.

Third, by considering perceptions across domains, we add to a small literature examining trust in institutions of the criminal justice system [Tyler and Huo 2002]. Much of this has focused on whether citizen-police interactions impact reporting of crime or trust in law enforcement institutions [Desmond *et al.* 2016, Zoorob 2020, Blattman *et al.* 2021, Ang *et al.* 2023, Facchetti 2024]. Our work highlights there is much to be understood on how experiences unrelated to interactions with actors employed by the state, still translate into views towards state institutions.

Finally, by considering the role that favorable post-victimization experiences in the justice system have on mitigating impacts of the initial victimization, we start to open the black box of interactions between victimization and the criminal justice system. As noted by Ketel *et al.* [2020], such issues have not been studied in the economics literature, and we start to fill this void by documenting the extent to which consequences for victims depend on what happens to the offender. A natural direction to take these ideas, building on recent work examining restorative justice interventions [Shem-Tov *et al.* 2024, Adukia *et al.* 2025], would be to integrate them with the mature literature exploring the drivers of future recidivism [Doleac 2023], but through the lens of consequences for past victims.

[24] As Giuliano and Spilimbergo [2025] discuss, the time periods that matter for belief formation are encapsulated in three hypotheses in social psychology. The impressionable years hypothesis states core beliefs are formed in early adulthood – the 'impressionable years' between ages 18 and 25 [Krosnick and Alwin 1989]. The increasing persistence hypothesis argues individuals are malleable and more responsive to the social environment when they are young and malleability decreases with age. Finally, the lifelong openness hypothesis argues individuals are malleable throughout their lives [Brim and Kagan 1980] – consistent with our earlier results that the association between crime-related experiences and perceptions do not vary much by age.

A Appendix

A.1 Data

Construction Our analysis uses the annual CSEW files for survey waves 2001-02 to 2017-18 provided by the UK Data Service. Each survey year contains two questionnaires: (i) a non-victim form, which records individual-level responses to questions asked to all respondents, regardless of victimization status; (ii) a victim form, which contains responses collected only from respondents who report having been victimized in the 12 months prior to the survey. Victim forms can be administered multiple times to the respondent if multiple victimizations are experienced, up to a maximum of six. The dataset used for our analysis is created by processing the person-level (non-victim) and victimization-level (victim) files for each survey wave, and merging them into a single individual-level dataset.[25]

Sampling and Weights The sampling frame is based on home addresses. Hence offenses against individuals not living in private households (such as those in student housing or prison) are excluded. The victimization surveys also exclude crimes against businesses, homicides, and other victimless offenses (such as drug possession). We use the individual survey weights provided by the CSEW for each wave. As the number of observations per wave varies (from $28,859$ to $43,160$), all regressions are weighted using the probability weights provided by the CSEW, and then adjusting for the number of observations by year.

Module Ordering The CSEW follows a fixed questionnaire structure in which survey modules are administered in a consistent order across waves. After collecting demographic information, the survey begins with a *Perceptions of Crime* module that includes questions on quality of life, personal safety, and perceptions of the local neighborhood. This is followed by the *Victimization* module, in which respondents are asked about experiences of crime in the previous 12 months and post-victimization outcomes. Subsequent modules cover *Confidence in the Performance of the Criminal Justice System*, including perceptions of the criminal justice system as a whole and of the police. Finally, in survey waves with the *Experiences of the Criminal Justice System* module, respondents are asked about experiences of witnessing crime and anti-social behavior.

A.2 Variable Definitions

We harmonize key variables across years, accounting for changes in question wording, response categories, and occasional differences in availability. We code 'don't know' or 'refused' responses

[25] The CSEW was previously known as the British Crime Survey. In some years, the CSEW also releases separate datasets for a youth sample (ages 11-15) and an ethnic boost sample. These are excluded from our analysis.

as missing. The variables related to perceptions and individual characteristics are drawn from the non-victim forms.

A.2.1 Experiences of Crime

Witnessing Crime To consistently identify individuals who have witnessed crime or experienced anti-social behavior (ASB), we combine four survey questions. For 2003-04 to 2007-08, we use a question that asks if one has witnessed crime or anti-social behavior. Specifically, we use a sequence of variables [`seecri1a-seecri1k`] that ask, "*In the last 12 months, that is since[...], have you seen any of these actually happening? CODE ALL THAT APPLY*" where individuals could answer: *someone vandalising property or a vehicle, someone stealing a vehicle or something from a vehicle, threatening or violent behaviour including fights, someone being mugged or robbed, someone breaking into or attempting to break into a property, shoplifting, antisocial behaviour or disorder, someone driving dangerously, none of these.*

For 2011-12 to 2014-15 and 2017-18, we combine a question that asks if respondents witnessed crime, with a question that asks if they have experienced or witnessed anti-social behavior. Specifically, we use a sequence of variables [`secr12ma-secr12mi`] that ask "*In the last 12 months have you seen any of these things actually happening? CODE ALL THAT APPLY*" where individuals could answer: *someone vandalising property or a vehicle, someone stealing a vehicle or something from a vehicle, threatening or violent behaviour including fights, someone being mugged or robbed, someone breaking into or attempting to break into a property, shoplifting, someone driving dangerously, none of these.* For 2017-18 we also use the variable [`witcri`] that asks, "*In the last 12 months, have you witnessed a crime?*" We combine this with [`asbexp`] that asks "*Have you personally experienced or witnessed any sort of anti-social behaviour in your local area in the last 12 months? IF NECESSARY: Anti-social behaviour is any behaviour that causes people nuisance, annoyance, alarm, or distress. This can include behaviours that are aggressive or intimidating or that impact upon a person's quality of life.*" This results in a consistent classification of this group for survey waves 2003-04 to 2007-08, 2011-12 to 2014-15, and 2017-18.[26]

Victims of Crime For victims of crime, the date of the crime, the crime type, and post-victimization variables are drawn from the incident-level victim form. The CSEW distinguishes between single incidents and a series of incidents, where a series is defined by the interviewer as 'the same thing, done under the same circumstances and probably by the same people.' If multiple incidents are classified as a series, the survey records only the most recent incident, and the set of incidents is counted as a single victimization. We restrict our analysis to respondents with single-victimization and single-incident experiences of crime, thus excluding respondents who report a series of incidents (19% of victims) and those with more than one valid non-series victimization

[26] For witnesses we restrict the sample to those who witness at most one of seven types of crime (criminal damage, stealing (from) a vehicle, burglary, threats or assaults, robberies, theft) or anti-social behavior.

(26% of victims). The time since victimization is calculated as the number of months between the incident and interview dates.

The original CSEW data contains 80 crime types. We remove cases flagged as duplicate victim forms, invalid victim forms, or incidents occurring outside the survey's coverage, leaving 67 crime types. We drop obscene and nuisance telephone calls, fraud, and computer misuse – the latter two categories are excluded because they are available only from 2015-16. This leaves 49 crime types which are aggregated by the CSEW into assault, sex offense, robbery, burglary, theft, criminal damage, threats, and sex threats. We categorize sex offenses as assault, sex threats as threats, and, due to their small number, we code robberies as assaults. Our final classification retains five crime types: criminal damage, theft, burglary, threats, and assaults.

In some parts of the analysis we exploit information of the seriousness of the crime as reported by victims. For survey waves 2001-02 to 2004-05 we use a question [`scorcrim`] that asks, "*I would now like to ask you how serious a crime you personally think this was. On this card is a scale to show the seriousness of different crimes, with the scale going from 0 (zero) for a very minor crime like theft of milk bottles from a doorstep, to 20 for the most serious crime, murder. How would you rate this crime on the scale from 0 to 20?*" For survey waves 2005-06 to 2017-18 the wording was changed slightly [`scorcrm2`] to, "*I would now like to ask you how serious a crime you personally think this was. On a scale of 1 to 20 with 1 indicating a very minor crime like theft of milk bottles from a doorstep, to 20 for the most serious crime, murder. How would you rate this crime on the scale from 1 to 20?*".

Post-victimization To measure whether a crime is reported to the police we use the following question [`copsknow`]: "*Did the police come to know about the matter?*" To measure whether an offender was identified we use the following question [`findoff`]: "*Did the police find out or know who did it?*" To measure whether an offender was charged we use the following question [`polcharg`]: "*Did the police charge or caution someone for committing this offense?*"

A.2.2 Perceptions

The perception measures used in our analysis are all taken from the non-victim forms and each is coded so that higher values correspond to more positive answers.

Institutions For the *confidence in the criminal justice system* measure we combine two questions available from 2001-02 to 2007-08 [`confoff`] and 2008-09 to 2017-18 [`csjovb1`]. In the first period, respondents were asked , "*Thinking about the Criminal Justice System as a whole, that is, the police, the Crown Prosecution Service, the courts, prison and probation services, please choose a phrase from this card to show how confident you are that it is effective in people who commit crimes to justice?*" In the second period, respondents were asked, "*Thinking about all of the*

agencies within the Criminal Justice System: the police, the Crown Prosecution Service, the courts, prisons, and the probation service. How confident you are that the Criminal Justice System as a whole is effective?" In both periods individuals could answer *very confident, fairly confident, not very confident, not at all confident.*

For the *confidence in the police* measure we combine two questions available from 2001-02 to 2007-08 [`jobpol`] and 2008-09 to 2017-18 [`ratpol2`]. In the first period, respondents were asked, "*How good of a job do you think the police are doing?*" In the second period, respondents were asked, "*Taking everything into account, how good of a job do you think the police in this area are doing*?" In both periods individuals could answer *excellent, good, fair, poor, very poor.*

Local Neighborhoods For the *perception of your local neighborhood* measure we combine seven questions that ask respondents how much of a problem noisy neighbors [`noisneigh`], teenagers hanging out [`teenhang`], rubbish or littering [`rubbish`], vandalism [`vandals`], drugs [`druguse`], drunkenness [`drunk`], and abandoned cars [`abancar`], are in their neighborhood. As a precursor to these questions individuals were told, "*For the following things I read out, can you tell me how much of a problem they are in your area. By our area I mean within 15 minutes walk from here.*" The question than asked "*How much of a problem are/is....*": "*noisy neighbours or loud parties?*", "*teenagers hanging around on the streets?*", "*rubbish or litter lying around?*", "*graffiti and other deliberate damage to property or vehicles?*", "*people using or dealing drugs?*", "*people being drunk or rowdy in public places?*", "*abandoned or burnt out cars?*" In all cases individuals could answer *very big problem, fairly big problem, not a very big problem, not a problem at all.* We assign values 0-3 to each response, and average the resulting values across the seven outcomes.

Own Safety The *feeling safe walking alone in the dark* measure is taken directly from the survey [`walkdark`] where respondents were asked, "*How safe do you feel walking alone in this area after dark? Would you say you feel...*", where individuals could answer *very safe, fairly safe, a bit unsafe, very unsafe.* This question is unavailable in the 2016-17 survey.

For the *worried about becoming a victim* measure we combine three variables that ask respondents if they are worried about being burgled [`wburgl`], mugged [`wmugged`] or attacked [`wattack`]. These asked respondents, "*How worried are you about...*": "*having your home broken into and something stolen?*", "*being mugged and robbed?*", "*being physically attacked by strangers?*" In all cases individuals could answer *very worried, fairly worried, not very worried, not at all worried*. We assign values 0-3 to each response, and average the resulting values across the three outcomes.

Quality of Life The *effect of crime on quality of life* measure is taken directly from the survey [`qualif2`] where respondents were asked, "*How much is your own qualify of life affected by crime, on a scale from 1 to 10 where 1 is no effect and 10 is a total effect on your quality of life?*" This question is unavailable in the 2016-17 survey.

A.2.3 Other Variables

We define the following variables to include as controls in the regression analyses: gender, age, age-squared, if there are any children in the household, a dummy for white, a dummy for living in a rural area, education in eight levels from none to having a higher degree, marital status categorized into six groups (married, cohabiting, single, separated, divorced, and widowed), housing type classified into three groups (privately owned, privately rented, and socially rented), and socioeconomic class based on respondents' occupational status. For the latter we use the National Statistic Socio-economic classification (NS-SEC), which splits respondents into ten categories depending on if the respondent is an employer, self-employed or employee, if they are a supervisor, and the number of employees at their workplace.

A.3 Omitted Variable Biases

The primary econometric concern is there are omitted unobservables, correlated to crime-related experiences and that have a direct impact on the formation of crime-related perceptions. To provide intuition on the nature of such biases, suppose the true model linking crime-related experiences (V_i, W_i) and crime-related perceptions Y_i is:

$$Y_i = \alpha + \beta_1 V_i + \beta_2 W_i + R_i'\delta + u_i, \qquad \mathbb{E}[u_i \mid V_i, W_i, R_i] = 0, \tag{9}$$

where $\widetilde{R}_i \equiv R_i'\delta$ denotes a single latent index capturing unobserved risks of exposure to crime-related experiences. This latent factor is assumed to affect all perception outcomes in the same direction and to generate the systematic part of the omitted-variable bias. This risk factor is unobserved to the researcher, who estimates the following model:

$$Y_i = \tilde{\alpha} + \tilde{\beta}_1 V_i + \tilde{\beta}_2 W_i + \varepsilon_i, \tag{10}$$

where $\epsilon = R_i'\delta + u_i$. As the regression includes only V_i and W_i, excluding R_i generates omitted-variable bias in $(\tilde{\beta}_1, \tilde{\beta}_2)$. To derive these biases, we take the following OLS population moment condition:

$$\mathbb{E}\Big[Z_i\left(Y_i - Z_i'\tilde{\beta}\right)\Big] = 0 \quad \Longrightarrow \quad \mathbb{E}[Z_i Y_i] = \mathbb{E}[Z_i Z_i']\tilde{\beta}. \tag{11}$$

where,

$$Z_i \equiv \begin{pmatrix} V_i \\ W_i \end{pmatrix}, \qquad \tilde{\beta} \equiv \begin{pmatrix} \tilde{\beta}_1 \\ \tilde{\beta}_2 \end{pmatrix}, \qquad \beta \equiv \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}, \tag{12}$$

that can be separated into two equations:

$$\begin{aligned} (\beta_1 - \tilde{\beta}_1)\mathbb{E}[V_i^2] + (\beta_2 - \tilde{\beta}_2)\mathbb{E}[V_i W_i] + \mathbb{E}[V_i R_i']\delta + \mathbb{E}[V_i u_i] &= 0, \\ (\beta_2 - \tilde{\beta}_2)\mathbb{E}[W_i^2] + (\beta_1 - \tilde{\beta}_1)\mathbb{E}[V_i W_i] + \mathbb{E}[W_i R_i']\delta + \mathbb{E}[W_i u_i] &= 0. \end{aligned} \tag{13}$$

Given $E[u|V,W,R]=0$, $\mathbb{E}[V_i u_i]=0$ and $\mathbb{E}[W_i u_i]=0$, these equations become:

$$\mathbb{E}[V_i(\widetilde{R})] = (\tilde{\beta}_1-\beta_1)\mathbb{E}[V_i^2]+(\tilde{\beta}_2-\beta_2)\mathbb{E}[V_iW_i] \tag{14}$$

$$\mathbb{E}[W_i(\widetilde{R})] = (\tilde{\beta}_2-\beta_2)\mathbb{E}[W_i^2]+(\tilde{\beta}_1-\beta_1)\mathbb{E}[V_iW_i]. \tag{15}$$

Define the biases $b_1=\tilde{\beta}_1-\beta_1$ and $b_2=\tilde{\beta}_2-\beta_2$. Multiplying (14) by $\mathbb{E}[W_i^2]$ and (15) by $\mathbb{E}[V_iW_i]$:

$$\begin{cases} \mathbb{E}[W_i^2]\mathbb{E}[V_iW_i]\,b_2 = & \mathbb{E}[W_i^2]\mathbb{E}\Big[V_i(\widetilde{R})\Big]-\mathbb{E}[W_i^2]\mathbb{E}[V_i^2]\,b_1, \\ \mathbb{E}[W_i^2]\mathbb{E}[V_iW_i]\,b_2 = & \mathbb{E}[V_iW_i]\mathbb{E}\Big[W_i(\widetilde{R})\Big]-\mathbb{E}[V_iW_i]\mathbb{E}[V_iW_i]\,b_1 \end{cases} \tag{16}$$

Solving for b_1 and b_2 gives:

$$b_1 = \tilde{\beta}_1-\beta_1 = \frac{\mathbb{E}[W_i^2]\mathbb{E}\Big[V_i(\widetilde{R})\Big]-\mathbb{E}[V_iW_i]\mathbb{E}\Big[W_i(\widetilde{R})\Big]}{\mathbb{E}[V_i^2]\mathbb{E}[W_i^2]-\mathbb{E}[V_iW_i]^2} \tag{17}$$

$$b_2 = \tilde{\beta}_2-\beta_2 = \frac{\mathbb{E}[V_i^2]\mathbb{E}\Big[W_i(\widetilde{R})\Big]-\mathbb{E}[V_iW_i]\mathbb{E}\Big[V_i(\widetilde{R})\Big]}{\mathbb{E}[V_i^2]\mathbb{E}[W_i^2]-\mathbb{E}[V_iW_i]^2} \tag{18}$$

In the special case where $Cov(W,V)=0$, these expressions reduce to the single-regressor omitted-variable bias formulas:

$$b_1=\frac{Cov[V_i\widetilde{R}_i]}{Var[V_i]}, \qquad b_2=\frac{Cov[W_i\widetilde{R}_i]}{Var[W_i]}, \tag{19}$$

in which case each bias depends on the covariance between the experience and latent victimization risk. If $Cov[\widetilde{R}_i,V_i]>Cov[\widetilde{R}_i,W_i]$, then $b_1>b_2$.

More generally, when $Cov[V_i,W_i]>0$, if we also assume the latent risk factor is more strongly related to victimization than to witnessing, then it is convenient to parameterize $Cov[\widetilde{R}_i,V_i]=\gamma Cov[\widetilde{R}_i,W_i]$, with $\gamma>1$. Substituting this into the expressions above yields:

$$b_1=\frac{Var[W_i]\gamma Cov[W_i,\widetilde{R}_i]-Cov[V_iW_i]Cov[W_i,\widetilde{R}_i]}{Var[V_i]Var[W_i]-Cov[V_iW_i]^2}=Cov[W_i,\widetilde{R}_i]\frac{(\gamma Var[W_i]-Cov[V_iW_i])}{Var[V_i]Var[W_i]-Cov[V_iW_i]^2}. \tag{20}$$

$$b_2=\frac{Var[V_i]Cov[W_i,\widetilde{R}_i]-Cov[V_iW_i]\gamma\,Cov[W_i,\widetilde{R}_i]}{Var[V_i]Var[W_i]-Cov[V_iW_i]^2}=Cov[W_i,\widetilde{R}_i]\frac{Var[V_i]-\gamma Cov[V_iW_i]}{Var[V_i]Var[W_i]-Cov[V_iW_i]^2}. \tag{21}$$

The magnitude and direction of the biases (20) and (21) depend on: (i) the covariance between the omitted latent risk factor and victimization via γ; (ii) the covariance between the omitted factor and witnessing, $Cov[\widetilde{R}_i,W_i]$; (iii) the correlation between the two regressors, $Cov[V_i,W_i]$. Provided that V_i and W_i are not perfectly collinear, the denominator of the expressions is strictly positive, so the sign of the biases are determined by the numerators. Assuming the omitted factor

is only weakly correlated with witnessing so $Cov[\widetilde{R}_i, W_i]$ is small, b_1 and b_2 are necessarily small as well.

A key implication of the bias formulas is that for any fixed value of γ, the ratio,

$$\frac{b_1}{b_2} = \frac{\gamma Var(W_i) - Cov(V_i, W_i)}{Var(V_i) - \gamma Cov(V_i, W_i)}, \tag{22}$$

implies $b_1 = b_2 \cdot (...)$, that is, the omitted-variable bias shifts the victim and witness coefficients in a consistent direction across outcomes. As $\tilde{\beta}_1 - \tilde{\beta}_2 = (\beta_1 - \beta_2) + (b_1 - b_2)$, differences in the perception gaps $\tilde{\beta}_1 - \tilde{\beta}_2$ across outcomes can arise only if the causal difference $(\beta_1 - \beta_2)$ itself varies across outcomes. Observing that $\tilde{\beta}_{1k} > \tilde{\beta}_{2k}$ for some outcomes k but $\tilde{\beta}_{1j} < \tilde{\beta}_{2j}$ for other outcomes j is therefore difficult to reconcile with a single latent risk factor generating omitted variables bias. Such reversals necessarily point to true heterogeneity in the perception-specific causal effects of victimization and witnessing experiences.

Finally, the sign of the witness bias b_2 can change only if the numerator in (21) switches sign , that is, $Var[V_i] - \gamma\, Cov[V_i, W_i] < 0$, which is equivalent to $\gamma > \frac{Var[V_i]}{Cov[V_i, W_i]}$. In our data $Cov[V_i, W_i] \approx .0154 > 0$, so this threshold is approximately 8. Hence, b_2 becomes negative only if the latent factor is more than eight times more strongly correlated with victimization than with witnessing. If such values of γ are considered less plausible, reversals in the sign of the witness coefficients across outcomes is less likely to be driven by any single-factor selection model.

Adding the Interaction Term Consider now the model with the interaction between V_i and W_i, that to ease notation we define as $I_i \equiv V_i W_i$:

$$Y_i = \alpha + \beta_1 V_i + \beta_2 W_i + \beta_3 I_i + R_i'\delta + u_i, \qquad \mathbb{E}[u_i \mid V_i, W_i, I_i, R_i] = 0, \tag{23}$$

where $\widetilde{R}_i \equiv R_i'\delta$ again denotes the unobserved risk factor introduced in (9). Suppose instead that the researcher estimates:

$$Y_i = \tilde{\alpha} + \tilde{\beta}_1 V_i + \tilde{\beta}_2 W_i + \tilde{\beta}_3 I_i + \varepsilon_i, \qquad \varepsilon_i = \widetilde{R}_i + u_i, \tag{24}$$

which omits the latent factor. Our goal is to characterize the corresponding omitted-variable bias in the interaction coefficient $b_3 \equiv \tilde{\beta}_3 - \beta_3$. To simplify derivations, it is useful to partial out the main effects of V_i and W_i. Let r_{Yi} denote the part of Y_i not explained by V_i and W_i. Similarly, define r_{Ii} as the residual part of the interaction term I_i not predicted by V_i and W_i additively, and define $r_{\widetilde{R}_i}$ as the component of the latent risk factor $\widetilde{R}_i$ that is not captured by V_i and W_i separately. It reflects the additional risk an individual face beyond what can be inferred from their individual victimization or witnessing experiences.

By the Frisch-Waugh theorem, the coefficient on the interaction in the restricted regression is

obtained by regressing the residualized outcome r_{Yi} on the residualized interaction r_{Ii}:

$$\tilde{\beta}_3 = \frac{\mathbb{E}[r_{Ii} r_{Yi}]}{\mathbb{E}[r_{Ii}^2]}, \tag{25}$$

Substituting in (23) and using $\mathbb{E}[r_{Ii} u_i] = 0$, the bias of the interaction coefficient is:

$$b_3 = \tilde{\beta}_3 - \beta_3 = \frac{\mathbb{E}[r_{Ii} r_{\widetilde{R}_i}]}{\mathbb{E}[r_{Ii}^2]}. \tag{26}$$

The direction of bias depends on the sign of the numerator of (26), $Cov[r_{Ii} r_{\widetilde{R}_i}]$, that captures the covariance between the part of $V_i W_i$ that is not explained by the additive impacts of V_i and W_i and the part of the unobserved risk factor that is not already predicted by V_i and W_i individually.

The intuition is as follows. The interaction term captures whether being a victim and a witness has an effect that goes beyond the sum of the individual effects. When we omit the latent risk factor, the interaction coefficient is biased only if the omitted risk generates *extra* co-occurrence of victimization and witnessing, that is, if high-risk individuals are disproportionately likely to be both victims and witnesses, over and above what one would predict from the additive effects of V_i and W_i. If the latent risk raises V_i and W_i individually but does not make them occur together more often than additively, then the covariance $\mathbb{E}[r_{Ii} r_{\widetilde{R}_i}]$ is close to zero. In this case the omitted-variable bias in the interaction term is small, even if $\tilde{\beta}_1$ and $\tilde{\beta}_2$ are biased.

As we restrict our analysis to single-victim, single-witness episodes, there is little scope for scenarios in which individuals experience repeated or overlapping crime-related events, or when crime is concentrated in specific networks or locations. As a result, it is less plausible that the omitted risk factor generates disproportionately more joint exposure than separate exposure, making a large bias in the interaction term less likely.

A.4 Robustness Checks on Perceptions and Experiences

A.4.1 Omitted Variables

We probe the data to underpin the idea that the observed patterns of how crime-related experiences relate to crime-related perceptions are not merely driven by omitted variables. These are all presented using the same survey waves, and Column 1 of Table A2 shows our baseline estimates from (4). We first examine the assumption that there are no missing covariates that determine perceptions and that correlate with crime-related experiences. Following Altonji *et al.* [2005] and Oster [2019], we estimate bounds on the effects of each group, accounting for selection on unobservables. This bounded treatment effect approach assumes there are potentially many unobserved factors omitted from (4). This set of unobservables is denoted W_2, capturing a linear combination of j unobserved variables w_j^u, multiplied by their coefficients, $W_2 = \sum_{j=1}^{J_u} w_j^u \gamma_j^u$. We then need to make an assumption on how the unobserved and observed covariates driving per-

ception outcomes relate to each other. Altonji *et al.* [2005] and Oster [2019] assume they relate through a proportional selection relationship where the coefficient of proportionality is denoted τ. It can then be shown that the true causal impact for group i, β_i^*, depends on β (and other factors): $\beta_i^* = \beta_i(\tau, .)$. Bounds on β_i are established by considering a range of plausible τ's. At one extreme, if $\tau = 0$ the unobserved covariates do not bias estimation and $\beta_i^* = \beta_i$. At the other extreme, Altonji *et al.* [2005] and Oster [2019] suggest equal selection ($\tau = 1$): intuitively, the set of unobservables cannot be *more* important than the available covariates in explaining the effect of crime-related experiences on perceptions. In Column 2a of Table A2 we report bounds $\beta_i(0) = \beta_i$ and $\beta_i(1)$ using $R^2_{\max} = 1.3R^2$ following Oster [2019], and in Column 2b we report the coefficient of proportionality τ required for $\beta_i(\tau) = 0$. In nearly all cases, across perceptions and for both experiences, the bounds remain away from zero and in all cases, τ would need to be larger than five (in absolute value) for the bounds to cross zero.

We next narrow in on the concern that geographic variation in actual crime confounds the results. We address this in three ways. First, we include fixed effects for local authorities rather than police force area. These cover jurisdictions smaller than police force areas: the average police force area for example includes seven local authorities. The results in Column 3 show that for all margins of perception, the partial correlations with both crime-related experiences remain stable and precisely estimated. Second, we go one step further to control for highly localized crime rates – at the LSOA level. Column 4 show that the partial correlations with either experience remain precisely estimated across perceptions, including towards the neighborhood, feeling safe to walk alone in the dark and worrying about being a victim. Third, we control for LSOA fixed effects. This specification is in Column 5. We see that within LSOA, there remain significant differences between non-victims and those that experience crime – either as a witness or a victim. This is the case for all 12 estimated coefficients, where the magnitudes of impact in most cases remain close to those from our baseline specification in Column 1.

We next examine the robustness of the results to changing the sampling restrictions when defining witnesses or victims of crime. Figure A2 shows how the results from (4) change when varying the definition of witnessing crime by restricting the sample to individuals who reported not only a single crime but also either a single type of ASB or just one ASB incident (rather than risk confounding the effects for those subject to multiple experiences of ASB). We see that the estimates for both crime-related experiences remain similar to the baseline estimates.

A.4.2 Experiences and the Distribution of Perception Outcomes

We detail how crime-related experiences impact perceptions using the full discrete distribution of each outcome rather than continuous normalized outcomes. To do so we estimate separate linear probability models for each response category. Figure A5 plots the estimated coefficients along with the underlying distribution of the perception outcome category among non-victims. The first

panel shows how each category of confidence in the criminal justice system is shifted by being a witness of crime (left hand panel) and be being a victim (right hand panel). The negative impact of both experiences is driven primarily by a reduction in the share of respondents that express being *fairly confident* in the criminal justice system, and then being more likely to report being either *not very confident* or *not at all confident*. Across remaining outcomes, we continue to see shifts in perception arise from reductions in those expressing the most positive beliefs, and these patterns are very similar when individuals are either a witness to crime or are a victim of crime.

A.4.3 Dynamics

Given the large shifts in crime-related perceptions associated with crime-related experiences, it is natural to ask whether such effects persist. We examine the issue for victims of crime because the month of the incident is recorded, as well as the month of interview (the exact month of witnessing crime is not recorded). We estimate the following specification:

$$y_{i(t)} = \alpha Victim_{i(t)} + \gamma Month_victim_{i(t)} + X'_{i(t)}\theta + \phi_P + \omega_t + \omega_m + \varepsilon_{i(t)}, \tag{27}$$

where $Victim_{i(t)}$ is a dummy equal to one if individual i was victimized in the month of the survey or the preceding 12 months, $Month_victim_{i(t)}$ is the number of months since the victimization incident and survey month (so ranging from 1 to 13). All other variables are as previously defined. The omitted group is non-victims, where we later show the robustness of the results to narrowing down to other counterfactual groups. α captures the immediate change in perceptions at the time of victimization, while γ captures the average change in perceptions for each additional month thereafter. Assuming linear dynamics, α/γ measures the implied recovery rate, that is the number of months until perceptions return to their pre-victimization level (if $\gamma > 0$).

Figure A6 summarizes the results (the coefficients of interest are in Table A3). For each perception we show: (i) $\widehat{\alpha}$, the immediate victimization effect (darker bars); (ii) $\hat{\alpha} + (\hat{\gamma} \times 12)$, the estimated impact 12 months after victimization (lighter bars). In most cases the drop in perceptions is persistent. We cannot reject the null that $\gamma = 0$ for five out of six perceptions: the one exception is confidence in the criminal justice system where $\widehat{\gamma} < 0$, so perceptions appear to worsen with time. In all other cases, $\widehat{\gamma}$ is a precise zero so there is no recovery in perceptions from the initial victimization experience.

Experiences should exhibit recency effects on perceptions being cued, as more recent events are more similar to the present context and therefore more likely to be retrieved from memory. However, we do not observe recency gradients *within* the 12-month window. This might however just be because all such experiences are best considered to still be recent as far the memory retrieval-simulation process.[27]

[27] Johnston *et al.* [2017] use panel data from the HILDA survey in Australia to examine the persistence of effects from violent crime victimization on life satisfaction. They find: (i) persistent but diminishing impacts over the

Robustness The persistence of experience effects is robust to restricting the counterfactual group to include: (i) non-victims who witnessed a crime but no ASB; (ii) non-victims who witnessed anti-social behavior but no other crime types; (iii) the combination of both groups (Table A4, Columns 2 to 4); (iv) narrowing in on the concern that geographic variation in actual crime confounds the results (Table A5, Columns 2 to 4); (v) using entropy balancing to account for observable differences between victims and non-victims (Table A5, Column 5); (vi) replacing the continuous variable for months since victimization, $Month_victim_{i(t)}$ in (27), with separate dummies for each month since victimization to examine whether a nonparametric approach validates the assumption of linear recovery rates (Figure A7).[28]

We also examine how these dynamics vary by gender and crime type (Figures A8 and A9). The persistence of effects across perceptions is largely common to both genders. The slight exception is for confidence in the criminal justice system, where men have smaller initial impacts and their perception worsens over time, while for women the initial fall is maintained. The dynamic impacts are also mostly similar across crime types.

A.5 Social Costs of Crime

A.5.1 Set up

We build on the methodology that Heeks *et al.* [2018] use to measure the social costs of crime born by victims. They decompose these costs into: (i) *anticipation costs*, including defensive expenditures and insurance administration; (ii) *consequences of crime*, including the value of property stolen or damaged, physical and emotional harm, lost output, health service costs, and victim service costs; (iii) *response costs*, including costs borne by the police, courts, and wider criminal justice system.

Denote the Heeks *et al.* unit social cost of crime type k on victims as $V^k = \sum_{i \in \mathcal{I}} V_i^k$, where $i \in \mathcal{I}$ indexes the set of cost components covering anticipation, consequence, and response costs, and V_i^k denotes the unit social cost for victims of crime type k associated with cost component i. Our analysis uses a more aggregated crime categorization than in Heeks *et al.* They report unit costs for 22 crime types, distinguishing between 15 categories of crimes against the individual (homicide, violence with injury, violence without injury, rape, other sexual offenses, robbery, domestic burglary, theft of vehicle, theft from vehicle, theft from person, criminal damage, arson, other criminal damage, fraud, and cyber crime). These map into four categories overlapping with

first year since victimization: the estimated quarter effects for life satisfaction are 62%, 40%, 45% and 32% of a standard deviation for women and 28%, 39%, 71% and 18% of a standard deviation for men; (ii) for both genders, there is (almost) complete adaptation after one year; (iii) there are longer adaptation profiles for other major life events such as a major worsening in finances and the death of a spouse or child.

[28] For the checks in Table A5 that include controlling for LSOA fixed effects, these are all conducted in the same sample from 2011-17 to ensure comparability. This is the time period for which LSOA identifiers are available. In Column 1 of Table A5 we shows results from (27) in this subsample – that closely match the estimated coefficients from the full sample.

our analysis: assaults, burglaries, thefts, and criminal damage. We assign homicide, violence with and without injury, and robbery to our assaults category; domestic burglary to burglary; theft of and from vehicles and theft from person to theft; criminal damage, arson, and other criminal damage to criminal damage. We exclude fraud, cyber crime, commercial crime, rape and other sexual offenses, because the CSEW is not well suited to measure them. From our aggregated categories, we exclude threats as these do not clearly map to the crime types in Heeks *et al.*

To make our unit costs comparable to Heeks *et al.* that are in 2015-16 prices, we compute category-level unit costs using weights based on the number of victimization incidents from the 2015-16 CSEW. Let h index the detailed crime types in Heeks *et al.*, k indexes our four broad categories, ω_{hk} denotes the share of CSEW incidents of type h belonging to category k, based on CSEW 2015-16 victimization counts reported in Heeks *et al.*, with $\sum_h \omega_{hk} = 1$ for each k. For each component i and category k we define:

$$V_i^k = \sum_h \omega_{hk} V_i^h, \tag{28}$$

where V_i^h are the component-specific per-incident unit costs reported by Heeks *et al.* for crime type h. The crime type mapping is summarized in Table A10. This shows the frequency weights of each crime type (Column 2), and the resulting average unit cost when we aggregate the unit costs from the more disaggregated crime types in Heeks *et al.* (Column 3) to our four crime types (Column 4).

A.5.2 Accounting for Witnesses

We extend the conventional estimates by incorporating the fact that witnesses bear a subset of these costs, while always taking all other aspects of the Heeks *et al.* methodology as given. Denoting the unit social cost for witnesses of crime type k as W^k, the unit total social cost of crime type k once witnesses are taken into account is:

$$\text{Unit Social Cost}^k = V^k + W^k, \tag{29}$$

We first extend the victim-based Heeks *et al.* estimates by assuming witnesses bear the same unit cost as victims, but only for a subset of cost components, that given our results on how crime-related experiences associate with crime-related perceptions, are plausibly relevant for both groups. Specifically, we identify the following components from Heeks *et al.* for which witnesses may incur costs: (i) defensive expenditures; (ii) physical and emotional harm; (iii) lost output. We exclude other cost components in Heeks *et al.* such as health service costs, victim service costs, insurance administration, and property loss, which are by construction borne only by victims of crime. For each of the cost components borne by witnesses, $i \in \mathcal{I}_W (\subset \mathcal{I})$, we assign witnesses the same unit costs as victims, i.e. $W_i^k = V_i^k$ for $i \in \mathcal{I}_W$, and $W_i^k = 0$ for $i \notin \mathcal{I}_W$. The unit social cost

borne by witnesses of crime type k is then:

$$W^k = \sum_{i \in \mathcal{I}_W} V_i^k. \tag{30}$$

The unit social cost of crime type k becomes:

$$\text{Unit Social Cost}_{(1)}^k = V^k + W^k = V^k + \sum_{i \in \mathcal{I}_W} V_i^k. \tag{31}$$

We compute these costs for each of our four crime categories and compare them to the corresponding Heeks *et al.* benchmark ($W^k = 0$). The calculations are reported in Columns 5 and 6 of Table A10. The unit social costs of crime averaged across all crime types rise from £6081 in Heeks *et al.* to £9699 once witnesses are accounted for – an increase of 59%. The costs of witnessing crime (W^k = £3929) are around 65% of the costs to victims.

Our second approach incorporates the fact that for any given cost component, witness and victim unit costs can differ. We use our estimates of the impact of crime-related experiences on perceptions to construct lower- and upper-bound estimates of the extent to which witnesses and victims are differentially impacted through any cost component. We proceed in three steps.

First, we map each cost component $i \in \mathcal{I}_W$ to one or more perception outcomes: (i) *defensive expenditure*: money spent on crime detection and prevention (alarms, CCTV, car alarms) is linked to perceptions of *own safety*, such as feeling safe walking alone in the dark and worrying about becoming a victim; (ii) *physical and emotional harm*: the reduction in quality of life due to physical and emotional harm (quantified by Heeks *et al.* using QALYs based on Dolan *et al.* [2005]) is mapped to our measure of *quality of life*; (iii) *lost output*: lost productivity due to time off work and reduced productivity at work is also related to our *quality of life* outcome.

We denote as $\widehat{\lambda}_v^{k,i}$ the estimated effect of being a victim of crime type k on the perception outcome(s) associated with component i. This is computed as weighted average of the victimization effects for non-witness victims and victim-witnesses, estimated from (5), with weights given by their respective shares among victims (60% and 40%). $\widehat{\lambda}_w^{k,i}$ are the corresponding effects of being a witness of crime type k on the perception outcome(s) associated with component i. This is calculated as weighted average of the witness effects for witness-non victims and witness-victims, estimated from (5), with weights given by their respective shares among witnesses (82% and 18%). We construct a multiplier m_i^k to scale victim costs into witness costs:

$$m_i^k = \frac{\widehat{\lambda}_w^{k,i}}{\widehat{\lambda}_v^{k,i}}. \tag{32}$$

For the defensive expenditure component, which is linked to two safety outcomes (feeling safe walking alone in the dark and worrying about becoming a victim), we construct both a minimum

and a maximum multiplier using these outcomes, yielding lower- and upper-bounds. The estimated multipliers m_i^k are reported in Columns 1 to 4 of Table A11. Where witnesses are affected less (more) than victims, m_i^k is below (above) one. We then define witness unit costs for each cost component i and crime type k as:

$$W_i^k = m_i^k V_i^k, \quad \text{for } i \in \mathcal{I}_W, \tag{33}$$

and set $W_i^k = 0$ for $i \notin \mathcal{I}_W$. The resulting unit social cost is:

$$\text{Unit Social Cost}_{(2)}^k = V^k + W^k = V^k + \sum_{i \in \mathcal{I}_W} m_i^k V_i^k. \tag{34}$$

Columns 7a to 8b of Table A10 show the resulting unit social costs of crime averaged across all crime types and for each crime type k. Relative to the first approach, the unit costs of witnessing crime (averaged across all crime types) fall by 39% using the lower bound estimate (from £3929 to £1532). There is variation across crime types, and for criminal damage, the witness costs remain almost unchanged across approaches (from £393 to £405).

A.5.3 Accounting for Post Victimization Experiences

Our findings show that favorable post-victimization outcomes in the justice system can potentially mitigate some of the negative impacts of initial victimization on crime-related perceptions, and hence the costs of victimization. We build on this insight to measure the social costs of crime victimization. To be clear, we do not consider witness costs, and only adjust victim costs to reflect perception shifts following favorable positive post-victimization outcomes, namely cases in which an offender is found and charged.

We adopt the same mapping of cost components used in approach 2. We denote the set of such cost components for victims by $\mathcal{I}_V$. For all other components, victim costs are left unchanged from Heeks *et al.* We denote as $\widehat{\lambda}_v^{k,i}$ the estimated effects of being a victim of crime type k on the perception outcome(s) associated with cost component i. We compute this as a weighted average of the victimization effects for non-witness victims and victim-witnesses, estimated from (5), with weights given by their respective shares among victims (60% and 40%). We denote as $\hat{\delta}_3^{k,i} - \hat{\delta}_1^{k,i}$ the estimated effects of experiencing the most favorable post-victimization outcome, relative to the least favorable outcome among victims who reported the crime. We take the estimates of $\hat{\delta}_3^{k,i} - \hat{\delta}_1^{k,i}$ from (7).

For each cost component $i \in \mathcal{I}_V$ and crime type k, we construct a post-victimization multiplier:

$$r_i^k = \max\left\{0,\ 1 - \frac{\hat{\delta}_3^{k,i} - \hat{\delta}_1^{k,i}}{|\widehat{\lambda}_v^{k,i}|}\right\}, \tag{35}$$

that captures how much of the initial adverse effect of victimization on perceptions is left after a favorable post-victimization experience. When post-victimization outcomes more than fully offset the initial negative effect of victimization, we set $r_i^k = 0$ to avoid assigning negative costs. If instead the most favorable post-victimization outcome worsens perceptions, r_i^k can be greater than one. Estimates of the multipliers r_i^k are reported in Columns 5 to 8 of Table A11.

In our working sample, only 4% of victims experience a favorable outcome, where an offender is both identified and charged within 12 months of the incident. This share varies across crime types: 13% for violent crimes, 6% for burglaries, 1.7% for thefts and 2.6% for criminal damage. To reflect this, we scale the post-victimization multiplier by the prevalence of favorable post-victimization outcomes. Let π^k denote the share of victims of crime type k for whom an offender is identified and charged, and let $V_{i,pos}^k = r_i^k \; V_i^k$, for $i \in \mathcal{I}_V$. The victim unit cost becomes:

$$\tilde{V}_i^k = (1 - \pi^k) V_i^k + \pi^k V_{i,pos}^k, \text{ for } i \in \mathcal{I}_V, \tag{36}$$

while for all other components $i \notin \mathcal{I}_V$ victim costs are left unchanged as $\tilde{V}_i^k = V_i^k$. The resulting unit social cost is the given by:

$$\text{Unit Social Cost}_{(3)}^k = \tilde{V}^k = \sum_i \tilde{V}_i^k. \tag{37}$$

Columns 9a to 10b of Table A10 show the resulting unit social costs of victimization averaged across all crime types, and for each crime type k. We do so both for those that experience a favorable post-victimization outcome, and for the average victim (irrespective of actual outcomes in the justice system). Relative to victimization costs in Heeks *et al.* the first approach, we see that for those experiencing a favorable outcome, victimization costs *rise*: averaging across all crime types these rise by 27% using the lower bound estimate (from £6081 to £7730). This rise is also seen across crime types with the exception of victims of burglary or criminal damage.

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Table 1: Sources Used to Form Crime-related Perceptions

	(1) Criminal justice system	(2) Police	(3) Crime rate in country	(4) Crime rate in local area
Number of respondents	37,227	16,783	38,125	34,596
Experiences				
Personal	.170	.191	.175	.378
Vicarious	.330	.330	.343	.579
Media				
Broadsheet newspapers	.227	.212	.233	.074
Tabloid newspapers	.302	.278	.316	.084
Local newspapers	.344	.362	.296	.468
News programmes on tv/radio	.652	.618	.671	.296
Internet	.062	.037	.185	.094

Notes: The sample consists of individual responses from pooled CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. We show means of dummy indicators for respondents reporting the sources they use to form the perceptions indicated on the Columns. Column 1 consists of responses for survey waves 2003-04 to 2007-08, Column 2 uses survey waves 2004-05 to 2007-08, and Columns 3 and 4 use survey waves 2011-12 to 2014-15. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave.

Table 2: Perceptions by Crime-related Experiences

Sample: 2003-2007, 2011-2014 and 2017
Means, standard deviation in parentheses

	(1) Non-victims Non-witness	(2) Non-victims Witness	(3) Victims Non-witness	(4) Victims Witness	Differences (1) - (2)	Differences (1) - (3)	Differences (2) - (3)	Within LSOA Differences (1) - (2)	Within LSOA Differences (1) - (3)	Within LSOA Differences (2) - (3)
Number of respondents	172,063	63,812	21,248	14,280						
Perceptions (normalized)										
Confidence in the criminal justice system	.082	-.021	.005	-.058	.103***	.077***	.026**	.179***	.089***	.085**
Confidence in the police	.069	-.071	-.057	-.194	.140***	.126***	.014	.151***	.121***	.043**
Neighborhood problems	.129	-.369	-.241	-.617	.498***	.370***	.127***	.468***	.283***	.210***
Feel safe walking alone after dark	.032	.043	-.045	-.053	.011*	.076***	.087***	.007	.037	.038
Worried about being victimized	.015	-.102	-.196	-.254	.116***	.211***	.094***	.062**	.168**	.022
Quality of life affected by crime	.088	-.110	-.312	-.404	.198***	.400***	.202***	.201***	.328***	.011

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists of individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. We present means with standard deviations in parentheses.Each perception outcome is normalized in this working sample and coded so that higher values indicate a more positive outcome: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. We report absolute differences, and absolute differences conditional on Lower Layer Super Output Area (LSOA) fixed effects. These are available for 2011-17. Differences are calculated from the corresponding OLS regression using robust standard errors. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave.

Table 3: Trends in Witnessing and Victimization

Sample: 2003-2007, 2011-2014
Means

	2003-04	2004-05	…	2013-14	2014-15	Total
Number of respondents	12,325	33,276	…	27,641	12,834	252,110
Panel A: All crimes						
Witness rate	.149	.140	…	.148	.146	.145
Victimization rate	.162	.156	…	.123	.121	.145
Witness-victimization ratio	**.920**	**.899**	…	**1.21**	**1.21**	**1.03**
Panel B: By crime type						
Violent crime						
Witness rate	.074	.074	…	.095	.095	.086
Victimization rate	.016	.017	…	.016	.016	.016
Witness-victimization ratio	**4.69**	**4.39**	…	**6.01**	**5.92**	**5.40**
Criminal Damage						
Witness rate	.022	.020	…	.008	.008	.015
Victimization rate	.037	.039	…	.027	.028	.036
Witness-victimization ratio	**.604**	**.497**	…	**.298**	**.294**	**.413**
Theft						
Witness rate	.045	.041	…	.041	.038	.039
Victimization rate	.083	.078	…	.063	.059	.074
Witness-victimization ratio	**.548**	**.518**	…	**.658**	**.651**	**.548**
Burglary						
Witness rate	.007	.006	…	.004	.005	.006
Victimization rate	.026	.021	…	.017	.018	.019
Witness-victimization ratio	**.282**	**.288**	…	**.243**	**.294**	**.289**

Notes: The sample consists of individual responses from pooled data of the 2003-04 to 2007-08 and 2011-12 to 2014-15 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave. Panel A shows witness and victimization rates by year (where witness rates exclude witnessing antisocial behavior). Panel B decomposes these witness and victimization rate by crime type. The witness-victimization ratio is calculated by dividing the number of respondents who witnessed a crime by the number of respondents who were victimized by that (type of) crime.

Table 4: Perceptions and Crime-related Experiences

Sample: 2003-2007, 2011-2014 and 2017

OLS regression estimates, robust standard errors

	(1) Confidence in the criminal justice system	(2) Confidence in the police	(3) Problems in neighborhood	(4) Feel safe walk in dark	(5) Worried to be a victim	(6) Crime on quality of life
Panel A: Experiences						
Witness	-.152***	-.150***	-.423***	-.122***	-.128***	-.198***
	(.006)	(.005)	(.007)	(.005)	(.006)	(.015)
Victim	-.099***	-.121***	-.258***	-.127***	-.167***	-.354***
	(.008)	(.007)	(.009)	(.007)	(.008)	(.021)
Panel B: Interaction of Experiences						
Witness	-.160***	-.151***	-.437***	-.129***	-.139***	-.214***
	(.007)	(.006)	(.007)	(.006)	(.007)	(.016)
Victim	-.118***	-.121***	-.292***	-.144***	-.192***	-.389***
	(.010)	(.009)	(.011)	(.009)	(.011)	(.027)
Witness x victim	.048***	.002	.084***	.041***	.061***	.092**
	(.016)	(.015)	(.018)	(.014)	(.017)	(.043)
A: Witness = Victim [p-value]	[.000]	[.001]	[.000]	[.576]	[.000]	[.000]
B: Witness = Victim [p-value]	[.000]	[.003]	[.000]	[.129]	[.000]	[.000]
Year, month of interview and police force area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared (panel A)	.061	.037	.157	.233	.110	.061
Observations (panel A)	190,809	254,031	175,791	204,243	173,406	34,791

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. The outcomes in Columns 1 to 6 are the perception measures, each coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. All columns report OLS estimates with robust standard errors in parentheses. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race , whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects. At the foot on each Column we show the p-value of the witnessing and victimization effects being equal. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave.

Table 5: Similarity of Crime-related Experiences

Sample: 2003-2007 and 2011-2014

OLS regression estimates, robust standard errors

	(1) Confidence in the criminal justice system	(2) Confidence in the police	(3) Problems in neighborhood	(4) Feel safe walk in dark	(5) Worried to be a victim	(6) Crime on quality of life
Witness	-.160***	-.151***	-.437***	-.129***	-.139***	-.214***
	(.007)	(.006)	(.007)	(.006)	(.007)	(.016)
Victim	-.118***	-.121***	-.292***	-.144***	-.192***	-.389***
	(.010)	(.009)	(.011)	(.009)	(.011)	(.027)
Witness x victim [dissimilar experience]	.031*	-.013	.035*	.037**	.067***	.072
	(.017)	(.016)	(.019)	(.015)	(.017)	(.045)
Witness x victim [similar experience]	.134***	.085***	.317***	.061**	.034	.189**
	(.030)	(.029)	(.034)	(.027)	(.031)	(.086)
Total Effect = Witness + Victim + Interaction						
Dissimilar experiences	-.248***	-.285***	-.694***	-.236***	-.264***	-.531***
	(.013)	(.012)	(.015)	(.011)	(.013)	(.035)
Similar experiences	-.145***	-.187***	-.412***	-.212***	-.297***	-.413***
	(.028)	(.028)	(.032)	(.026)	(.029)	(.081)
Witness = Victim [p-value]	[.000]	[.003]	[.000]	[.129]	[.000]	[.000]
Total effect dissimilar = similar [p-value]	[.001]	[.001]	[.000]	[.393]	[.294]	[.179]
Year, month of interview and police force area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.061	.037	.158	.233	.110	.061
Observations	190,809	254,031	175,791	204,243	173,406	34,791

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists of individual responses from pooled data of the 2003-04 to 2007-08 and 2011-12 to 2014-15 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave. The outcomes in Columns 1 to 6 are the perception measures, each coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. The similarity of witnessing and victimization experiences is defined as being of the same crime type. All columns report OLS estimates with robust standard errors in parentheses. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race , whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects. At the foot on each Column we show the p-value of the witnessing and victimization effects being equal.

Table 6: Unit Social Costs of Crime

Crime type	Approach 1	Approach 2		Post-victimization adjustment			
	Witnesses	Witness-adjusted costs		Favorable outcome		All victims	
	(1)	(2) Lower bound	(3) Upper bound	(4) Lower bound	(5) Upper bound	(6) Lower bound	(7) Upper bound
Average unit cost	1.59	1.25	1.26	1.27	1.30	1.04	1.04
Violent crime	1.69	1.28	1.28	1.36	1.40	1.05	1.05
Burglary	1.33	1.15	1.18	0.99	1.01	1.00	1.00
Theft	1.29	1.14	1.19	1.12	1.23	1.00	1.00
Criminal damage	1.26	1.27	1.29	0.85	0.80	1.00	0.99

Notes: We report ratios of unit social costs of crime that account for both victims and witnesses relative to the victim-only benchmark of Heeks et al. [2018]. The first row reports the average ratio of unit social costs, across crime categories. In Columns 1 and 2, witnesses are assigned the same unit cost as victims for selected cost components from Heeks et al. [2018 . In Columns 3 and 4, we use perception-based multipliers to scale victim costs into witness costs. In Columns 4 to 7, we adjust victim unit costs to account for post-victimization outcome effects. Columns 4 and 5 shows multipliers only for victims with positive post-victimization outcomes. Column 6 and 7 weight this by share of victims that experience a favorable post-victimization outcome, i.e. for whom an offender is identified and charged. The lower- and upper-bound estimates are based on alternative sets of multipliers.

Table 7: Perceptions of Recent Changes in Crime Rates

Sample: 2003-2007 and 2011-2014

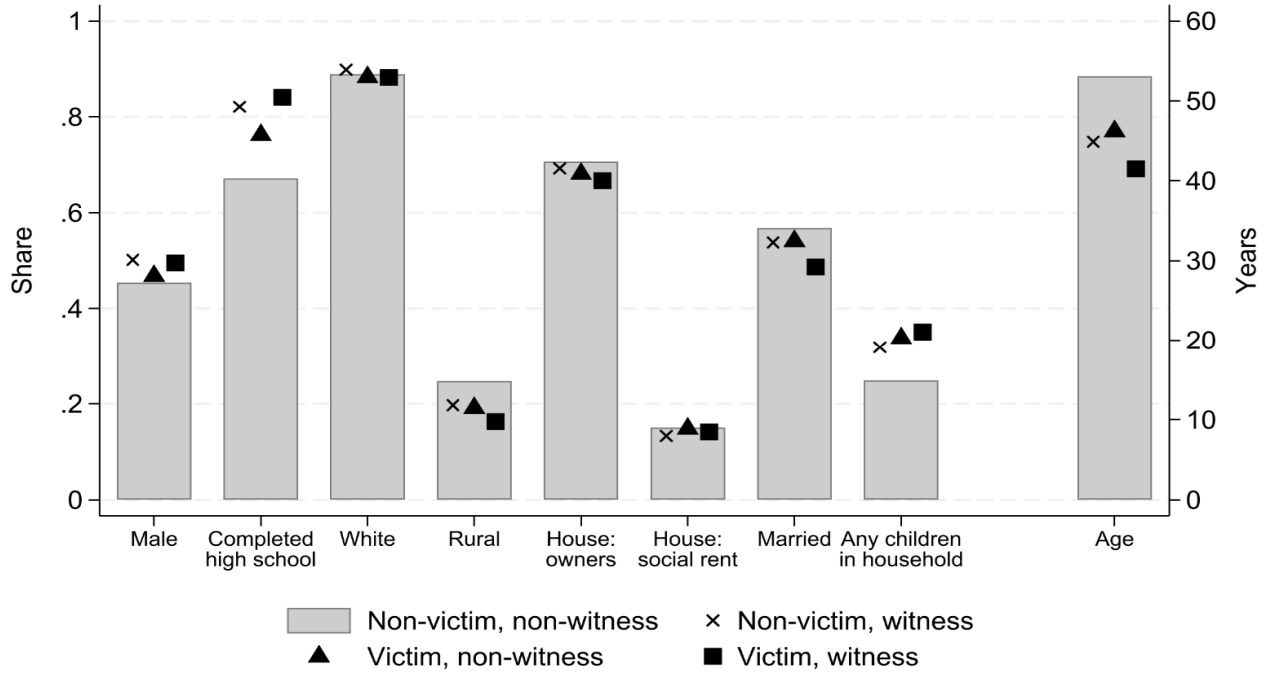
OLS regression estimates, robust standard errors

	(1) Change in national crime rate	(2) Change in local area crime rate
Panel A: baseline		
Witness	.104***	.188***
	(.007)	(.006)
Victim	.078***	.199***
	(.010)	(.009)
Panel B: by crime type		
Witness=criminal damage	.136***	.194***
	(.033)	(.025)
Witness=theft	.102***	.149***
	(.019)	(.016)
Witness=burglary	.093**	.321***
	(.047)	(.042)
Witness=violent	.095***	.124***
	(.013)	(.012)
Witness=ASB	.107***	.210***
	(.010)	(.008)
Victim=criminal damage	.080***	.204***
	(.019)	(.017)
Victim=theft	.072***	.151***
	(.014)	(.012)
Victim= burglary	.072***	.336***
	(.026)	(.025)
Victim=violent	.072**	.187***
	(.031)	(.027)
P-values:		
A: Witness = Victim	[.037]	[.352]
B: Witness crime types equal	[.807]	[.000]
B: Victim crime types equal	[.987]	[.000]
Year, month of interview and police force area fixed effects	Yes	Yes
R-squared (Panel A)	.119	.045
Observations (both panels)	121,327	196,859

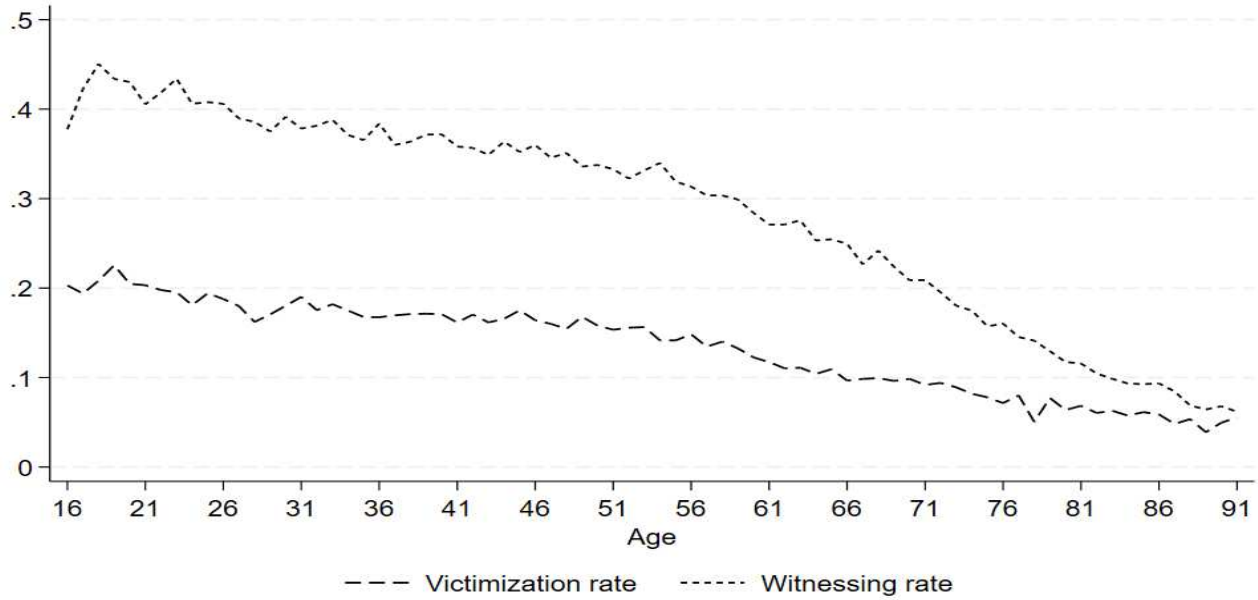
Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists of individual responses from pooling the 2003-04 to 2007-08, 2011-12 to 2014-15 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave. The outcomes in Columns 1 and 2 are perceptions of changes in the crime rate in the past two or few years (with there being slight variation in the wording of the survey question). Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. All columns report OLS estimates with robust standard errors in parentheses. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects. At the foot on each Column we show the p-value of the witnessing and victimization effects being equal in the specification in Panel A, and the p-value of a joint test for equality of crime types for the specification in Panel B.

Figure 1: Characteristics of Witnesses and Victims

A. Characteristics by Experience

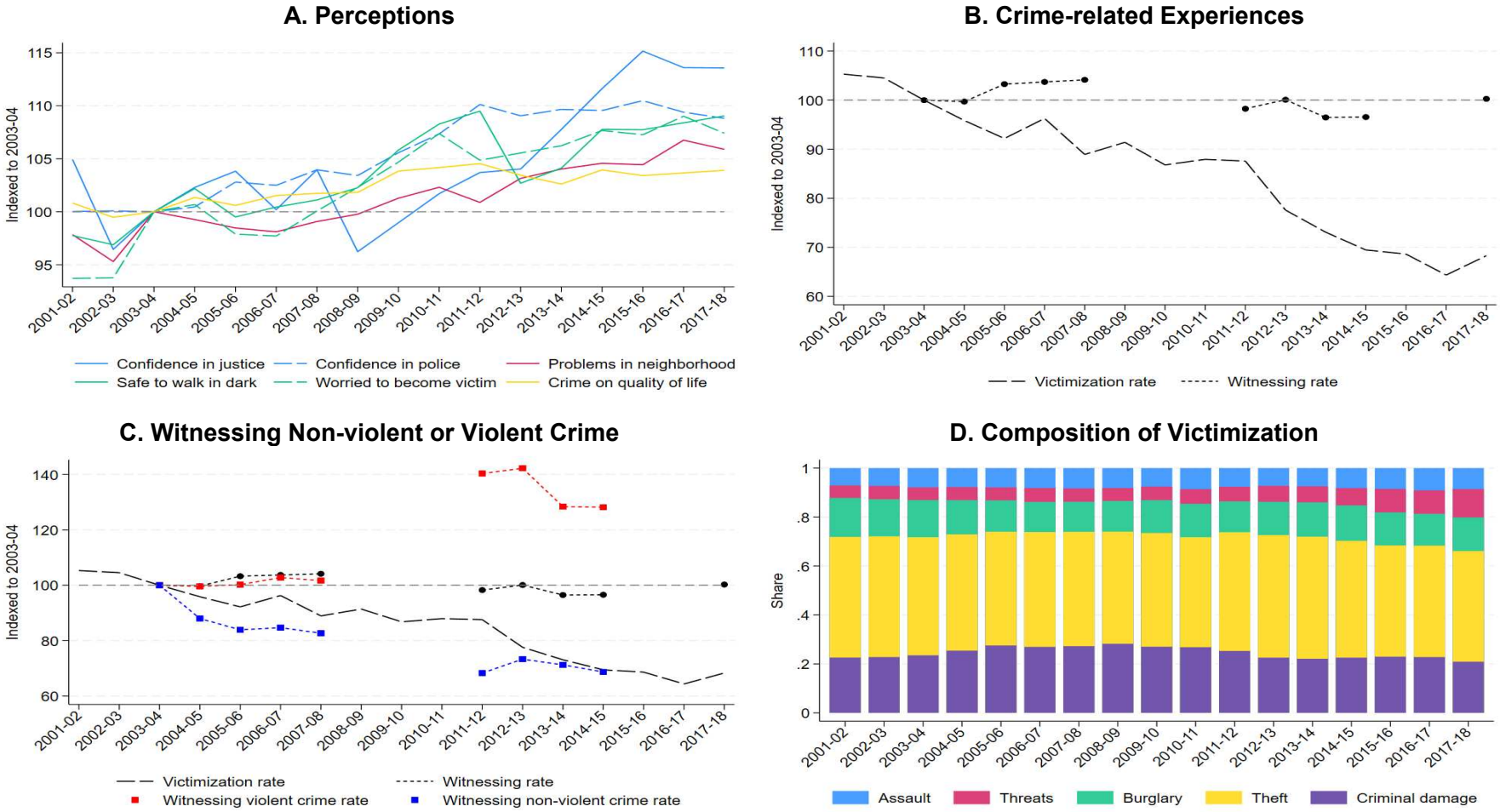


B. Victimization and Witnessing Age Profiles



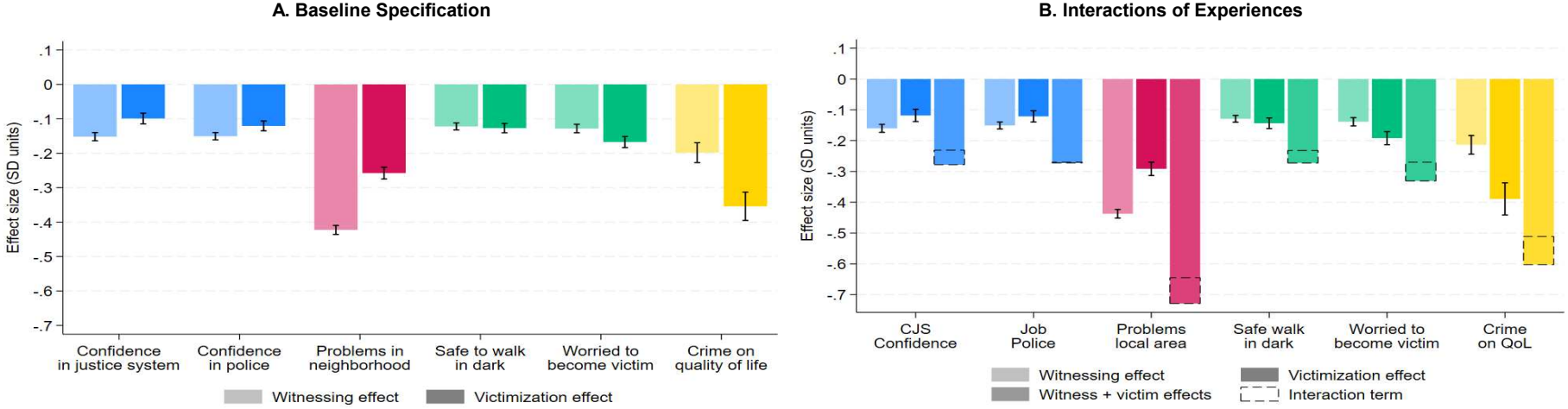
Notes: The sample consists of individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

Figure 2: Time Trends in Perceptions and Crime-related Experiences



Notes: The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW survey waves, excluding individuals with multiple victimizations. Data on witnessing is not available in all years. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave. In Panels A, B and C, all variables are indexed to their level in the 2003-04 survey wave. Panel A shows trends in each perception outcome where higher values indicate a more positive outcome: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Panel B shows trends in victimization and witnessing rates. Panel C breaks down the witnessing rate separately for violent and non-violent crime. Panel D shows the composition of crime type for victims for each survey year.

Figure 3: Perceptions and Crime-related Experiences



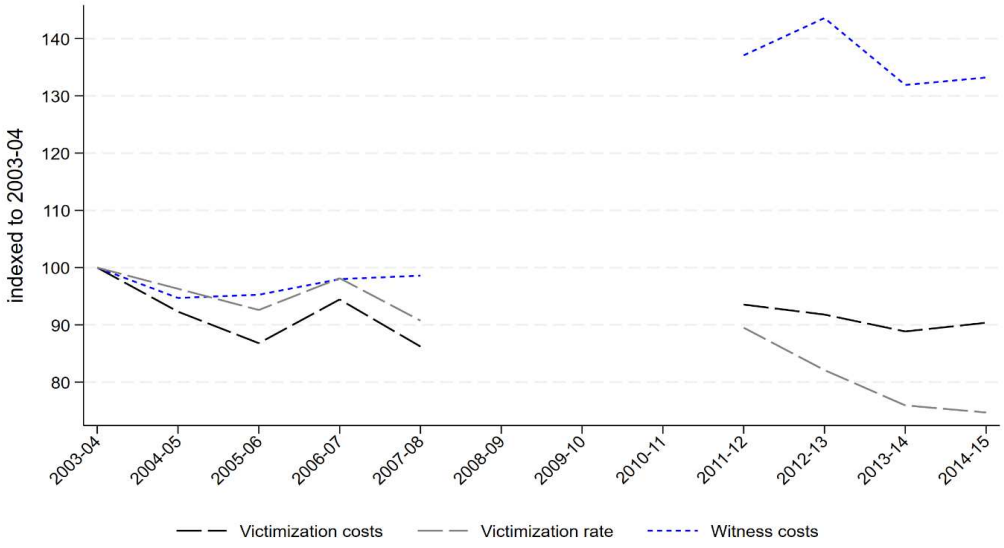
Notes: The sample consists of individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. We show estimates of witnessing effects (lighter bars) and victimization effects (darker bars) across six perception outcomes, and highlight their interacted effect on Panel B. The error bars represent 95% confidence intervals of both estimates using robust standard errors. The perception outcome variables are coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception outcome is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. The bars report OLS estimates of the witnessing and victimization effects, Each regression includes controls for gender, age, age-squared, six levels of marital status, if there are any children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental or social rental, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview, and police force area fixed effects. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

Figure 4: Perceptions and Post-victimization Experiences



Notes: The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW waves, excluding individuals with multiple victimizations. For each perception outcome variable, the bars report OLS estimates of a favorable post-victimization outcome, namely the victim-respondent's offender being found and charged conditional on the crime being reported, minus the estimated coefficient on a dummy for the crime being reported. The error bars represent 95% confidence intervals of both estimates using robust standard errors. The perception outcome variables are coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception outcome is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. The bars report OLS estimates of the witnessing and victimization effects, and highlight their interacted effect. The error bars represent 95% confidence intervals of both estimates using robust standard errors. Each regression includes controls for gender, age, age-squared, six levels of marital status, if there are any children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental or social rental, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview, and police force area fixed effects. We also control for dummies for five crime types (criminal damage, theft, burglary, threats, and assault) and dummies for twenty levels of self-reported severity of the crime. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

Figure 5: Aggregate Social Costs of Crime



Note: We show time trends in victimization rates, and the aggregate social costs of crime, separately when only victimization costs are accounted for as in Heeks et al. [2018] and when victimization and witnessing costs are also accounted for (using our second approach and lower bound multipliers). All time-series are indexed to their levels in 2003–04. Annual unit social costs are constructed using item-level cost components from Heeks et al. [2018], aggregated into four crime categories and weighed by annual crime-type shares derived from the CSEW. Crime-type shares and population counts are computed using our main estimation sample, which restricts to single-incident victims and single-incident witnesses. Sampling weights are rescaled within each wave to account for observations dropped during sample construction. Aggregate annual costs are obtained by multiplying unit social costs by the estimated number of victims and witnesses in each year. As witnessing variables are not available in all CSEW waves, we show only years in which witnessing information exists.

Table A1: Perceptions and Crime-related Experiences

Sample: 2003-2007, 2011-2014 and 2017

OLS regression estimates, robust standard errors

	(1) Confidence in the criminal justice system	(2) Confidence in the police	(3) Problems in neighborhood	(4) Feel safe walk in dark	(5) Worried to be a victim	(6) Crime on quality of life
Witness	-.152***	-.150***	-.423***	-.122***	-.128***	-.198***
	(.006)	(.005)	(.007)	(.005)	(.006)	(.015)
Victim	-.099***	-.121***	-.258***	-.127***	-.167***	-.354***
	(.008)	(.007)	(.009)	(.007)	(.008)	(.021)
Male	-.027***	-.085***	.042***	.627***	.374***	.079***
	(.006)	(.005)	(.006)	(.005)	(.006)	(.014)
Age	-.022***	-.007***	-.013***	.015***	-.012***	-.016***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.002)
White	-.287***	-.056***	.129***	.080***	.327***	.181***
	(.012)	(.010)	(.014)	(.011)	(.014)	(.031)
Rural	-.002	-.045***	.295***	.301***	.134***	.094***
	(.006)	(.006)	(.006)	(.005)	(.006)	(.014)
Housing: owners	-.125***	-.136***	-.053***	.042***	-.029***	-.059***
	(.010)	(.008)	(.011)	(.008)	(.011)	(.021)
Housing: social rent	-.067***	-.128***	-.325***	-.112***	-.079***	-.137***
	(.012)	(.010)	(.013)	(.010)	(.013)	(.028)
Witness = Victim [p-value]	[.000]	[.001]	[.000]	[.576]	[.000]	[.000]
Year, month of interview and police force area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.061	.037	.157	.233	.110	.061
Observations	175,504	234,086	161,582	187,802	159,422	31,953

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave. The outcomes in Columns 1 to 6 are the perception measures, each coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. All columns report OLS estimates with robust standard errors in parentheses. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race , whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects. At the foot on each Column we show the p-value of the witnessing and victimization effects being equal.

Table A2: Perceptions and Crime-related Experiences, Robustness

Sample: 2011-2014 and 2017

OLS regression estimates, robust standard errors

		(1) Baseline	(2a) SoU Bounds	(2b) τ for β=0	(3) LAD FE	(4) LSOA Crime Rate	(5) LSOA FE
Confidence in the criminal justice system	**Witness**	-.179***	[-.190, -.179]	-21	-.179***	-.180***	-.190***
		(.012)			(.012)	(.012)	(.015)
	Victim	-.091***	[-.093, -.091]	-54.9	-.089***	-.090***	-.072***
		(.016)			(.016)	(.016)	(.021)
Confidence in the police	**Witness**	-.184***	[-.188, -.184]	367	-.183***	-.185***	-.171***
		(.008)			(.008)	(.008)	(.009)
	Victim	-.143***	[-.143, -.141]	35.7	-.142***	-.145***	-.138***
		(.011)			(.011)	(.011)	(.012)
Problems in neighborhood	**Witness**	-.506***	[-.506, -.469]	5.88	-.504***	-.487***	-.458***
		(.015)			(.015)	(.015)	(.019)
	Victim	-.252***	[-.252, -.210]	5.3	-.252***	-.244***	-.222***
		(.020)			(.019)	(.020)	(.025)
Feel safe walk in dark	**Witness**	-.158***	[-.190, -.158]	-4.97	-.154***	-.146***	-.124***
		(.010)			(.010)	(.010)	(.012)
	Victim	-.133***	[-.145, -.133]	-12.4	-.125***	-.119***	-.103***
		(.013)			(.013)	(.014)	(.016)
Worried to become victim	**Witness**	-.133***	[-.138, -.133]	-49.9	-.134***	-.130***	-.140***
		(.016)			(.016)	(.016)	(.027)
	Victim	-.156***	[-.156, -.151]	22.1	-.149***	-.148***	-.160***
		(.022)			(.022)	(.022)	(.038)
Crime on quality of life	**Witness**	-.214***	[-.214, -.209]	15.8	-.220***	-.219***	-.269***
		(.021)			(.021)	(.021)	(.044)
	Victim	-.392***	[-.392, -.380]	14.8	-.390***	-.386***	-.351***
		(.033)			(.033)	(.033)	(.064)
Individual characteristics		Yes			Yes	Yes	Yes
Interview month fixed effects		Yes			Yes	Yes	Yes
Year fixed effects		Yes			Yes	Yes	Yes
Police force area fixed effects		Yes					
Local authority fixed effects					Yes	Yes	
LSOA crime rate						Yes	
LSOA fixed effects							Yes

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave. The outcomes (in rows) are the perception measures, each coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. Column 1 reports OLS estimates with robust standard errors in parentheses. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race , whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects. Column 2 reports selection on unobservables bounds for proportionality parameter 0 and 1, and Column 2b reports the proportionality parameter needed for the estimated effect to equal zero. Column 3 replaces police force area fixed effects (42 levels) with local authority district (LAD) fixed effects (347 levels). Column 4 retains the LAD FE and adds a control for the crime rate of the respondent's Lower-layer Super Output Area (LSOA). Column 5 shows estimates from the regression with all individual characteristics and month of interview fixed effects, but uses LSOA fixed effects instead of year effects, police force area fixed effects or local authority district fixed effects.

Table A3: Dynamics of Perceptions and Victimization Experiences

Sample: 2001-2017

OLS regression estimates, robust standard errors

	(1) Confidence in the criminal justice system	(2) Confidence in the police	(3) Problems in neighborhood	(4) Feel safe walk in dark	(5) Worried to be a victim	(6) Crime on quality of life
Victim	-.105***	-.138***	-.310***	-.141***	-.157***	-.357***
	(.009)	(.009)	(.011)	(.009)	(.010)	(.027)
Months since victimization	-.004***	-.002	-.001	-.001	-.002	.001
	(.001)	(.001)	(.001)	(.001)	(.001)	(.003)
Male	-.045***	-.088***	.022***	.632***	.376***	.062***
	(.004)	(.003)	(.004)	(.003)	(.004)	(.010)
Age	-.025***	-.006***	-.013***	.013***	-.013***	-.018***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.002)
White	-.296***	-.074***	.044***	.074***	.302***	.163***
	(.008)	(.007)	(.009)	(.007)	(.010)	(.021)
Rural	.017***	-.026***	.344***	.313***	.156***	.113***
	(.004)	(.004)	(.004)	(.004)	(.005)	(.010)
Housing: owners	-.105***	-.124***	-.039***	.054***	-.018**	-.041***
	(.006)	(.005)	(.007)	(.005)	(.007)	(.014)
Housing: social rent	-.088***	-.157***	-.363***	-.116***	-.088***	-.131***
	(.007)	(.007)	(.008)	(.007)	(.009)	(.019)
Year, month of interview and police force area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.055	.032	.138	.225	.109	.056
Observations	478,670	594,887	389,114	464,724	342,291	73,555

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists individual responses from pooled data of the 2001-02 to 2017-18 CSEW waves, excluding individuals with multiple victimizations. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave. The outcomes in Columns 1 to 6 are the perception measures, each coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. All Columns report OLS estimates with robust standard errors in parentheses. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race , whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects.

Table A4: Dynamics of Victimization Experiences, Alternative Counterfactuals

Sample: 2003-2007, 2011-2014 and 2017
OLS regression estimates, robust standard errors

		(1) All	(2) Witness Crime	(3) Witness ASB	(4) Witness Crime or ASB
Confidence in the criminal justice system	**Victim**	-.076***	.006	-.090***	-.040
		(.016)	(.036)	(.034)	(.025)
	Months since	-.006***	-.009**	.001	-.004
		(.002)	(.004)	(.004)	(.003)
Confidence in the police	**Victim**	-.124***	-.071**	-.139***	-.103***
		(.015)	(.035)	(.032)	(.024)
	Months since	-.002	-.006	.001	-.002
		(.002)	(.004)	(.004)	(.003)
Problems in neighborhood	**Victim**	-.307***	-.281***	-.250***	-.254***
		(.018)	(.041)	(.038)	(.028)
	Months since	.002	.011**	.003	.007*
		(.002)	(.005)	(.005)	(.003)
Feel safe walk in dark	**Victim**	-.123***	-.089***	-.111***	-.097***
		(.014)	(.031)	(.031)	(.022)
	Months since	-.002	-.002	.000	-.001
		(.002)	(.004)	(.004)	(.003)
Worried to become victim	**Victim**	-.164***	-.164***	-.050	-.108***
		(.016)	(.037)	(.033)	(.025)
	Months since	-.002	.001	-.008*	-.003
		(.002)	(.005)	(.004)	(.003)
Crime on quality of life	**Victim**	-.378***	-.261***	-.279***	-.270***
		(.044)	(.010)	(.099)	(.070)
	Months since	.001	-.006	-.002	-.004
		(.005)	(.012)	(.012)	(.009)

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists individual responses from pooled data of the 2003 -04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW waves, excluding individuals with multiple victimizations . Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave. The outcomes (across rows) are the perception measures, each coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. All Columns report OLS estimates with robust standard errors in parentheses. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race , whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects. Column 1 retains respondents regardless of whether they witness a crime or anti-social behavior (ASB). Column 2 estimates victimization effects and dynamics within respondents who witness a crime. Column 3 estimates the same effect within respondents who report witnessing ASB, and Column 4 estimates the effect within respondents witnessing a crime or ASB.

Table A5: Dynamics of Victimization Experiences, Robustness

Sample: 2011-2017

OLS regression estimates, robust standard errors

		(1) Baseline	(2) LAD FE	(3) LSOA Crime Rate	(4) LSOA FE	(5) Entropy Balancing
Confidence in the criminal justice system	**Victim**	-.120***	-.120***	-.200***	-.114***	-.118***
		(.021)	(.021)	(.062)	(.023)	(.021)
	Months since	-.002	-.002	.006	-.002	-.002
		(.002)	(.002)	(.008)	(.003)	(.003)
Confidence in the police	**Victim**	-.176***	-.175***	-.183***	-.159***	-.172***
		(.016)	(.016)	(.047)	(.016)	(.016)
	Months since	-.001	-.001	-.007	-.002	-.001
		(.002)	(.002)	(.006)	(.002)	(.002)
Problems in neighborhood	**Victim**	-.355***	-.342***	-.233***	-.304***	-.350***
		(.028)	(.028)	(.081)	(.031)	(.028)
	Months since	.002	.001	-.008	-.001	.002
		(.004)	(.003)	(.010)	(.004)	(.003)
Feel safe walk in dark	**Victim**	-.154***	-.145***	-.221***	-.108***	-.153***
		(.021)	(.021)	(.063)	(.024)	(.021)
	Months since	-.002	-.002	-.005	-.003	-.002
		(.003)	(.003)	(.008)	(.003)	(.003)
Worried to become victim	**Victim**	-.179***	-.176***	-.178**	-.183***	-.174***
		(.030)	(.030)	(.075)	(.042)	(.030)
	Months since	.001	.001	-.001	.003	.001
		(.004)	(.004)	(.010)	(.005)	(.004)
Crime on quality of life	**Victim**	-.393***	-.394***	-.208	-.349***	-.384***
		(.050)	(.050)	(.131)	(.080)	(.049)
	Months since	.002	.002	-.020	.002	.001
		(.006)	(.006)	(.016)	(.010)	(.006)
Individual characteristics		Yes	Yes	Yes	Yes	Yes
Interview month fixed effects		Yes	Yes	Yes	Yes	Yes
Year fixed effects		Yes	Yes	Yes		Yes
Police force area fixed effects		Yes				Yes
Local Authority fixed effects			Yes	Yes		
LSOA crime rate				Yes		
LSOA fixed effects					Yes	

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists individual responses from pooled data of the 2011-12 to 2017-18 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave. The outcomes (in rows) are the perception measures, each coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. Column 1 reports OLS estimates with robust standard errors in parentheses. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race , whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects. Column 2 replaces police force area fixed effects (42 levels) with local authority district (LAD) fixed effects (347 levels). Column 3 retains the LAD FE and adds a control for the crime rate of the respondent's Lower-layer Super Output Area (LSOA), using only respondents living in London. Column 4 shows estimates from the regression with all individual characteristics and month of interview fixed effects, but uses LSOA fixed effects instead of year effects, police force area fixed effects or local authority district fixed effects. Column 5 shows estimates using entropy balancing weights based on all controls used in Column 1.

Table A6: Perceptions and Multiple Crime-related Experiences

Sample: 2003-2007, 2011-2014, and 2017

OLS regression estimates, robust standard errors

	(1) Confidence in the criminal justice system	(2) Confidence in the police	(3) Problems in neighborhood	(4) Feel safe walk in dark	(5) Worried to be a victim	(6) Crime on quality of life
Witness: single	-.151***	-.148***	-.384***	-.126***	-.131***	-.194***
	(.006)	(.005)	(.006)	(.005)	(.006)	(.013)
Witness: multiple	-.354***	-.322***	-.656***	-.234***	-.203***	-.405***
	(.007)	(.006)	(.007)	(.006)	(.007)	(.016)
Victim: single	-.096***	-.112***	-.226***	-.119***	-.147***	-.290***
	(.007)	(.006)	(.007)	(.006)	(.007)	(.017)
Victim: multiple	-.224***	-.271***	-.562***	-.287***	-.340***	-.609***
	(.009)	(.009)	(.009)	(.008)	(.009)	(.024)
P-values:						
Witness single = multiple	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Victim single = multiple	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Year, month of interview and police force area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.072	.055	.241	.233	.124	.107
Observations	254,814	333,527	236,141	273,056	232,716	45,365

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. The outcomes in Columns 1 to 6 are the perception measures, each coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. All columns report OLS estimates with robust standard errors in parentheses. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race , whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects. At the foot on each Column we show the p-value of the witnessing and victimization effects being equal. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave. At the foot on each Column we show the p-value of the witnessing and victimization effects being equal, for single and multiple experiences.

Table A7: Age, Perceptions and Crime-related Experiences

Sample: 2003-2007, 2011-2014, and 2017
OLS regression estimates, robust standard errors

	(1) Confidence in the criminal justice system	(2) Confidence in the police	(3) Problems in neighborhood	(4) Feel safe walk in dark	(5) Worried to be a victim	(6) Crime on quality of life
Panel A: Age 16-25						
Witness	-.083***	-.115***	-.301***	-.053***	-.109***	-.151***
	(.022)	(.020)	(.025)	(.019)	(.025)	(.049)
Victim	-.079***	-.142***	-.230***	-.136***	-.161***	-.355***
	(.026)	(.026)	(.030)	(.023)	(.029)	(.069)
Panel B: Age 26-45						
Witness	-.147***	-.139***	-.385***	-.107***	-.101***	-.170***
	(.010)	(.009)	(.011)	(.008)	(.010)	(.024)
Victim	-.103***	-.138***	-.249***	-.134***	-.153***	-.326***
	(.013)	(.012)	(.014)	(.011)	(.013)	(.034)
Panel C: Age 46+					[a]	
Witness	-.171***	-.164***	-.481***	-.150***	-.150***	-.229***
	(.008)	(.007)	(.009)	(.007)	(.008)	(.020)
Victim	-.105***	-.097***	-.274***	-.123***	-.177***	-.382***
	(.011)	(.010)	(.012)	(.009)	(.011)	(.029)
P-values:						
Witness: Age 16-25 = Age 26-45	[.005]	[.191]	[.001]	[.005]	[.974]	[.737]
Witness: Age 26-45 = Age 46+	[.093]	[.056]	[.000]	[.000]	[.000]	[.061]
Victim: Age 16-25 = Age 26-45	[.330]	[.883]	[.497]	[.925]	[.916]	[.634]
Victim: Age 26-45 = Age 46+	[.957]	[.004]	[.301]	[.400]	[.196]	[.227]
Year, month of interview and police force area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists of individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave. The outcomes in Columns 1 to 6 are the perception measures, each coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. Panels A, B and C show the baseline specification within the subsample of those aged 16-25 (6%), those aged 26-45 (29%) and those aged 46+ (64%) respectively. All columns report OLS estimates with robust standard errors in parentheses. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects. At the foot on each Column we show the p-value of the witnessing and victimization effects being equal across age groups.

[a] Omitted because of collinearity.

Table A8: Local Crime Rates, Perceptions and Crime-related Experiences

Sample: 2011-14 and 2017

OLS regression estimates, robust standard errors

	(1) Confidence in the criminal justice system	(2) Confidence in the police	(3) Problems in neighborhood	(4) Feel safe walk in dark	(5) Worried to be a victim	(6) Crime on quality of life
A. Baseline						
Witness	-.176***	-.179***	-.461***	-.141***	-.127***	-.204***
	(.012)	(.008)	(.014)	(.010)	(.016)	(.021)
Victim	-.089***	-.141***	-.224***	-.118***	-.151***	-.376***
	(.016)	(.011)	(.019)	(.013)	(.022)	(.033)
Mid crime-rate LSOA's	-.011	-.046***	-.198***	-.129***	-.042**	-.059***
	(.012)	(.008)	(.014)	(.010)	(.018)	(.022)
High crime-rate LSOA's	.008	-.057***	-.409***	-.251***	-.068***	-.104***
	(.014)	(.010)	(.017)	(.012)	(.020)	(.025)
B: low crime-rate LSOA's						
Witness	-.173***	-.148***	-.383***	-.091***	-.076***	-.179***
	(.018)	(.013)	(.021)	(.015)	(.026)	(.033)
Victim	-.062**	-.119***	-.199***	-.098***	-.147***	-.280***
	(.026)	(.019)	(.029)	(.021)	(.035)	(.050)
C: mid crime-rate LSOA's						
Witness	-.182***	-.202***	-.463***	-.139***	-.144***	-.187***
	(.020)	(.014)	(.024)	(.017)	(.026)	(.035)
Victim	-.085***	-.128***	-.226***	-.111***	-.145***	-.358***
	(.026)	(.019)	(.032)	(.023)	(.036)	(.056)
D: high crime-rate LSOA's						
Witness	-.179***	-.183***	-.533***	-.189***	-.155***	-.259***
	(.021)	(.015)	(.028)	(.018)	(.030)	(.038)
Victim	-.112***	-.171***	-.254***	-.146***	-.168***	-.495***
	(.027)	(.019)	(.036)	(.024)	(.042)	(.057)
P-values:						
Witness low = Witness mid	[.669]	[.004]	[.013]	[.035]	[.054]	[.879]
Witness mid = Witness high	[.957]	[.367]	[.052]	[.037]	[.838]	[.179]
Victim low = Victim mid	[.581]	[.770]	[.541]	[.636]	[.912]	[.351]
Victim mid = Victim high	[.458]	[.132]	[.619]	[.332]	[.670]	[.079]
Year, month of interview and police force area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists individual responses from pooled data of the 2011-12 to 2014-15 and 2017-18 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave. The outcomes in Columns 1 to 6 are the perception measures, each coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. Panel A shows the baseline specification with dummies for LSOA crime rate terciles based on offical police records, including the third (12% crime rate) and second (6% crime rate) tercile dummies compared to the leave-out first tercile (3.4% crime rate). Panels B to D then show the results for subsamples based on tercile of crime rates at the LSOA level. All Columns report OLS estimates with robust standard errors in parentheses. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race , whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects. At the foot on each Column we show the p-value of the witnessing and victimization effects being equal across crime rate terciles.

Table A9: Newspaper Readership, Perceptions and Crime-related Experiences

Sample: 2003-2007 and 2011-2014

OLS regression estimates, robust standard errors

	(1) Confidence in the criminal justice system	(2) Confidence in the police	(3) Problems in neighborhood	(4) Feel safe walk in dark	(5) Worried to be a victim	(6) Crime on quality of life
A. Baseline						
Witness	-.152***	-.142***	-.417***	-.123***	-.128***	-.194***
	(.006)	(.006)	(.007)	(.005)	(.006)	(.015)
Victim	-.010***	-.113***	-.258***	-.128***	-.166***	-.360***
	(.008)	(.008)	(.009)	(.007)	(.008)	(.022)
Newspaper=Tabloid	-.070***	-.021***	-.053***	.002	-.075***	-.016
	(.006)	(.005)	(.006)	(.005)	(.006)	(.015)
Newspaper=Broadsheet	.100***	.041***	.040***	.141***	.087***	.071***
	(.010)	(.009)	(.011)	(.009)	(.011)	(.022)
B: Tabloid						
Witness	-.169***	-.151***	-.436***	-.141***	-.146***	-.201***
	(.009)	(.008)	(.010)	(.008)	(.009)	(.022)
Victim	-.080***	-.109***	-.249***	-.127***	-.177***	-.379***
	(.012)	(.011)	(.014)	(.010)	(.013)	(.031)
C: No national daily (none or local daily)						
Witness	-.145***	-.138***	-.417***	-.111***	-.108***	-.195***
	(.010)	(.009)	(.010)	(.008)	(.010)	(.025)
Victim	-.113***	-.120***	-.278***	-.132***	-.154***	-.364***
	(.012)	(.012)	(.013)	(.011)	(.013)	(.035)
D: Broadsheet						
Witness	-.118***	-.127***	-.339***	-.096***	-.133***	-.148***
	(.018)	(.015)	(.019)	(.015)	(.018)	(.039)
Victim	-.128***	-.103***	-.219***	-.115***	-.169***	-.299***
	(.023)	(.020)	(.026)	(.020)	(.024)	(.054)
P-values:						
Witness: tabloid = no national	[.082]	[.271]	[.199]	[.008]	[.005]	[.842]
Witness: broadsheet = no national	[.179]	[.547]	[.000]	[.402]	[.215]	[.300]
Victim: tabloid = no national	[.054]	[.511]	[.135]	[.738]	[.197]	[.756]
Victim: broadsheet = no national	[.585]	[.484]	[.043]	[.429]	[.583]	[.307]
Year, month of interview and police force area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists of individual responses from pooled data of the 2003-04 to 2007-08 and 2011-12 to 2014-15 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave. The outcomes in Columns 1 to 6 are the perception measures, each coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. Panel A shows the baseline specification with dummies for most frequently reading tabloids (49%) or broadsheet (11%) newspapers, compared to the leave out category of not reading any national newspaper (41%). All Columns report OLS estimates with robust standard errors in parentheses. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race , whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects. At the foot on each Column we show the p-value of the witnessing and victimization effects being equal across news sources.

Table A10: Mapping Crime Types from Heeks *et al.* [2018] and Cost Calculations

					Approach 1: Accounting for witnesses		Approach 2: Witness-adjusted costs				Post-victimization adjustment			
							Witness		Total		Victims with post-victimization outcomes		All victims	
Crime type	**(1) Crime categories, Heeks *et al.* [2018]**	**(2) Frequency weights**	**(3) Heeks *et al.* [2018] unit cost**	**(4) Heeks *et al.* [2018] average unit cost**	**(5) Witness**	**(6) Total**	**(7a) Lower bound**	**(7b) Upper bound**	**(8a) Lower bound**	**(8b) Upper bound**	**(9a) Lower bound**	**(9b) Upper bound**	**(10a) Lower bound**	**(10b) Upper bound**
Average unit cost				6,081	3,929	9,699	1,532	1,595	7,613	7,677	7,730	7,928	6,303	6,324
Violent crime	Violence with Injury	0.51	14,060											
	Violence without Injury	0.40	5,940	10,594	7,306	17,900	2,947	2,988	13,542	13,583	14,424	14,787	11,108	11,157
	Robbery	0.09	11,320											
Burglary	Domestic burglary	1.00	5,920	5,920	1,950	7,870	875	1,046	6,795	6,966	5,869	5,989	5,917	5,924
Theft	Theft of Vehicle	0.06	10,290											
	Theft from Vehicle	0.52	870	1,665	479	2,145	235	310	1,900	1,975	1,871	2,053	1,669	1,671
	Theft from Person	0.42	1,370											
Criminal damage	Criminal damage – arson	0.02	8,420	1,486	393	1,879	405	429	1,891	1,915	1,268	1,194	1,480	1,476
	Criminal damage – other	0.98	1,330											

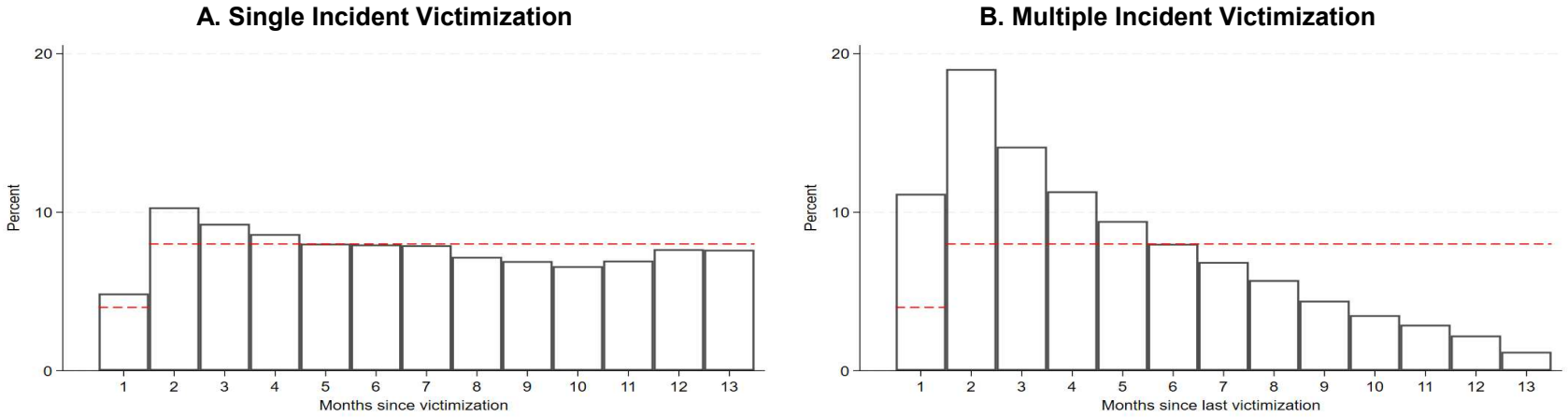
Notes: This shows how we map our crime categories to the crime types used in Heeks et al. [2018]. We use four crime categories for this analysis: assaults, burglaries, thefts, and criminal damage. Column 1 lists the corresponding Heeks *et al.* [2018] crime types included in each of our four categories. Column 2 reports the share of incidents within each category accounted for by each Heeks *et al.* [2018] crime type, based on CSEW 2015/16 victimization counts reported in Heeks *et al.* [2018]. Column 3 gives the unit social cost for each Heeks *et al.* [2018] crime type, in 2015/16 prices. Column 4 reports the average unit social cost for each crime category, obtained as the weighted average of Column 3 using the frequency weights in Column 2. The first row reports the average unit social cost across the four categories (weighted by incident counts). Columns 5 and 6 correspond to Approach 1, in which witnesses are assigned the same unit cost as victims for selected cost components (defensive expenditures, physical and emotional harm, and lost output). Column 5 shows the resulting witness unit cost, and Column 6 shows the total unit social cost. Columns 7a to 8b correspond to Approach 2, which uses perception-based multipliers to scale victim costs into witness costs. Columns 7a and 7b report the lower- and upper-bound witness unit costs implied by the alternative sets of multipliers. Columns 8a and 8b report the corresponding lower- and upper-bound total unit social costs. Columns 9a to 10b correspond to estimates of victimization costs which adjust victim costs using multipliers based on post-victimization outcome effects. Columns 9a and 9b report the lower- and upper-bound victim unit costs implied by the alternative sets of multipliers for victims with favorable post victimization outcomes. Columns 10a and 10b report the lower- and upper-bound victim unit costs implied by the alternative sets of multipliers for all victims. The first row reports the average unit cost across the four crime categories. All monetary amounts are in pounds per experience in 2015/16 prices.

Table A11: Multipliers

Cost component from Heeks *et al.* [2018]	Perception outcome	Approach 2: Witness-adjusted costs				Post-victimization adjustment			
		(1) Violent crime	(2) Burglary	(3) Theft	(4) Criminal damage	(5) Violent crime	(6) Burglary	(7) Theft	(8) Criminal damage
Defensive expenditures	Feel safe walk alone in dark	0.29	0.91	1.08	0.74	0.00	0.85	0.54	1.01
	Worried to be a victim	0.46	0.98	0.87	1.84	0.00	0.66	0.39	0.20
	Crime on Quality of Life	0.41	0.45	0.49	1.05	1.57	1.04	1.81	0.46
Physical and emotional harm	Crime on Quality of Life	0.41	0.45	0.49	1.05	1.57	1.04	1.81	0.46
Lost output	Crime on Quality of Life	0.41	0.45	0.49	1.05	1.57	1.04	1.81	0.46

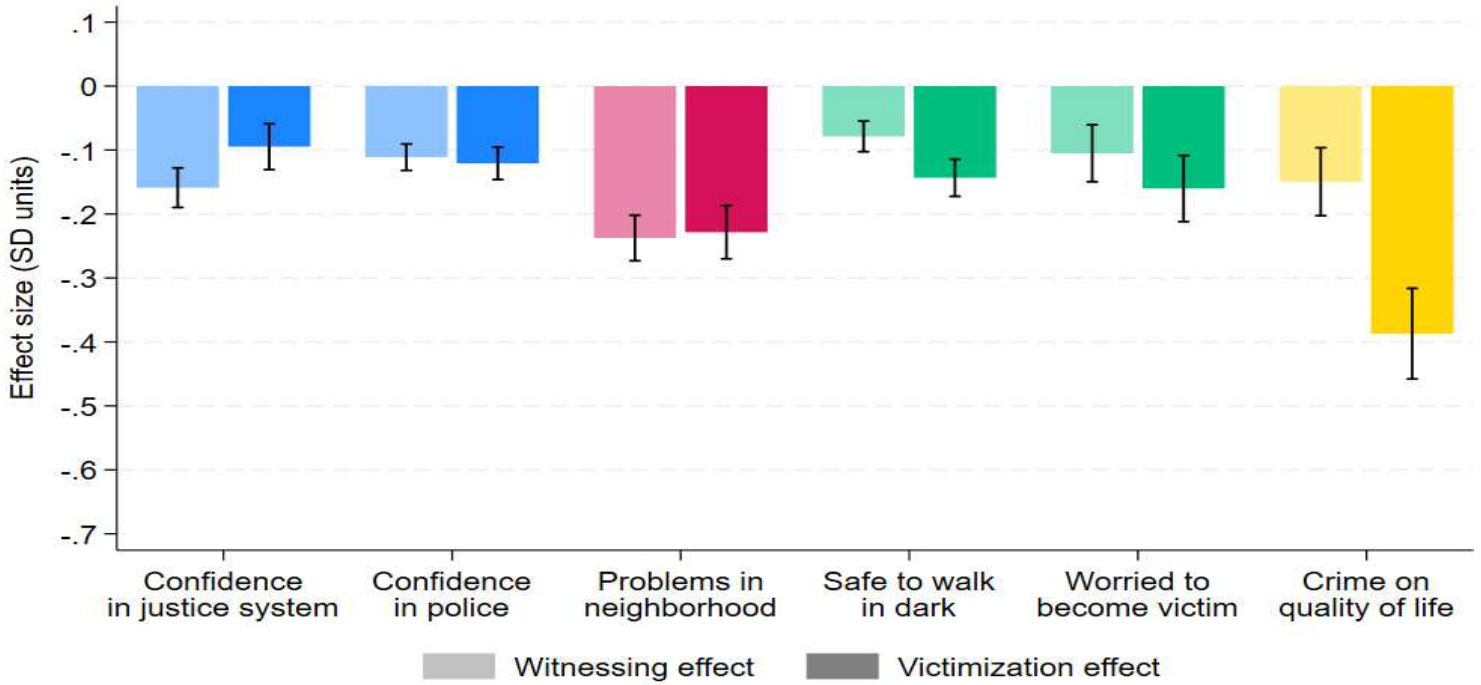
Notes: In Columns 1 to 4 we report the multipliers used in Approach 2 to scale victim unit costs into witness unit costs. Each row corresponds to the cost component from Heeks *et al.* [2018] (defensive expenditures, physical and emotional harm, and lost output). We then link each cost component to a perception outcome used to identify the multiplier for that component. We show for each of our four crime categories, the estimated multiplier, defined as the ratio between the effect of witnessing and the effect of victimization on the corresponding perception outcome. These effects are taken from equation 2 and computed as weighted averages using the shares of victims who are non-witnesses and witnesses (60% and 40%) and the shares of witnesses who are non-victims and victims (82% and 18%). In Columns 5 to 8 we report the multipliers used to adjust victim unit costs to account for favorable post-victimization outcomes. The reported multipliers capture the share of the initial adverse effect of victimization that remains after a positive post-victimization outcome, defined as the offender being identified and charged. The underlying victimization effects are taken from equation 2 and computed as weighted averages of the estimated effects for non-witness victims and victim-witnesses, using their respective shares among victims (60% and 40%). A multiplier of zero indicates that favorable post-victimization outcomes fully offset the initial adverse effect associated with that cost component. In both exercises, for defensive expenditures, we report three sets of multipliers based on alternative perception outcomes (feeling safe walking alone in the dark, worrying about becoming a victim, and the impact of crime on quality of life), which are used to construct lower and upper bounds. For physical and emotional harm and for lost output, we map both components to the quality-of-life outcome, implying the same set of multipliers for these components.

Figure A1: Months Since Last Victimization



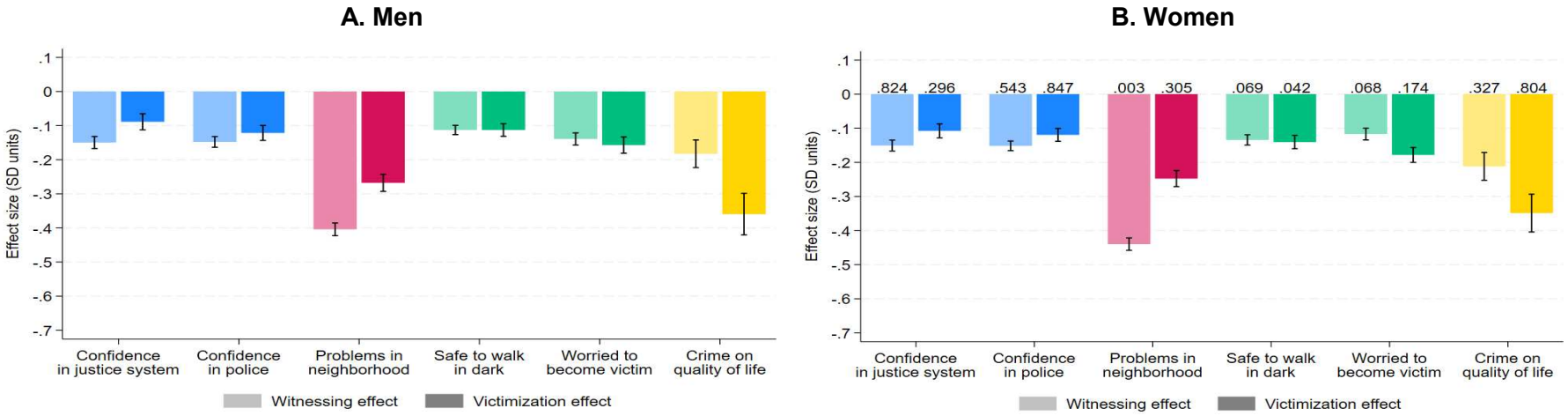
Notes: The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW waves, excluding individuals with multiple victimizations. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave. Panel A shows the distribution of months since victimization for respondents with a single victimization. Panel B shows the distribution of months since last victimization for respondents with multiple victimizations. The dashed red line indicates the hypothetical distribution of months since victimization if its timing were random. The months since victimization variable is equal to one if the victimization occurred in the month of the interview and since interviews take place continuously through a month, half the number of victimizations of any other month should occur.

Figure A2: Perceptions and Crime-related Experiences Alternative Definition of Witnessing Crime



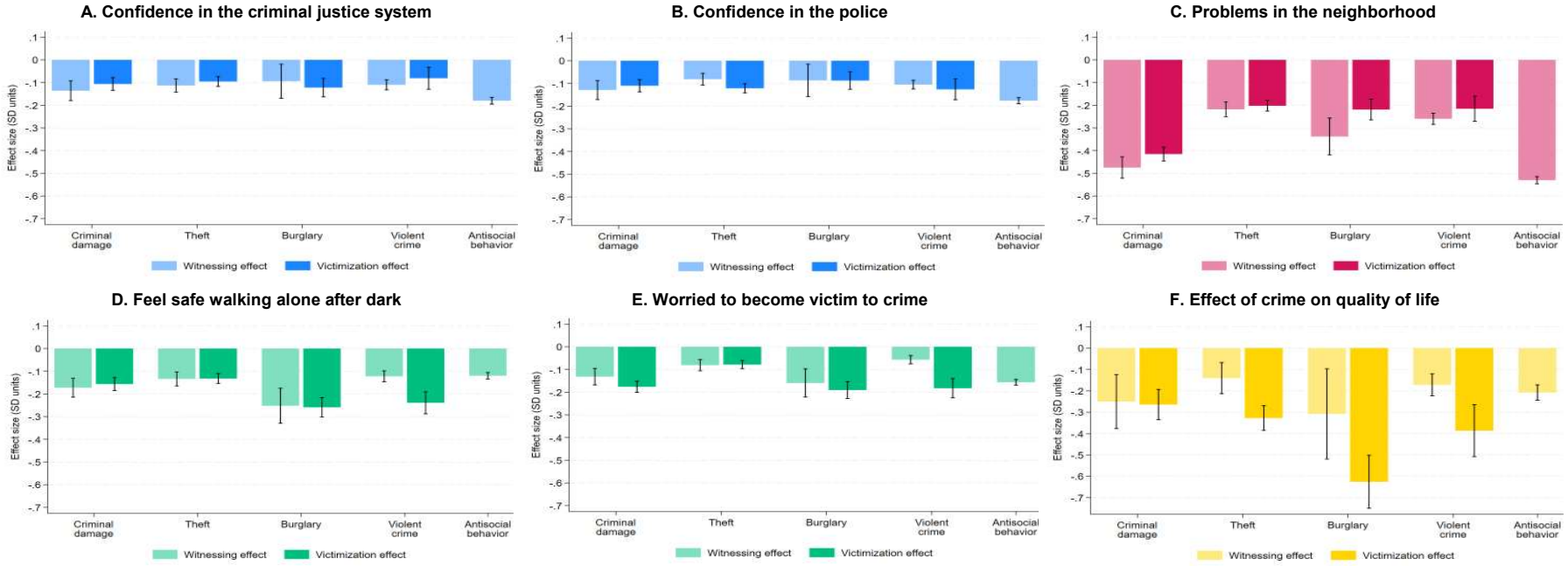
Notes: The sample consists of individual responses from pooled data of the 2011-12 to 2014-15 CSEW waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types, or those who witness more than one of six crime plus fifteen types of anti-social behaviors if any of these is witnessed multiple times. We show estimates of witnessing effects (lighter bars) and victimization effects (darker bars) across six perception outcomes. The error bars represent 95% confidence intervals of both estimates using robust standard errors. The perception outcome variables are coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception outcome is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. The bars report OLS estimates of the witnessing and victimization effects, Each regression includes controls for gender, age, age-squared, six levels of marital status, if there are any children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental or social rental, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview, and police force area fixed effects. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

Figure A3: Perceptions and Victimization Experiences, by Gender



Notes: The sample consists of individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. We show estimates of witnessing effects (lighter bars) and victimization effects (darker bars) across six perception outcomes. The error bars represent 95% confidence intervals of both estimates using robust standard errors. The specifications are run by gender. On Panel B we report p-values on the null of equal effects across genders from a specifiction that pools across genders. The perception outcome variables are coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception outcome is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. The bars report OLS estimates of the witnessing and victimization effects, Each regression includes controls for gender, age, age-squared, six levels of marital status, if there are any children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental or social rental, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview, and police force area fixed effects. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

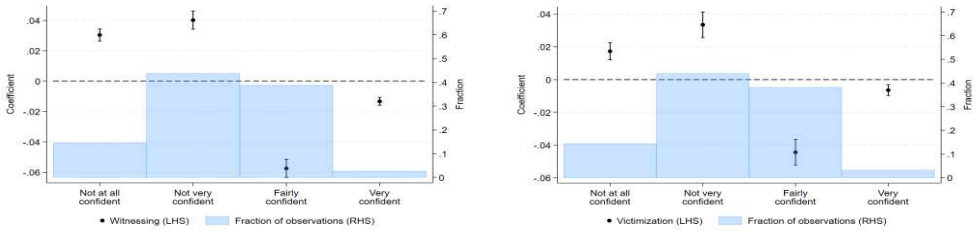
Figure A4: Perceptions and Victimization Experiences, by Crime Type



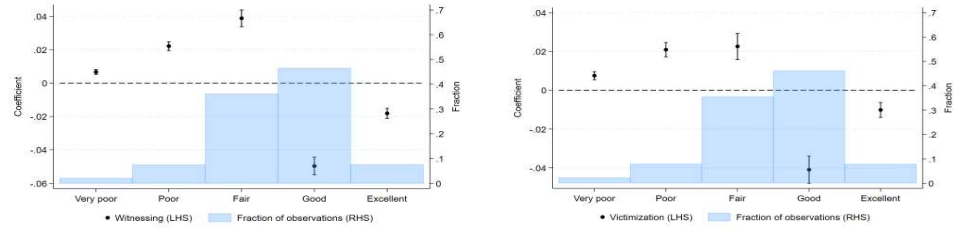
Notes: The sample consists of individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. We show estimates of witnessing effects (lighter bars) and victimization effects (darker bars) across six perception outcomes. The error bars represent 95% confidence intervals of both estimates using robust standard errors. The perception outcome variables are coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception outcome is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. The bars report OLS estimates of the witnessing and victimization effects, Each regression includes controls for witnessing or being a victim of each crime type, gender, age, age-squared, six levels of marital status, if there are any children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental or social rental, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview, and police force area fixed effects. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

Figure A5: Perceptions and Victimization Experiences, Detailed Outcomes

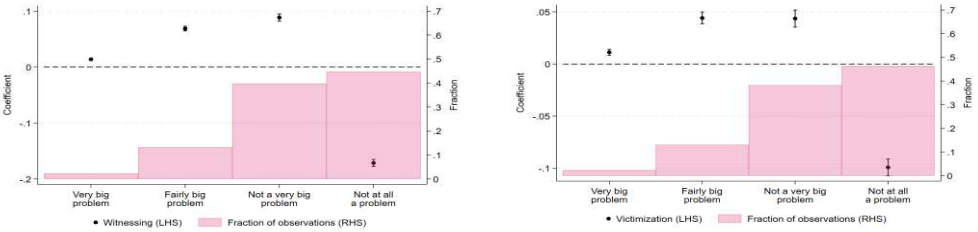
A. Confidence in the criminal justice system



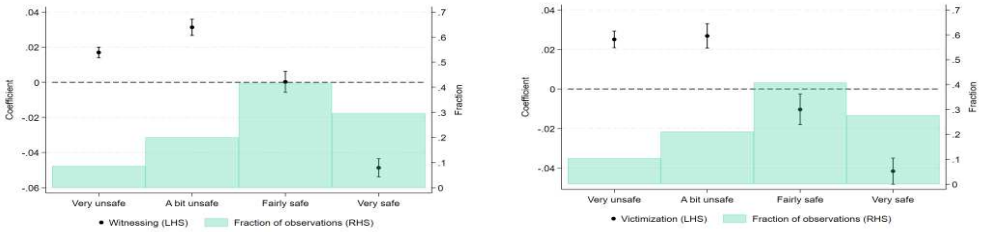
B. Confidence in the police



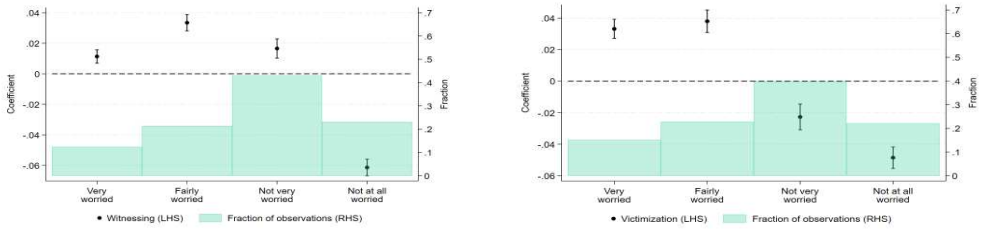
C. Problems in the neighborhood



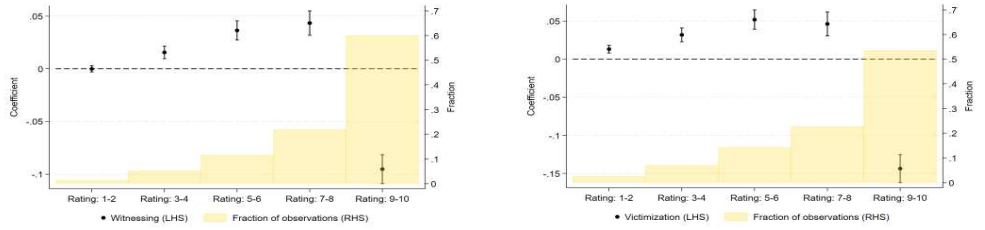
D. Feel safe walking alone after dark



E. Worried to become victim to crime

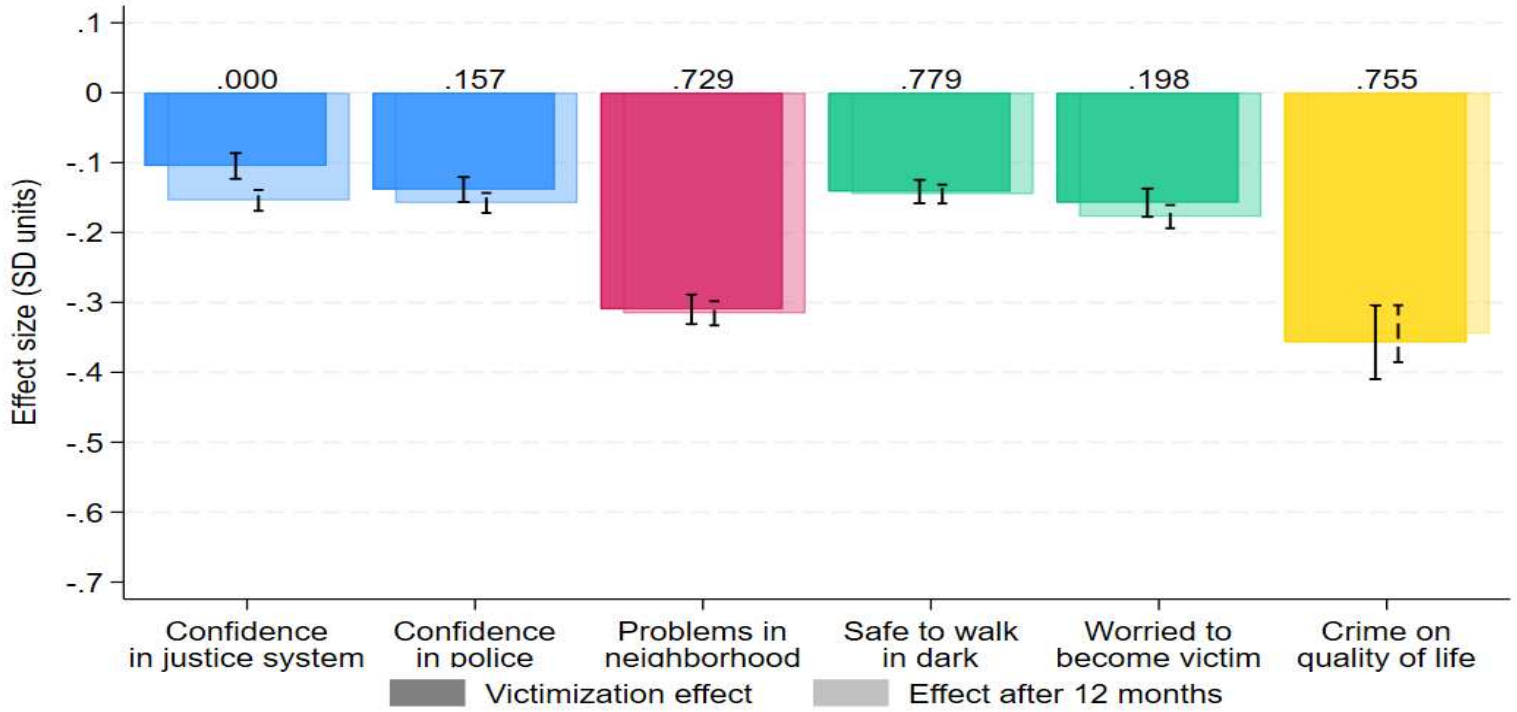


F. Effect of crime on quality of life



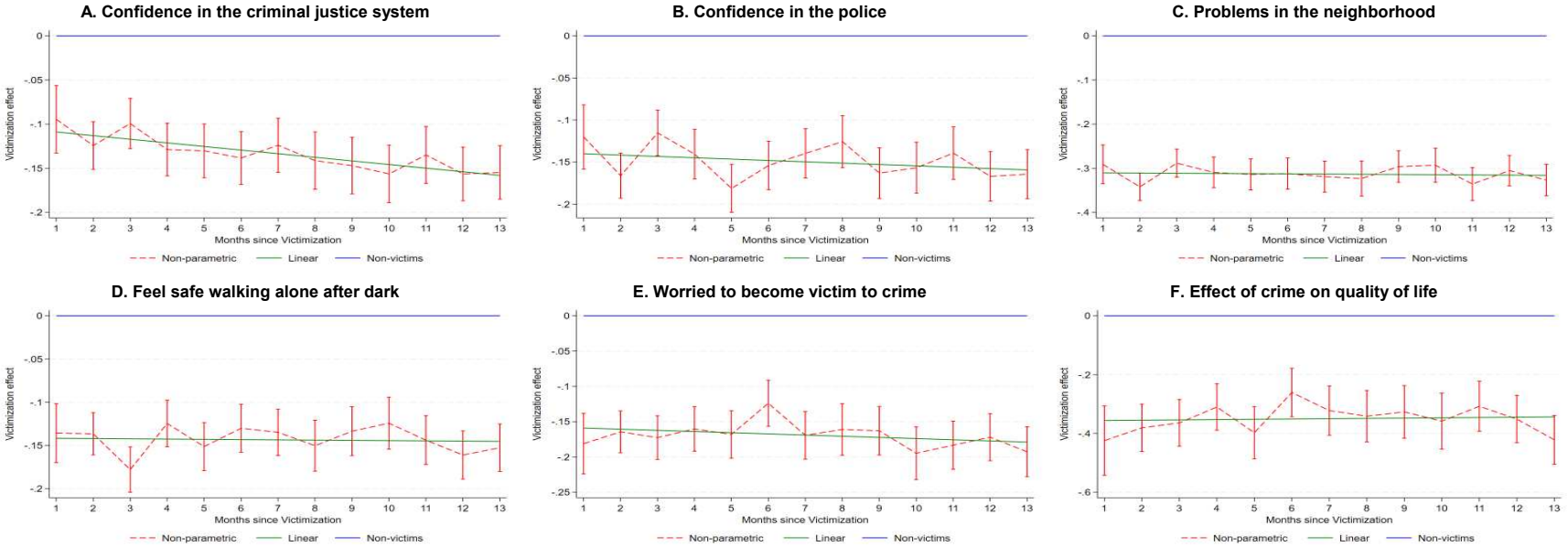
Notes: The sample consists of individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. The first Column of Panels show the estimates of witnessing effects, and the second Column of Panels shows the estimates of victimization effects. For each dependent variable and experience, four to five regressions are estimated with a dummy dependent variable for a particular response category (with the exception of the effect of crime on the quality of life outcome). The perception outcomes are each coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. Each specification controls for gender, age, age-squared, six levels of marital status, if there are children in the household, race , whether the respondent lives in a rural area, whether their housing is owned, a private rental, or socially rented, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview and police force area fixed effects. For each perception outcome, the bars report OLS estimates of the witnessing effect within non-victims and the victimization effect within victims. The error bars represent 95% confidence intervals of both estimates using robust standard errors. Observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave.

Figure A6: Dynamics of Perceptions and Victimization Experiences



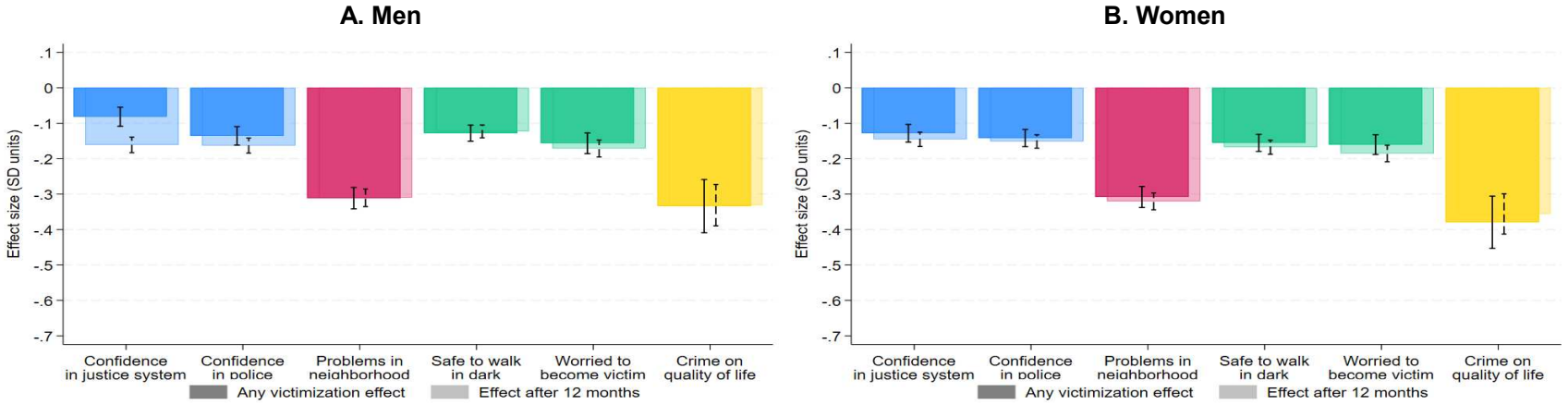
Notes: The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW waves, excluding individuals with multiple victimizations. For each perception outcome variable, the bars report OLS estimates of the victimization effect (darker bars), and the estimated effect after twelve months by adding twelve times the estimated monthly linear recovery rate to the coefficient on the victimization dummy (lighter bars). The error bars represent 95% confidence intervals of both estimates using robust standard errors. The perception outcome variables are coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception outcome is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. The bars report OLS estimates of the witnessing and victimization effects, and highlight their interacted effect. The error bars represent 95% confidence intervals of both estimates using robust standard errors. Each regression includes controls for gender, age, age-squared, six levels of marital status, if there are any children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental or social rental, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview, and police force area fixed effects. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

Figure A7: Dynamics of Perceptions and Victimization Experiences, Robustness



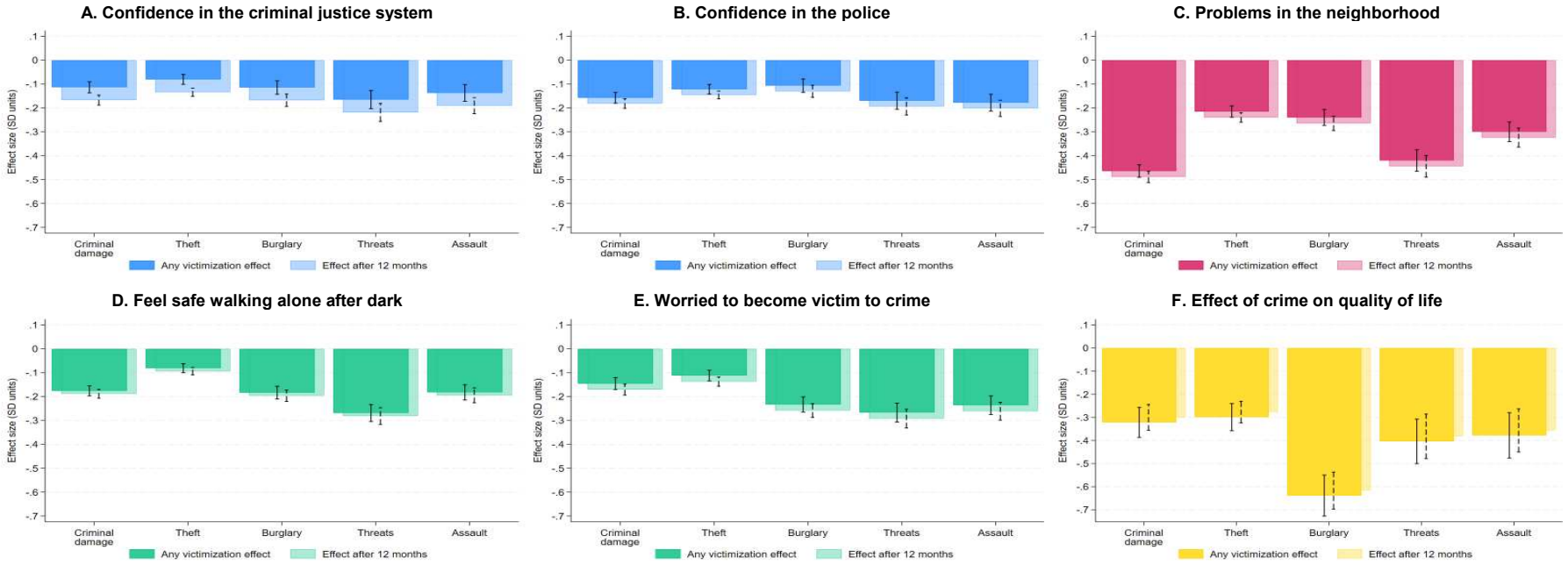
Notes: The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW waves, excluding individuals with multiple victimizations. Each Panel shows the estimates of victimization effects and months since victimization from two regressions. The first regression includes months since victimization as a continuous variable (green line) and the second includes month dummies (red line), along with the 95% confidence intervals. The perception outcome variables are coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception outcome is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. Each regression includes controls for gender, age, age-squared, six levels of marital status, if there are any children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental or social rental, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview, and police force area fixed effects. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

Figure A8: Dynamics of Perceptions and Victimization Experiences, by Gender



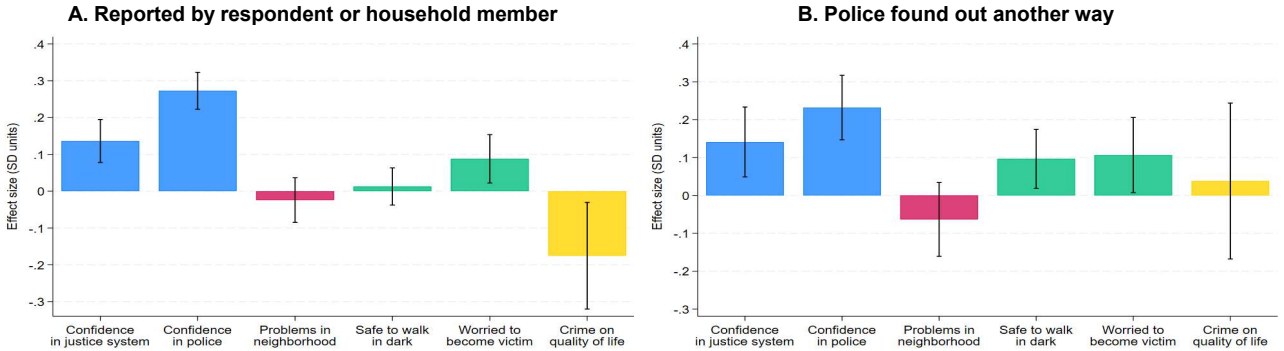
Notes: The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW waves, excluding individuals with multiple victimizations. For each perception outcome variable, the bars report OLS estimates of the victimization effect (darker bars), and the estimated effect after twelve months by adding twelve times the estimated monthly linear recovery rate to the coefficient on the victimization dummy (lighter bars). The error bars represent 95% confidence intervals of both estimates using robust standard errors. The perception outcome variables are coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception outcome is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. The bars report OLS estimates of the witnessing and victimization effects, and highlight their interacted effect. The error bars represent 95% confidence intervals of both estimates using robust standard errors. Each regression includes controls for gender, age, age-squared, six levels of marital status, if there are any children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental or social rental, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview, and police force area fixed effects. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

Figure A9: Dynamics of Perceptions and Victimization Experiences, by Crime Type



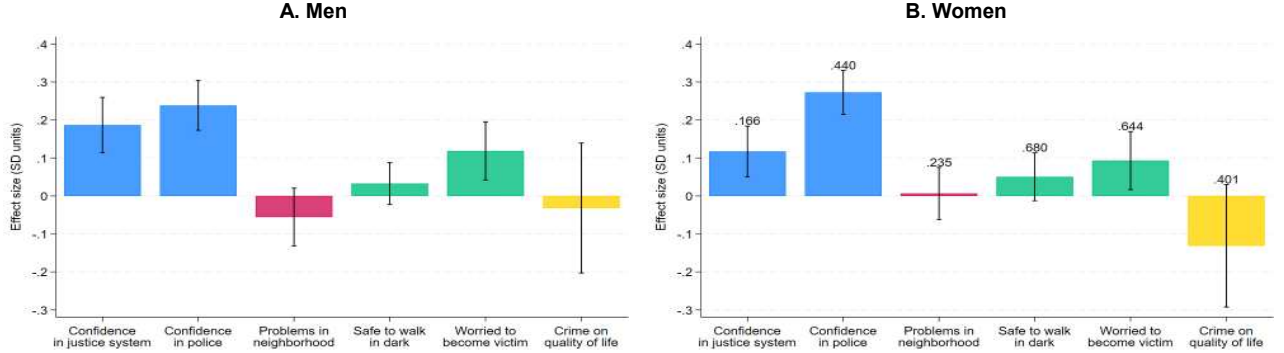
Notes: The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW waves, excluding individuals with multiple victimizations. For each perception outcome variable, the bars report OLS estimates of the victimization effect (darker bars), and the estimated effect after twelve months by adding twelve times the estimated monthly linear recovery rate to the coefficient on the victimization dummy (lighter bars). The error bars represent 95% confidence intervals of both estimates using robust standard errors. The perception outcome variables are coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception outcome is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. The bars report OLS estimates of the witnessing and victimization effects, and highlight their interacted effect. The error bars represent 95% confidence intervals of both estimates using robust standard errors. Each regression includes controls for gender, age, age-squared, six levels of marital status, if there are any children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental or social rental, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview, and police force area fixed effects. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

Figure A10: Perceptions and Post-victimization Experiences, Robustness



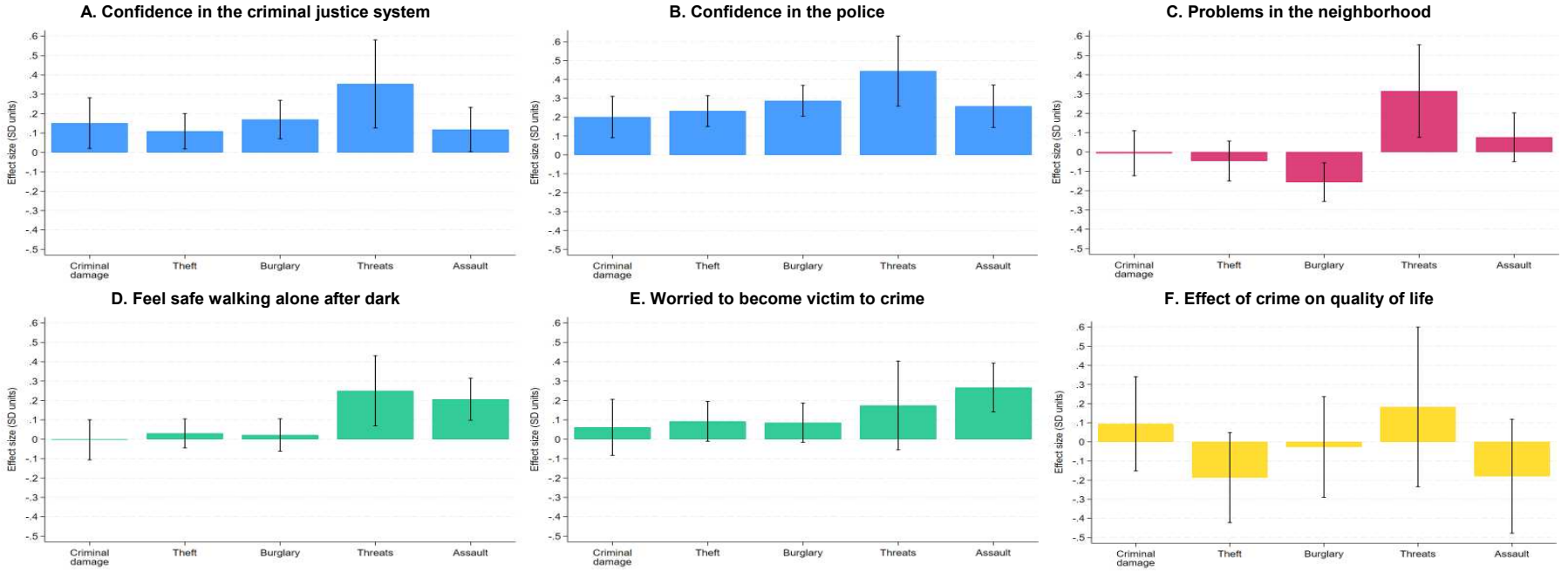
Notes: The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW waves, excluding individuals with multiple victimizations. For each perception outcome variable, the bars report OLS estimates of a favorable post-victimization outcome, namely the victim-respondent's offender being found and charged conditional on the crime being reported, minus the estimated coefficient on a dummy for the crime being reported. The error bars represent 95% confidence intervals of both estimates using robust standard errors. The sample in Panel A consists of observations where the crime was reported by the respondent or someone in their household, and Panel B consists of respondents who's victimization the police found out about in another way (combining: 'the police was told by another person', 'police were there', and 'police found out another way'). On Panel B we report p-values on the null of equal effects across reporting methods. The perception outcome variables are coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception outcome is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. The bars report OLS estimates of the witnessing and victimization effects, and highlight their interacted effect. The error bars represent 95% confidence intervals of both estimates using robust standard errors. Each regression includes controls for gender, age, age-squared, six levels of marital status, if there are any children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental or social rental, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview, and police force area fixed effects. We also control for dummies for five crime types (criminal damage, theft, burglary, threats, and assault) and dummies for twenty levels of self-reported severity of the crime. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

Figure A11: Perceptions and Post-victimization Experiences, by Gender



Notes: The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW waves, excluding individuals with multiple victimizations. For each perception outcome variable, the bars report OLS estimates of a favorable post-victimization outcome, namely the victim-respondent's offender being found and charged conditional on the crime being reported, minus the estimated coefficient on a dummy for the crime being reported. The error bars represent 95% confidence intervals of both estimates using robust standard errors. On Panel B we report p-values on the null of equal effects across genders. The perception outcome variables are coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception outcome is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. The bars report OLS estimates of the witnessing and victimization effects, and highlight their interacted effect. The error bars represent 95% confidence intervals of both estimates using robust standard errors. Each regression includes controls for gender, age, age-squared, six levels of marital status, if there are any children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental or social rental, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview, and police force area fixed effects. We also control for dummies for five crime types (criminal damage, theft, burglary, threats, and assault) and dummies for twenty levels of self-reported severity of the crime. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

Figure A12: Perceptions and Post-victimization Experiences, by Crime Type



Notes: The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW waves, excluding individuals with multiple victimizations. For each perception outcome variable, the bars report OLS estimates of a favorable post-victimization outcome, namely the victim-respondent's offender being found and charged conditional on the crime being reported, minus the estimated coefficient on a dummy for the crime being reported. The error bars represent 95% confidence intervals of both estimates using robust standard errors. The perception outcome variables are coded so that higher values indicate more positive outcomes: having more confidence in the criminal justice system, more confidence in the police, the neighborhood having fewer problems, feeling safe about walking alone after dark, worrying less about being a victim of crime, and crime having less of an impact on quality of life. Each perception outcome is normalized to mean zero and standard deviation one so that coefficients represent effect sizes. The bars report OLS estimates of the witnessing and victimization effects, and highlight their interacted effect. The error bars represent 95% confidence intervals of both estimates using robust standard errors. Each regression includes controls for gender, age, age-squared, six levels of marital status, if there are any children in the household, race, whether the respondent lives in a rural area, whether their housing is owned, a private rental or social rental, eight levels of educational attainment, socioeconomic class using ten levels of the National Statistical Socioeconomic Classification (NS-SEC), and year, month of interview, and police force area fixed effects. We also control for dummies for five crime types (criminal damage, theft, burglary, threats, and assault) and dummies for twenty levels of self-reported severity of the crime. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.