WITNESSING CRIME*

ELISA FACCHETTI IMRAN RASUL JOOST SIJTHOFF

AUGUST 2026

Abstract

Many individuals encounter the justice system through being a victim of crime. What is less appreciated is that many more individuals experience being a witness to crime. We study how both crime-related experiences, being a witness to crime and being a victim of crime, impact crime-related perceptions, spanning confidence towards institutions of the justice system, perceptions of neighborhoods, and personal safety. We combine 17 waves of the Crime Survey for England and Wales from 2001-18 to document: (i) witnessing crime is twice as prevalent as victimization; (ii) all perceptions worsen with crime-related experiences, with witnessing crime having larger associations with confidence in institutions and views of neighborhoods, while victimization is more strongly associated with perceptions of personal safety; (iii) positive post-victimization experiences in the justice system help restore confidence in institutions. We interpret these results through the lens of the Bordalo *et al.* [2025] experience-based learning model. We then consider implications for measuring the social cost of crime if witnessing experiences are accounted for. Despite long-run declines in victimization, the aggregate social costs of crime have remain unchanged over time once costs to witnesses are accounted for. This is due to a change in the composition of crime towards violent crime, that has higher social costs than other crime types, and is witnessed at far higher rates than other crime types. By incorporating witnessing experiences into the measurement of the costs of crime, our analysis helps explain a phenomenon observed in many countries: the general perception among the population that crime is rising, a view unanchored from persistent declines in the actual incidence of crime. *JEL: D63, K42.*

*We gratefully acknowledge financial support from the ESRC CPP (ES/T014334/1), the Nuffield Foundation (SFS /FR-000024397) and the Stone Centre at UCL. We thank Abi Adams, Randi Hjalmarsson, Pedro Bordalo, Adeline Delavande, Jeff Grogger, Sir Stephen Irwin, Patrick Kavanagh, Stephen Machin, Nikita Melnikov, Emily Owens, Joe Tomlinson, Miriam Venturini and numerous seminar participants for valuable comments. This work uses data accessed through the UK Data Service SecureLab. All outputs based on SecureLab data reported in this paper were subject to UK Data Service Statistical Disclosure Control and were released following output clearance. Refine.ink was used to check the paper for consistency and clarity. All errors remain our own. Facchetti: University of Rome Tor Vergata, EIEF, and IFS [elisa.facchetti@uniroma2.it]; Rasul: UCL and IFS [i.rasul@ucl.ac.uk]; Sijthoff: UCL and IFS [joost.sijthoff.22@ucl.ac.uk].

1 Introduction

Many individuals experience crime through being a victim of it. In our setting of England and Wales, among a nationally representative sample of adults in 2014-15, 18% reported being a victim of crime in the previous 12 months – corresponding to 8.4million individuals, or a victimization occurring every three seconds. However, crime-related experiences extend beyond victimization. In the same survey, 43% of individuals report personally witnessing a crime or anti-social behavior. We contrast how these crime-related experiences – being a victim of crime or witnessing crime – shape crime-related perceptions. We use our findings to reconsider the measurement of the social costs of crime once witnesses are accounted for, providing insights for why, as in many countries, the common perception in the population of England and Wales is that crime has been rising, a view unanchored from the actual incidence of crime, that has long been trending downwards.[1]

Literatures in psychology and economics have documented how personal experiences can shape individual beliefs and behavior [Malmendier 2021], and exert greater influence than statistical information [Nisbett and Ross 1980]. We extend this work to understand the importance of two prevalent experiences of crime – witnessing and victimization – in shaping crime-related perceptions. We consider perceptions spanning confidence towards institutions of the justice system, views of neighborhoods, and personal perceptions related to one's own safety, fears of being victimized, and how crime impacts quality of life.

We interpret the association between crime-related experiences and perceptions through the lens of experience-based learning [Bordalo *et al.* 2020, Malmendier 2021], especially the framework developed by Bordalo *et al.* [2025]. This emphasizes how salient experiences and information compete to be recalled from memory when an individual is cued to form a perception. Experiences more *similar* to the perception being asked about are more likely to be recalled, but as experiences and information compete for retrieval, some relevant experiences or information can be neglected when forming perceptions. We use this framework to guide the empirical analysis and interpret results on how crime-related perceptions are shaped by crime-related experiences, and how experiences shape perceptions of overall changes in the incidence of crime.

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

[1] That the incidence of crime has fallen in most Western countries is well documented [Pinker 2012]. Despite this, most individuals perceive crime to be rising – a fact documented in survey evidence across countries including the US and UK [Mastrorocco and Minale 2018]. Opinion polls also consistently show the same fact. For example, in 23 of 27 Gallup polls conducted in the US since 1993, at least 60% of adults stated there is more crime nationally than there was the year before, despite declining crime rates during most of that period [Pew Research 2024].

As in other countries, victimization rates in England and Wales have declined steadily year-on-year. In our main analysis sample, they are 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 impact of crime on quality of life are only 4% higher in 2017-18 than in 2003-04.

To see what might lead to such a wedge between crime-related experiences and perceptions, we document that in contrast to victimization, rates of witnessing crime have remained stable, being the same in 2017-18 as in 2003-04. Unpacking witness rates by crime type, we find that while rates of witnessing non-violent crime have declined, rates of witnessing violent crime have risen dramatically, being 28% higher in 2014-15 than in 2003-04. This is driven by three factors: (i) the composition of crime shifting towards violent crime; (ii) witnesses per violent crime being more than 10 times higher than for other crimes; (iii) witnesses per violent crime rising over time. These factors can combine to help explain why witnessing rates have remained stable and why declines in victimization have not translated into corresponding improvements in perceptions of the justice system, neighborhoods, personal safety and the effect of crime on the quality of life.[2]

Our first set of results link crime-related experiences and crime-related perceptions.

Both witnesses to crime and victims of crime report significantly worse perceptions across the board relative to those with neither experience. Witnessing crime has larger effect size associations than being a victim of crime for perceptions of institutions and neighborhoods, while being a victim of crime has larger associations than witnessing crime on more personal perceptions. For example, confidence in the criminal justice system is $.152\sigma$ lower for witnesses, and $.099\sigma$ lower for victims ($p = .000$). In contrast, for personal domains of perception, the reverse is true so that the victim-witness perceptions gap switches sign. For example, worrying about being a future victim of crime is $.128\sigma$ higher for witnesses, and $.167\sigma$ higher for victims ($p = .000$).

Viewed through the lens of the framework, the results confirm that both victimization and witnessing constitute salient crime-related experiences that enter the retrieval-simulation process and meaningfully shape the formation of crime-related perceptions. Victimization experiences are more strongly recalled, and form better material for simulating personal domains of perception, while witnessing experiences are more strongly recalled, and form better material for simulating institutional or local domains of perception.

A challenge lies in moving from these partial correlations to causal effects of both crime-related experiences. 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], household members being exposed to emotional cues [Card and Dahl 2011], or event

[2] The literature on victimization has often used victimization surveys that are available in many countries, but none of this work has considered witnesses. 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. On the consequences of victimization, earlier work has considered impacts on feelings of safety, quality of life, mental health and labor market outcomes [Cohen 2008, Cornaglia *et al.* 2014, Dustmann and Fasani 2016, Johnston *et al.* 2017, Bindler and Ketel 2022].

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.

We therefore take a more modest approach: rather than establishing causal estimates for each experience, we make precise the assumptions under which our findings allows us to reject the null that the true causal impact of each experience is zero. We derive the biases in our estimated coefficients of interest if the true model of perceptions includes a single latent index capturing unobserved risks of exposure to crime-related experiences. We formulate a test to rule out true null effects, and also derive plausible conditions under which the observed change in sign of the victim-witness perceptions gap across domains helps rule out true null effects. We complement this theoretical approach by empirically estimating bounds for the coefficients of interest accounting for selection on multiple unobservables [Oster 2019, Masten and Poirier 2026]; using a matching design to account for observable differences between witnesses and victims; narrowing in on the concern that local variation in actual crime is the key unobserved factor driving latent risks of having crime-related experiences by showing our baseline results to be robust to controlling for baseline neighborhood crime rates directly or highly granular neighborhood fixed effects.

Our second set of results examine whether experience effects are malleable to (positive) experiences arising from institutional responses to victimization. To do so, we exploit the richness of the CSEW data which records how the criminal justice system handled each reported victimization. We construct a categorical measure of post-victimization experience with the justice system to estimate the perceptions gap between individuals who experienced the most favorable post-victimization outcome (an offender being identified and charged) and the least favorable (no offender being identified). We find that favorable post-victimization experiences offset the initial negative impacts of victimization on perceptions of institutions. 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 who have experienced both events with higher confidence in the criminal justice system than non-victims. In contrast, favorable post-victimization experiences appear to do little to improve perceptions of neighborhoods, personal safety and how crime affects quality of life.

The asymmetry of impacts of positive and negative experiences is not something that has been the focus of earlier work on experience-based learning. Our results suggest positive post-victimization experiences with the justice system lead to updated perceptions in similar domains related to institutions, but not to other domains. This is in contrast to the initial responses to negative victimization experiences, that lead to updating across all perception domains – institutional, local and personal.

Our third set of results build on all our earlier findings to derive implications for measuring the social cost of crime when costs to witnesses are also accounted for.

To do so, we take an established approach to measuring the social costs of crime – based solely on victims – in our context and study period [Heeks *et al.* 2018]. We extend this standard approach to allow witnesses to bear a subset of costs that exist for victims. We do so for the cost components of the Heeks *et al.* [2018] decomposition that our first set of results suggest could plausibly be affected for witnesses, using our perception estimates to rescale them for witnesses, while setting witness costs to zero for the remaining components. We find that once witnesses are accounted for, the average social cost of the average committed crime rises by 25% relative to conventional methods. The underestimation varies across crime types: they are underestimated by 28% for violent crime, and by 14% for theft.

In short, 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. *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 accounted for.

Given the long run divergence between rates of crime victimization and witnessing crime described earlier, we then move to measure the change in aggregate costs of crime over time, and implications for understanding the wedge between perceived and actual crime rates.

Key to this is the changing composition of crime toward violent crime, that is a crime type more likely to be witnessed, and that has substantial costs on witnesses and victims. As a result, trends in the aggregate social costs of crime might not be as pronounced downwards as otherwise implied by long-run trends of falling victimization rates. We construct 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 although victimization rates have fallen by 25%: (i) using a standard methodology to measure costs 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 16% – reflecting the shift towards violent crime; (ii) social costs of crime borne by witnesses *rise* by 36%; (iii) as a result, the total social costs of crime, accounting for both witnesses and victims, fall by only around 3%. Hence accounting for witnesses offsets any decline in total social costs of crime implied by conventional victim-only measures.

The result helps explain why the majority of individuals consistently perceive crime to be worsening over time, despite falling victimization rates – a puzzle that has long been considered across the social sciences [Garland 2001, Duffy *et al.* 2008, Esberg and Mummolo 2018, Campedelli *et al.* 2023]. Consistent with this, we find that experiences of witnessing crime increase the perception that national and local crime rates are rising to the same extent as victimization experiences, again suggestive of witnessing crime helping to explain diverging trends between actual and perceived crime.

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 witnessing crime being more prevalent than victimization, witnesses being impacted across a range of perceptions, and witness experiences having implications for measuring the social costs of crime and hence the evaluation of crime-reducing policy 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 survey data to administrative records. While this has generated numerous insights, a limitation is that information on witnessing crime is almost never recorded in administrative data, either in our study setting or in other countries – leaving an important void that we start to fill.[3]

Second, we extend the empirical literature on experience-based learning, that has shown how experiences affect individual beliefs and behavior in domains such as stock market participation, inflation expectations, consumption and home ownership. We take these ideas to crime-related experiences and in so doing we extend earlier work by: (i) examining impacts of individual rather than aggregate experiences such as growing up a recession; (ii) contrasting different types of direct experience; (iii) considering negative and positive experiences. We show how key ideas underlying experience-based learning help interpret our suite of findings.[4]

The paper is organized as follows. Section 2 describes the Bordalo *et al.* [2025] framework through which to understand the link between experiences and perceptions. Section 3 describes the data. Section 4 presents our main results. Section 5 examines interactions between experiences. Section 6 discusses measuring the social cost of crime once witnesses are accounted for. Section 7 describes directions for future research. The Appendix describes the data, presents further results and robustness checks, and derives the social cost of crime calculations.

2 Framework

To motivate the importance of experiences in shaping crime-related perceptions, Table 1 presents evidence from our CSEW working sample on the sources individuals report using to form per-

[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, Cabral *et al.* 2025]. Another strand of literature has explored indirect exposure to victimization, where exposure is measured through proximity to victims such as being a family member [Cohen 2005, Bindler and Ketel 2019], in the same school [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, becoming informed of the crime, or being affected through spillovers from victims themselves.

[4] The term *experience effects* was coined in the context of individuals experiencing aggregate macroeconomic, financial, or political shocks. Giuliano and Spilimbergo [2025] synthesize findings from across disciplines on how a variety of aggregate shocks shape beliefs 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 effects coming from personal experience.

ceptions of: (i) crime-related institutions (Columns 1 and 2); (ii) national and local crime rates (Columns 3 and 4). Almost one in five respondents state using personal experiences to form perceptions of institutions and national crime rates, and more than a third report they help form perceptions of local crime. Indirect experiences of others (such as friends, relatives or through word-of-mouth) and news sources also shape perceptions. While our primary focus is on direct personal experiences, we later discuss how indirect experiences and news sources shape perceptions.

We interpret the link between crime-related experiences and perceptions through the lens of experience-based learning [Bordalo *et al.* 2020, Malmendier 2021]. Such approaches place structure on how individuals update their perceptions in light of experiences. We organize our empirical analysis and the interpretation of results around models of memory [Malmendier and Wachter 2024], drawing closely on the framework developed by Bordalo *et al.* [2025] because: (i) victimization and witnessing are highly salient crime-related experiences for individuals; (ii) these experiences enter an individual's memory retrieval process when cued to form crime-related perceptions by in-person CSEW interviewers.[5]

When cued to form a crime-related perception, individuals draw on all the kinds of sources described in Table 1 – their experiences and information. Experiences can be more or less similar to the perception being formed, depending on: (i) whether the perception relates to beliefs about institutions, local neighborhoods or the person; (ii) whether they have experienced being a witness to crime or a victim; (iii) the type of crime experienced.

The central idea, 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 some experiences can be partially neglected because of a process of *interference*, even those that provide better material to simulate the perception with. This diverges from standard Bayesian updating, in which more informative experiences always receive greater weight in forming perceptions.[6]

Following Bordalo *et al.* [2025], 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) 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 CSEW interviewer. Experiences more similar to the cue in the database E are more likely to be retrieved, and they inhibit recall of

[5] We find this is a useful way to organize and interpret the empirical analysis, although it is not the only model for which this can be done – and indeed we refer to alternative interpretations of the results throughout. Nor do we aim to empirically distinguish the Bordalo *et al.* [2025] framework from Bayesian learning or other models of experience-based learning. 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]. Benjamin [2019] provides an excellent overview of the literature on biased beliefs or beliefs deviating from correct reasoning about probabilities or Bayesian updating.

[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, driven by similarity and interference of experiences.

less similar experiences. A symmetric function $S : E \times E \rightarrow [0, 1]$ measures the similarity between experiences. Consider a set of experiences, A, that in our context could capture: (i) having been a witness (e^w), and specific features of the witnessing experience such as the type of crime seen, its location etc. (e^w_{type}, $e^w_{location}, ...$); (ii) all other experiences, that embody other information from news or social networks ($\Im$). Hence $A = \{e^w_{type}, e^w_{location}, ..., \Im\}$. 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 $e \in E$, denoted $r(e)$, is proportional to its similarity to the experience, $S(e, \pi)$:*

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

The numerator implies experience $e \in E$ is sampled more frequently when it is more similar to π. The denominator captures interference: all experiences and information compete for retrieval. Individuals might therefore neglect information relevant for the perception being formed because of recent salient experiences of witnessing or being a victim of crime.

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 common features, 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 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 their database, 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 impact of a given crime-related experience can thus vary across perceptions, depending on its similarity to the perception. For example, if victimization more similar to domains of perception related to local or personal circumstances, then these perceptions will respond more strongly to experiences of victimization than to witnessing. Conversely, if witnessing is considered to be more similar to domains of perception related to institutions, these perceptions will react more strongly to experiences of witnessing crime than to victimization. Our results can be naturally interpreted within this mapping between experiences and domains of perception, which Bordalo *et al.* [2025] refer to as a similarity-based hierarchy of experience effects.[7]

3 Data and Descriptives

3.1 Crime Survey of England and Wales

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

First and foremost, it records instances of individuals witnessing crime – something not typically recorded in administrative data. The wording of the witnessing question refers to direct experiences, namely events actually observed by the respondent (rather than learned from others or the news media). Second, the CSEW samples victims and non-victims, with a detailed module specifically administered to victims. Third, it captures experiences of victimization that are unreported to the police, and so is unaffected by changes in police recording practices. The data suggests only 39% of offenses are reported, so the CSEW provides a more comprehensive picture than administrative data on victimization experiences. Finally, the survey gathers information on post-victimization outcomes in the justice system such as whether an offender was identified or charged. We use this to distinguish positive and negative experiences, to understand whether they differentially enter the retrieval-simulation process when forming crime-related perceptions.

We combine and harmonize 17 survey waves from 2001-02 to 2017-18, covering $684,581$ 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. Some parts of the analysis exploit comparisons within very small geographies – in England and Wales these are known as Lower Layer Super Output Areas (LSOAs), comprising 400 to 1200 households – far smaller than US census tracts. LSOA identifiers are available from 2011 onwards. The Data Appendix further details the sample, variable definitions and data construction.

[7] We diverge from Bordalo *et al.* [2025] 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.

3.2 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 records whether respondents have experienced witnessing a crime or forms of anti-social behavior (ASB), in the preceding 12 months. 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 behaviors, which 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. We later show how each type of witnessing experience relates to perceptions.

Victims All survey waves ask respondents whether they have been a victim of crime in the preceding 12 months. Information is recorded for multiple victimizations. For each victimization, the CSEW records the month of occurrence, the type of crime, whether it was reported to the police, and information on subsequent case handling and outcomes.

Single Experiences We exclude respondents who witness multiple crimes or experienced multiple victimizations within the reference period – thus focusing on 55% of all witnesses and 64% of all victims. We focus on single incident experiences to isolate how perceptions evolve following a one-off experience and avoid confounding effects from multiple experiences occurring at different time horizons. For completeness, we later examine the wider sample of individuals with multiple experiences to document dose responses to victimization and witnessing in the formation of crime-related perceptions.

Post-victimization Experiences The CSEW records how the criminal justice system handled each case of victimization, in the period from victimization up until the 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 tentatively explore the extent to which positive post-victimization experiences offset impacts from the original victimization, across domains of perception.

3.2.2 Crime-related Perceptions

The domains of perception considered range from those related to institutions of the justice system, local neighborhoods, through to perceptions of personal well-being. This breadth allows us to link to a feature of the framework, that the impact of crime-related experiences on perceptions can vary depending on their similarity to the perception being formed. The domains of perceptions considered are as follows.

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

Neighborhood: We construct an index of the respondents' perceptions about their neighborhood, using seven questions on 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. The survey makes clear local is within 15 minutes walk from their home.

Personal: We consider three perceptions – how safe respondents feel when walking alone after dark; an index of worrying about specific types of future victimization (being burgled, mugged, or attacked); and 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 outcomes within our working sample. We thus relate crime-related experiences to effect size associations with each perception. We sign each perception so positive values indicate better outcomes: greater confidence in the criminal justice system, greater confidence in the police, perceiving the neighborhood to have fewer problems, feeling safe 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 local neighborhood, personal safety and quality of life are elicited before questions on victimization. The CSEW later asks about perceptions of institutions in the justice system. The last part of the survey asks respondents about other experiences, including witnessing crime. This ordering ensures that some perception measures are collected prior to respondents being prompted to recall crime-related experiences related to victimization, and all perception questions are asked prior to collecting information on witnessing. This ameliorates some concerns about anchoring or priming effects of experiences on perceptions.

3.3 Descriptive Evidence

Perceptions Our working sample of single incident victims and witnesses covers $271,403$ individuals: 29% report having witnessed a crime, 13% report having been a victim. Hence the incidence of victimization is less than half that of witnessing, underlining the importance of considering how both crime-related experiences associate with perceptions. Our 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 describes perceptions by crime-related experience. Those without any crime-related experience (Column 1) have more favorable perceptions than those with recent crime-related experiences – they report significantly higher confidence in the justice system and police, fewer problems in their neighborhood, 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) and focusing on the victim-witness perceptions gap, this gap is different from zero on all domains but its sign varies. For confidence in the justice system and perceptions of neighborhoods, witnesses to crime have worse perceptions than victims of crime: the magnitude of these differences is sizable relative to the average perception held among those with no crime-related experience. The sign of the victim-witness perceptions gap reverses for domains of personal perception, where victims feel more unsafe, worry more about future victimization, and express crime impacts their quality of life to a greater extent than witnesses. Again, these perceptions gap tend to be larger than the average perception held among those with no crime-related experience.

Characteristics Panel A of Figure 1 sheds light on characteristics of those with crime-related experiences. The underlying histogram benchmarks against characteristics of those that are non-victims and non-witnesses. As expected, witnesses and victims are more likely to be male, reside in urban areas, be younger, unmarried, and have children than non-victims/non-witnesses. Witnesses are closer in characteristics to victims than to non-victims on most margins, with the magnitude of differences in observables being small. However, one notable difference across groups is age: witnesses are older than victims. Panel B shows victimization- and witnessing-age profiles, making precise the incidence of each experience at any given age. The victimization-age profile is in line with evidence from other settings. The witnessing-age profile is far less established and shows that at any age, individuals are more likely to witness a crime than to be a victim, with this gap narrowing with age.[8]

Time Series of Perceptions, Victimization and Witnessing We next present novel evidence on how perceptions and experiences have changed over time. Panel A of Figure 2 shows the time series of crime-related perceptions, normalizing each series to 100 in 2003-04. 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 14% higher than in 2003-04. Confidence in the police is 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 4% higher (respectively) in 2017-18 than in 2003-04.

Panel B shows that, as in many countries, victimization rates have declined year-on-year. However, the fall in victimization rates is far larger – being 32% lower in 2017-18 than in 2003-04 – than improvements in any crime-related perception over the same period. To see what might

[8]The victimization- and witnessing-age profiles are very similar if we consider those with multiple experiences of victimization or witnessing crime. For England and Wales, Jansson [2008] used the CSEW to compare risk factors for violent crime victimization 25 years apart (1981 vs. 2005/6). In both surveys, 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, singles, 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].

lead to this wedge, we note that in contrast to declining victimization rates, rates of witnessing crime have remained stable: they are the same in 2017-18 as in 2003-04.

Panel C unpacks witness rates into those for violent and non-violent crime. While rates of witnessing non-violent crime follow the decline in victimization rates, rates of witnessing violent crime have risen dramatically, being 28% higher in 2014-15 than 2003-04. Increasing rates of witnessing violent crime can be due to the composition of crime shifting towards violent crime, and/or witnesses per violent crime rising.

On the first channel, Panel D shows rates of victimization by crime type. Violent crime has made up a larger share of all crimes over time: in 2003-04 it constituted 12% of all crimes; by 2017-18 it constituted 20%.[9]

On the second channel, Table 3 shows witnessing rates, victimization rates, and their ratio. Panel A aggregates across all crimes and shows that in most years, the share of adults that report witnessing crime is the same or higher than the share reporting victimization. The fall in victimization rates coupled with the constancy of witness rates means that while in 2003-04 the ratio of witnesses per victim was .920, this had risen to 1.21 by 2014-15. Panel B breaks this down by crime type. The ratio of witnesses to victims for violent crime is far higher than for other crime types – in 2003-04 it was 4.69, while the ratio is less than one for all other crime types. Moreover, over time the witness-victim ratio for violent crime has risen from 4.69 in 2003-4 to 5.92 by 2014-15, a 26% rise. In contrast, for other crimes the ratio has either fallen (criminal damage), remained largely constant (burglary), or risen less dramatically (theft).[10]

Two forces can drive the upward trend in the witness-victim ratio for violent crime: first, the threshold for what is considered having witnessed a violent crime might have shifted down over time. To the extent that such changes can be picked up in the characteristics of witnesses, Panel A of Figure A1 shows how these characteristics of witnesses to violent crime have changed between 2003-04 and 2017-18. Over the sample period witnesses to violent crime have become less likely to be white, be a home owner, be married or reside in a rural area.[11]

Second, the nature of violent crime might have changed over time, becoming more visible to potential witnesses. To assess this, we use information on changes in the location and time of violent crime between 2001-02 and 2017-18 (as reported by victims as witnesses are not asked such questions). The result is in Panel B of Figure A1. We see that: (i) at the start of our study

[9] The increase in violent crime may partly reflect salient shocks to local policing across police force areas in England and Wales over this period. For example, Facchetti [2024] shows that police station closures, prevalent in London and other police forces, increased local violent crime.

[10] We can compare these numbers to another context: Johnston *et al.* [2017] use the HILDA panel survey from Australia, which 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.

[11] We note that rates of reporting crime by victims has remained relatively constant over our sample period: 45% of crimes were reported in 2001-02, and 41% were reported at the end our study period. Rates of reporting crime do vary by crime type – being above 60% for burglary, below 30% for criminal damage, and around 40% for violent crime. Reporting rates by crime type have not on the whole changed much over our study period.

period, 9% of violent crime occurred at home – this has risen by 2.6pp over time; (ii) more violent crime is reporting occurring just outside the home; (iii) both substitute away from violent crime being reported as occurring in public; (iv) the timing of violent crime has also shifted from night time to day time. Both trends increase the observability of violent crime.

We do not take a stance on the relative importance of these channels – both help to understand the rise in the witness-victim ratio for violent crime. The issue is however relevant for the later analysis where we reconsider the social costs of crime when costs to witnesses are accounted for, because if changes in the incidence of witnessing crime are partially driven merely by changes in reporting thresholds rather than the true incidence of violent crime, that has implications for reconstructing the social costs of crime.

To summarize, the experience of witnessing crime has become relatively more common than being a victim of crime. This is because of a change in the composition of crime towards more violent crime, and because witnesses per violent crime are far higher than for other crime types, and trending upwards. All this can combine to explain why long-run declines in victimization have not translated into corresponding improvements in crime-related perceptions, underscoring the importance of studying the experience of witnessing crime.[12]

4 Results

Our focus is on comparing the associations between crime-related perceptions and two crime-related experiences: witnessing crime and being a victim of crime. For any given domain of perception, we estimate the following specification for the perception of respondent i surveyed in wave t, $y_{i(t)}$:

$$y_{i(t)} = \beta_0 + \beta_W Witness_{i(t)} + \beta_V Victim_{i(t)} + X'_{i(t)}\theta + \phi_P + \omega_m + \omega_t + \varepsilon_{i(t)}, \tag{4}$$

where $Witness_{i(t)}$ 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, and the omitted group are those with neither crime-related experience. $X'_{i(t)}$ is a vector of individual covariates that control for well-established correlates of victimization – including age (and its square). 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 perceptions. We assume that within police force area, month and year of interview, respondents' perceptions are independently formed and compute heteroskedasticity-robust standard errors. All estimations

[12] Repeating the analysis for the 40% of crimes that are reported to the police, the results replicate: rates of victimization have fallen, the share of reported crimes that are violent has risen, and the ratio of witnesses to victims for violent crime has risen.

apply survey weights.[13]

Table 4 shows the coefficients of interest, and these are graphically summarized in Panel A of Figure 3, along with their 95% confidence intervals. All perceptions are standardized, so we report the partial correlations (β_W, β_V) in effect sizes.

We find both experiences – being a witness or victim of crime – reduce crime-related perceptions across the board ($\widehat{\beta}_W < 0$, $\widehat{\beta}_V < 0$). Viewed through the lens of the framework, the results confirm that both victimization and witnessing constitute salient crime-related experiences that enter the retrieval-simulation process and meaningfully shape crime-related perceptions because they have a strong similarity to each perception (π) considered: $S(witness, \pi) >> 0$, $S(victim, \pi) >> 0$.

As with the unconditional estimates, the victim-witness perceptions gap varies in sign as shown in Panel B of Figure 3. For institutional and neighborhood domains, the association with witnessing is significantly larger than with victimization ($\left|\widehat{\beta}_W\right| > \left|\widehat{\beta}_V\right|$): 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 $.423\sigma$ less favorable for witnesses, and $.258\sigma$ less favorable for victims ($p = .000$). In contrast, for most personal domains, the reverse is true so that the association with witnessing is significantly smaller than with victimization ($\left|\widehat{\beta}_W\right| < \left|\widehat{\beta}_V\right|$): worrying about being a future victim of crime is $.128\sigma$ worse for witnesses, and $.167\sigma$ worse for victims ($p = .000$); the perceived effect of crime on quality of life is $.198\sigma$ worse for witnesses, and $.354\sigma$ worse for victims ($p = .000$). Both experiences have similar associations with feeling safe walking alone ($p = .576$).

The heterogeneous effects of each experience across domains align with a similarity-based hierarchy of experiences. This heterogeneity can be due to: (i) witnessing experiences are more likely to be recalled when institutional or local domains of perception ($\overline{\pi}$) are cued to be simulated: $r(witness) > r(victim)$, and: (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 personal domains of perception ($\underline{\pi}$): $S(witness, \underline{\pi}) \leq S(victim, \underline{\pi})$.

These results are robust to: (i) alternative approaches to clustering standard errors at a higher level such as police force area, removing controls, not weighting the estimates or allowing standard errors to be spatially correlated across police force areas (Table A1); (ii) accounting for multiple hypothesis testing (Table A1). We also consider how crime-related experiences impact perceptions using the discrete distribution of each outcome rather than continuous normalized outcomes. This shows that across domains, downward shifts in perception arise from a reduced likelihood of respondents expressing the most positive beliefs, and these patterns are very similar for witnesses and victims (Figure A2).[14]

[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.

[14] We estimate separate linear probability models for each response category. Figure A2 plots the estimated

We benchmark the magnitude of these experience effects against the partial correlations of both crime-related experiences to other covariates controlled for in (4). Table A2 shows that, for example, in terms of confidence in the criminal justice system, the partial correlations with crime-related experiences are four to six times larger than the partial correlation with gender. On personal domains, the partial correlations with crime-related experiences are around a quarter of the gender differential in feeling safe to walk alone in the dark, or around a third of the gender differential in being worried to be a victim of crime. Finally, in terms of the effect of crime on perceived quality of life, the partial correlations with both crime-related experiences are larger in absolute value than for all other covariates.

4.1 Ruling out a Zero-effect Null

A nascent literature identifies causal impacts of victimization by 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]. These research designs are not appropriate in our setting, nor do they extend to experiences of witnessing crime.

We address the issue by considering the primary concern: that the estimates are biased because of an omitted characteristic from (4), correlated to crime-related experiences and that directly impacts perceptions. We focus on understanding whether such a latent factor could generate non-zero coefficients when the true causal effects are zero, and whether it could generate the documented pattern of sign reversals across perception domains.[15]

To make this precise, suppose the true model linking crime-related experiences and perception domain d is:

$$Y_{id} = \alpha_d + \beta_{Wd} W_i + \beta_{Vd} V_i + \lambda_d \widetilde{R}_i + u_{id}, \qquad \mathbb{E}[u_{id} \mid W_i, V_i, \widetilde{R}_i] = 0, \tag{5}$$

where W_i denotes witnessing, V_i denotes victimization, and $\widetilde{R}_i$ is a single latent index capturing unobserved risks of exposure to crime-related experiences, such as risky routines, risks transmitted through social networks or precautionary behavior. The parameter λ_d allows this latent factor to affect perception domains with different strength. We consider the implications of the true model

coefficients along with the underlying distribution of the perception outcome category among non-victims. The first row shows how each category of confidence in the criminal justice system is shifted by being a witness of crime (left hand panel) and being a victim (right hand panel). The negative association of both experiences is driven by a reduction in the share of respondents who 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 also find shifts in perception arising from reductions in those expressing the most positive beliefs, and these patterns are very similar for witnesses and victims.

[15] We place more emphasis on this concern than potential reverse causality between crime-related perceptions and crime-related experiences because such concerns would typically generate a spurious positive correlation between the two. For example, perceiving the neighborhood to be safe can lead individuals to unknowingly take risks and then be more likely to have a crime-related experience.

being (5) but estimating a model analogous to (4):

$$Y_{id} = \tilde{\alpha}_d + \tilde{\beta}_{Wd} W_i + \tilde{\beta}_{Vd} V_i + \varepsilon_{id}, \tag{6}$$

where $\varepsilon_{id} = \lambda_d \widetilde{R}_i + u_{id}$. When $Cov[W_i, V_i] > 0$, it is convenient to parameterize $Cov[\widetilde{R}_i, V_i] = \gamma Cov[\widetilde{R}_i, W_i]$, with $\gamma > 0$ so the omitted factor is correlated with witnessing and victimization in the same direction. In the Appendix we show the OVB can be written as:

$$\tilde{\beta}_{Wd} - \beta_{Wd} = \lambda_d \phi_W, \qquad \tilde{\beta}_{Vd} - \beta_{Vd} = \lambda_d \phi_V, \tag{7}$$

where ϕ_W and ϕ_V depend on the covariance structure between witnessing, victimization, and the latent risk factor, but do not vary across perception domains.

In the case in which neither crime-related experience has any true causal effect, so $\beta_{Wd} = \beta_{Vd} = 0$ for all d, $\tilde{\beta}_{Wd} = \lambda_d \phi_W$ and $\tilde{\beta}_{Vd} = \lambda_d \phi_V$ and a single latent omitted factor can generate non-zero estimates. However, the observed ratio $\tilde{\beta}_{Wd}/\tilde{\beta}_{Vd}$ equals the ratio of omitted-variable biases, that is independent of the perception domain. As this ratio is a function of the covariance structure between witnessing, victimization, and the latent risk factor, it can be used to back out the value of γ required to rationalize the observed estimates in each domain under the zero-effect null. This exercise is summarized in Table A3: the implied values of γ range from .42 to 1.04, and we reject equality of multiple pairs of implied γ values across domains. This variation makes it difficult for a single omitted factor to explain our findings under the zero-effect null.

In the Appendix we develop a second argument: under the zero-effect null, a single latent factor implies that the victim-witness gap should have the same sign across domains, provided it affects crime-related perceptions in the same direction. In that scenario, the sign reversal documented in Table 4 is again difficult to reconcile with a true model of the form in (5).

4.2 Robustness

Building on these insights, we use four empirical strategies offering alternative approaches to assess whether the observed pattern of results is driven by omitted variables, and to assess the stability of the estimates in specific subsamples. These are presented in Table 5, where Column 1 reports our baseline estimates for the subsample where LSOA identifiers are available (2011 onwards) because this sample can be used for all the strategies.

Selection on Multiple Unobservables Following Altonji *et al.* [2005] and Oster [2019], we estimate the coefficients of interest accounting for selection on unobservables. Unlike the argument above, this allows for multiple omitted risk factors (not just a single-dimension unobservable $\widetilde{R}_i$). Column 2a of Table 5 reports coefficients adjusted for equal selection on observables and unobservables, and Column 2b reports the coefficient of proportionality (denoted δ following Oster

[2019]) across observed and unobserved covariates required for $\beta_i(\delta) = 0$. Across perception domains and for both experiences, the adjusted coefficients remain away from zero and δ would need to be larger than five (in absolute value) for true effect to be zero.[16]

Masten and Poirier [2026] reconsider this approach to show that bounds required for omitted variables to reverse the sign of the coefficient of interest can be smaller than those required to drive it to zero. In our context this is especially relevant as a sign reversal would imply the true causal effect of experiences is to improve perceptions. Following Masten and Poirier [2026], we vary OVB bounds and report the sign-change breakdown points for a maximum OVB up to 10 times the estimated coefficient $M_i = 10|\hat{\beta}_i|$. The results are reported in Columns 2c and 2d in Table 5. The sign-change breakdown values of $|\delta|$ remain close to the explain-away breakdown $|\delta|$'s at maximum OVB equal to twice the point estimate, and remain above one when allowing maximum OVB up to 10 times the effect size. Overall, the evidence suggests equal selection on observables and multiple unobservables would not be sufficient to reverse or explain away the estimated negative effects of crime-related experiences on crime-related perceptions.[17]

Matching Given observable differences between those with and without crime-related experiences, we estimate our coefficients of interest using a matching design based on entropy balancing. This only allows us to consider separately the association of each crime-related experience with perceptions. The results in Columns 3a and 3b of Table 5 show the estimated coefficients of interest to be very similar in magnitude and precision to our baseline estimates across all domains and both crime-related experiences.

Neighborhood Effects We next narrow in on the concern that local variation in actual crime is the key unobserved factor driving latent risks of having crime-related experiences, and that directly impacts perceptions. 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 includes seven local authorities. The results in Column 4a of

[16] This approach assumes there are potentially many omitted factors in (4). This set of unobservables is denoted W_2, capturing a linear combination of j unobserved variables w^u_j, multiplied by their coefficients, $W_2 = \sum_{j=1}^{J_u} w^u_j \gamma^u_j$. We then need to make an assumption on how the unobserved and observed covariates driving perception 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 δ. It can then be shown that the true causal impact for group i, β^*_i, depends on β (and other factors): $\beta^*_i = \beta_i(\delta, .)$. At one extreme, if $\delta = 0$ 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 ($\delta = 1$): intuitively, the set of unobservables should not be *more* important than the available covariates in explaining the effect of crime-related experiences on perceptions. Column 2a reports $\beta_i(\delta = 1)$ using $R^2_{\max} = 1.3R^2$ following Oster [2019].

[17] As Masten and Poirier [2026] discuss, Oster's breakdown statistic is the value of the proportional selection parameter $|\delta|$ required for $\beta_i(\delta) = 0$. This need not coincide with the sign-change breakdown point; the value of $|\delta|$ for which the identified set contains a coefficient with the opposite sign. They also show that absent any restriction on the magnitude of the bias, this sign-change breakdown point can never exceed one, so a large explain-away $|\delta|$ is not evidence that an estimate's sign is robust. To recover informative breakdown points, they propose to assume bounds on the magnitude of the omitted-variable bias: $|\beta^*_i - \hat{\beta}_i| \leq M_i$.

Table 5 show that for all margins of perception, the partial correlations with both crime-related experiences remain stable and precisely estimated. We next go one step further and control for LSOA fixed effects. LSOAs comprise 400 to 1200 households – far smaller than US census tracts. Accounting for unobserved heterogeneity across LSOAs in Column 4b, there remain significant associations with each crime-related experience, across all 12 estimated coefficients. Finally, we consider one particular form of heterogeneity across areas by controlling for highly localized LSOA crime rates using official police record data (controlling for local authority fixed effects). Column 4c shows the partial correlations of either experience across perceptions remain of similar magnitude as the baseline estimates, and remain precisely estimated. Relevant for the nascent literature on exposure to violence, our results highlight that crime-related experiences can shape perceptions of institutions, neighborhoods and personal safety, over and above effects of neighborhood exposure to violence or crime [Ang 2021, Cabral *et al.* 2025].

Stability Across Subsamples A final approach to assess whether our results reflect a causal relationship between experiences and perceptions is to examine their stability in subsamples.

We documented earlier that men are more likely to be witnesses or victims, and that men hold significantly different crime-related perceptions to women. If men are at higher latent risk of having crime-related experiences, the coefficients of interest should be more biased for men. Figure A3 shows results by gender, where Panel B reports p-values for the equality of impacts across genders for the same perception-experience combination. We find no gender differential for eight out of twelve estimates.[18]

We also showed earlier that witnessing and victimization rates vary by crime type. If the underlying latent risk of having crime-related experiences varies by crime type, the coefficients of interest should be more biased for crimes more likely to be witnessed or have victims. Figure A4 shows results by crime type. Focusing on violent crime, which has the highest rates of being witnessed, we find no evidence that witnessing violent crime affects perceptions differently to witnessing other crimes. Turning to theft, which has the highest rates of victimization, we find no evidence that being a victim of theft affects perceptions differently to being a victim of other crimes. Finally, it is notable that worrying about being a future victim of crime – constructed from concerns over 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, when individuals are cued to think about future victimization from certain crime types, the recall of crime-related experiences appears similar irrespective of the crime-type, even if that crime-type is unrelated to the one individuals are asked to simulate their perception of occurring in future.[19]

[18] 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 women's perception of feeling safe to walk alone after dark. At the same time, witnessing crime has a larger impact on the fear of future victimization for men ($.130\sigma$ vs. $.110\sigma$, $p = .068$).

[19] Our main results combine witnessing crime and witnessing anti-social behavior but Figure A4 pulls out the

5 Interactions of Experiences

The Bordalo *et al.* [2025] framework emphasizes that experiences compete to be recalled from memory when an individual is cued to simulate a perception. Experiences more similar to the perception being formed are more likely to be recalled, but as experiences compete for retrieval, the framework helps explain why some relevant experiences can be neglected. We examine these issues by considering three kinds of interaction: (i) between experiences; (ii) between negative experiences of victimization and positive-post victimization experiences in the justice system; (iii) experience effects by age.

5.1 Crime-related Experiences

We consider individuals who experience both witnessing crime and being a victim of it. How individual experiences interact to shape perceptions has not been considered much in earlier work [Malmendier 2021, Bordalo *et al.* 2025]. We estimate the following specification:

$$y_{i(t)} = \beta_0 + \beta_W Witness_{i(t)} + \beta_V Victim_{i(t)} + \beta_{WV}\left[Witness_{i(t)} \times Victim_{i(t)}\right] + X'_{i(t)}\theta + \phi_P + \omega_m + \omega_t + \varepsilon_{i(t)}. \tag{8}$$

The estimates are graphically summarized in Panel C of Figure 3 which shows $\widehat{\beta}_W$, $\widehat{\beta}_V$, $\widehat{\beta}_W + \widehat{\beta}_V$ and separates out the interaction term, $\widehat{\beta}_{WV}$.

Across domains, we find a positive interaction between crime-related experiences: namely, the worsening perceptions among 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 most cases the offsetting effect is around an eighth of the sum of the levels effect of each separate experience. The only exception is confidence in the police, for which we find no offsetting interaction of both experiences. Two implications follow.

First, these results run counter to the concern of omitted variables, because the interaction of both experiences offsets their individual association with perceptions rather than amplifying them. In the Appendix we extend the analysis of OVB to show how such a positive interaction effect is hard to reconcile with a one-factor confounding explanation for our estimates. This is because in the intuitive case in which higher latent risk worsens perceptions and is disproportionately concentrated among those with both experiences, omitted-variable bias would make the interaction more negative, not positive. The observed offsetting interaction under a zero-true-interaction null would instead require latent risk to be negatively associated with joint exposure, conditional on its separate associations with witnessing and victimization.

effects from witnessing anti-social behavior. These associations are greater than those for victimization for perceptions towards institutions and neighborhoods. This is consistent with 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.

Second, the offsetting interaction suggests victimization and witnessing experiences do not fully crowd out one another in memory retrieval when forming perceptions. Rather, these different sources of domain relevant information have additive effects, albeit at a diminishing rate. For those with both experiences, we can take this one step further by considering the effects of similarity between witnessing and victimization experiences, namely whether the individual witnessed and was a victim of the same crime type or not. Table 6 shows the similarity of experiences matters in how much they offset the combined effects of each experience. For perceptions related to institutions and neighborhoods, the offsetting effects of both experiences only exist if they relate to similar crime types. In contrast, for domains of personal perception, we cannot rule out that the offsetting effects of witnessing crime or being a victim of it are the same irrespective of whether they relate to similar crime types or not.[20]

5.2 Post Victimization Experiences

We have so far focused on how adverse crime-related experiences worsen crime-related perceptions. However, individuals can also be subject to positive crime-related experiences – another feature of experience effects that has not been considered much in earlier work [Malmendier 2021, Bordalo *et al.* 2025]. We examine the issue by considering experiences arising from institutional responses to victimization, a potentially positive experience. 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% have an offender identified, and 4% have an offender both identified and charged. We use this information to construct a categorical measure of post-victimization experience with the criminal justice system:

$$post\_victim_{i(t)} = \begin{cases} 0 & \text{not reported} \\ 1 & \text{reported, offender not found} \\ 2 & \text{reported, offender found but not charged} \\ 3 & \text{reported, offender found and charged.} \end{cases} \tag{9}$$

This ranges from victims deciding to have no engagement with the system to the most favorable outcome in which victims report the crime and an offender is charged. We estimate the following specification for the sample of victims, where those who did not report the incident to the police

[20] We also examine dose responses to the same crime-related experience. We extend the sample to include those who either witness or are victims of, multiple crimes in the 12 months preceding each survey. The results in Table A4 show strong dose responses: those with multiple experiences of either type have significantly lower perceptions across all domains. In nearly all cases, the magnitudes are near double those for single experiences. Hence multiple experiences of the same type do not crowd out one another in memory retrieval when forming perceptions, but each provides additional material to simulate the perception with.

($post\_victim_i = 0$) are the omitted category:

$$y_{i(t)} = \begin{array}{l} \delta_1 \mathbf{1}\{post\_victim_{i(t)} = 1\} + \delta_2 \mathbf{1}\{post\_victim_{i(t)} = 2\} + \delta_3 \mathbf{1}\{post\_victim_{i(t)} = 3\} \\ +\gamma Month\_victim_{i(t)} + X'_{i(t)}\theta + \phi_P + \omega_t + \omega_{c(i)} + w_{s(i)} + \varepsilon_{i(t)}. \end{array} \tag{10}$$

All terms are as previously defined but in addition, we include fixed effects for crime type ($\omega_{c(i)}$) and self-reported crime severity ($w_{s(i)}$), based on an indicator ranging from 1 to 20. This helps account for crime-specific characteristics that may influence respondents' 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.

Panel D of Figure 3 plots $\widehat{\delta}_3 - \widehat{\delta}_1$ for each perception. We see that within-individual favorable experiences offset the previously documented negative impacts of the initial victimization for some domains. 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 (reported in Table 4) is more than offset by the $.149\sigma$ rise in confidence following positive post-victimization experiences – leaving those who have experienced both events with higher confidence in the criminal justice system than non-victims. Similarly, the initial $.121\sigma$ fall in confidence in the police is more than offset by the $.257\sigma$ rise following positive post-victimization experiences – leaving those who 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.

Taken together, these results also reduce concerns that unobserved characteristics correlated to victimization and crime-related perceptions are likely driving our results because favorable post-victimization experiences, in some cases, offset the negative association between victimization and crime-related perceptions, leaving reported perceptions of victims similar to those of non-victims. We present evidence on the robustness of these findings, and how they differ by gender and crime type, in the Appendix.

The asymmetry between positive and negative experiences is of note, especially given this distinction has not been the focus of work on experience-based learning. More specifically, positive experiences from the justice system lead to updated perceptions in similar domains related to institutions, but not to other domains. This is in contrast to the earlier results, where negative crime-related experiences lead to updating across *all* perception domains – institutional, local and personal. Moreover, by considering the role that favorable post-victimization experiences in the justice system have on mitigating impacts of initial victimization, we start to open the black box of interactions between victimization and the criminal justice system. Beyond a nascent literature on restorative justice [Shem-Tov *et al.* 2024, Adukia *et al.* 2025], such issues have not been studied in the economics literature [Ketel *et al.* 2020].

5.3 Age Effects

Finally, we examine how experience effects vary with age, because experience-based learning can be more pronounced in impressionable years [Krosnick and Alwin 1989]. We use this to illustrate a more general phenomena, that there can be interactions between recent salient experiences and previously help information or priors. Table A5 shows that associations between victimization and crime-related perceptions do not vary much between age groups (16-25, 26-45, 46+). In contrast, associations between witnessing and perceptions show rising gradients by age, so older individuals are significantly *more* impacted by witnessing crime than younger individuals, across all perceptions. As a result, perception gaps across ages become wider among those witnessing crime. The same is not true for victims of crime – there we see relatively stable experience effects across age groups.

This suggests experiences of witnessing crime are more likely to be recalled for older individuals – perhaps because younger individuals have a greater flow of recent non-crime experiences that also compete to be recalled from memory – while experiences of victimization are as salient to the young and old when cued to form crime-related perceptions.

6 Implications for the Social Costs of Crime

We build on all our findings to consider the implications for measuring the social costs of crime. The key insights established are that these costs extend beyond victims to witnesses, and that victims and witnesses may be differentially affected by their experiences. After showing the consequences for measured social costs of crime, we draw implications for understanding the wedge between actual crime rates and individual perceptions of changes in crime rates, a long-standing puzzle across many countries.

6.1 Accounting for Witnesses

We root our approach in an established method for measuring the social costs of crime in our study context and 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 cost estimate can be decomposed into costs arising from anticipation/avoidance behaviors, consequences of victimization, and other costs borne by victims and institutions in the justice system. Our innovation is to extend their framework to incorporate costs of being a witness to crime. Denoting V^k as the victim cost for a single crime of type k and W^k the corresponding unit cost borne by witnesses, the social cost of a crime of type k is:

$$\text{Unit Social Cost}^k = V^k + W^k. \tag{11}$$

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 by 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. We describe the intuition behind each, and detailed derivations are in the Appendix.[21]

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 for personal domains of crime-related perceptions (feeling safe, worrying about victimization and quality of life) suggest are affected for both victims *and* witnesses. In the Heeks *et al.* decomposition of costs these relate to 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 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 association between crime-related experiences and personal domains of crime-related perceptions to determine the scale of W^k relative to V^k. We use perceptions most closely relating to these personal 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 ratio of estimated associations between witness and victim experiences and these perceptions from specification (8) to construct a multiplier of W^k relative to V^k. This multiplier is the ratio of witnessing to victimization effects. Given the multiple personal perceptions considered, we use estimates across personal domains to construct lower and upper bounds for this multiplier.[22]

[21] We maintain the definition of W^k as the social cost borne by an individual witness to crime, paralleling V^k as the cost borne by an individual victim. As an incident can be witnessed by more than one person, equation (11) measures the average social cost per direct experience of crime, rather than the social cost per incident. Scaling W^k by the average number of witnesses per incident would yield larger estimates.

[22] Two extensions for future work would be to include costs associated with: (i) the other perceptions considered – such as a loss of confidence in the criminal justice system or the police; (ii) impacts on labor market outcomes or avoidance responses arising from the experience of witnessing crime [Bindler and Ketel 2022].

6.2 Unit Social Costs of Crime

Table 7 summarizes findings using each approach, showing the proportionate change in unit social costs of crime relative to the established Heeks *et al.* method when: (i) averaging across all crime types; (ii) by crime type. 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 underestimated if only victims are accounted for. This underestimate varies between 26% and 69% across crime types, with the largest underestimate for violent crime and the smallest for criminal damage. Columns 2 and 3 show that under the second approach, the implied average unit social cost of crime rises 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.[23]

The bottom line is that standard approaches to calculating the social costs of crime that only consider victims substantially underestimate the true costs once we factor in other salient 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. While victimization rates have steadily declined over time, witnessing rates have remained stable over two decades, as the composition of crime has changed towards violent crime, which is witnessed to a greater extent than other crime types (Figure 2). *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 wider impacts on witnesses are accounted for.[24]

In the Appendix we consider implications for the social costs of crime from 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 discuss implications for the returns to investing in the criminal justice system to increase the likelihood of favorable post-victimization outcomes, and contrast this to investing in policies to reduce *ex ante* victimization rates.

[23] As the multiplier is the ratio of witnessing effects to victimization effects, we can derive confidence intervals for the lower and upper bounds. In practice, given the precision of the estimated experience effects, and the fact that the lower and upper bounds are close (because the ratio of experience effects are relatively constant across personal domains), the implied confidence interval for the unit social cost estimate is also small.

[24] There are alternative approaches aimed to capture a broader set of social costs than those borne directly by victims. One strand uses contingent valuation to elicit willingness to pay for reductions in crime or violence [Ludwig and Cook 2001]. Another uses hedonic approaches to infer the value of reductions in crime risk from their capitalization into house prices [Rosen 1974]. The latter approach has been applied to variation in property crime [Pope and Pope 2012], local exposure to drug crime [Adda *et al.* 2014] or convicted offenders [Linden and Rockoff 2008, Pope 2008], and violence [Besley and Mueller 2012]. Both approaches can capture costs extending beyond direct victims (including for witnesses), but also pick up impacts through many other channels such as neighborhood exposure to crime, or perceptions of crime driven through other indirect experiences and news sources. Our aim is to precisely establish social costs arising solely from direct crime-related experiences of witnessing and victimization.

6.3 Aggregate Social Costs of Crime

An implication of our finding for the unit social costs of crime is that trends in aggregate social costs of crime might not be as pronounced downwards as implied by falling victimization rates because: (i) costs to witnesses need to be accounted for; (ii) the composition of crime has changed towards violent crime, which has relatively high costs for both victims and witnesses and accounts for a large share of witnessing experiences. This has implications for understanding the wedge between perceived and actual crime rates.

We unpack this intuition in Panel A of Figure 4, where all time series are normalized to 100 in 2003-04. We first show the time series for victimization rates (gray): as described earlier, this has fallen over time, being 25% lower in 2014-15 than 2003-04. The second series shows aggregate social costs of crime calculated from Heeks *et al.* and based only on victims (black). These have fallen by 17% over the same period. This decline is smaller than the fall in victimization rates as the composition of victimization has tilted towards violent crime, which has a higher unit social cost. The third series shows the aggregate social costs borne by witnesses (red), for survey years in which witnessing is recorded. The costs borne by witnesses *rise* by 36% over the period. Once victim and witness costs are aggregated using their respective counts (blue), the total social costs of crime fall by only around 3% between 2003-04 and 2014-15. Hence accounting for witnesses almost entirely offsets any decline implied by conventional victim-only measures.

The dynamics of the witness-only cost component combines two forces. The first is the changing *composition* of witnessing experiences. Violent crime carries a far higher witness unit cost than other crime types, so the long-run shift in witnessing towards violent crime raises the average cost per individual witnessing experience even holding constant the number of witnesses. The second force is the changing number of individuals witnessing crime, and in particular the rise in reports of witnessing violent crime (Table 3). As described earlier, this could partly reflect changes in reporting thresholds, or increases in exposure to such crime (Figure A1).

It is normatively unclear whether changes in reporting thresholds should matter for the measurement of social costs: reasonable cases can be made for changes in reporting thresholds to be valid (or not) for this calculation. In Panel B of Figure 4 we gauge the importance of this channel for trends in social costs. We do so by overlaying the previous series from Panel A with an alternative scenario (green). This holds the number of witnesses fixed at its 2003-04 level, so allows part of the growth in witness counts to be an artifact of lower reporting thresholds rather than true exposure to crime. At the same time, this alternative allows the composition of crimes witnessed and the victim component to evolve as observed. Under this alternative scenario, which strips out the entire increase in witness numbers, the witness component of social costs still rises by 24% over time as witnessing shifts towards higher-cost violent crime.[25]

[25] The witness module was not fielded in 2008-09 to 2010-11; for these years we linearly interpolate each crime type's witness count between the observed waves, assuming a smooth transition of the crime mix.

Motivated by our earlier results on experience effects by age, we note that the change in social costs of crime need not be borne equally across groups. Panel C reports the change from 2003-04 to 2014-15 by age, separately for victim-only costs, witness-only costs, and aggregate social costs combining the weighted numbers of the two. For the young, social costs of crime rise by 12%, driven largely by rising victim costs. For older age groups, their victim-only costs fall by 18% – in line with the population as a whole. However, this is offset by a 53% increase in witness-only costs among this group, leaving the total social costs of crime borne by this group to remain unchanged over the period, despite the fall in victimization and victim-only costs.

6.4 Understanding the Wedge Between Actual and Perceived Crime

Once we account for costs borne by witnesses, the aggregate social costs of crime decline far less than either victimization rates or conventional victim-only costs imply. If we consider such monetary costs of crime to victims and witnesses translating into utility losses, this much flatter trend sheds light on why individual perceptions of crime need not improve in line with falling victimization rates – a puzzle long considered across the social sciences [Garland 2001, Duffy *et al.* 2008, Esberg and Mummolo 2018, Campedelli *et al.* 2023].

To support this idea, we consider how crime-related experiences associate with perceived changes in crime rates in recent years: nationally, and in locally. Figure 5 shows perceptions of how national and local crime rates are changing over our study period (irrespective of any crime-related experience). In nearly all years, the majority of respondents perceive national crime rates to be rising, with around a third of respondents also thinking local crime rates are rising. In any given year, only 10% of individuals ever report crime rates to have gone down. In short, perceptions of crime rates are not improving over time – despite long run declines in victimization rates. As Table 1 showed, respondents report personal experiences as a key source of these beliefs.

Second, to understand the link between crime-related experiences and perceptions of crime rates, we estimate a specification analogous to (4) but where the outcome is the belief that the national/local crime rate has increased in recent years (as opposed to remaining unchanged/falling). The results are in Panel A of Table 8: (i) experiences of witnessing crime increase the perception that national and local crime rates are rising to the same extent as victimization experiences, again suggestive of witnessing crime helping to explain diverging trends between actual and perceived crime; (ii) both crime-related experiences have larger associations with perceived increases in local crime than in national crime (in line with the descriptives in Table 1). Panel B repeats the analysis by crime type, where we see that: (i) experiences of witnessing crime of being a victim of crime have similar associations with perceived increases in national crime rates, irrespective of the crime type experienced; (ii) crime types do however matter for how witnessing and victimization experiences translate into perceptions that local crime rates have increased.

7 Conclusion

We study the link between crime-related experiences and two prominent crime-related perceptions: witnessing crime and being a victim of crime. Our aim is to make clear using multiple angles of evidence, that placing witnesses more centrally into the economics of crime is warranted. This is not least because we illustrate how accounting for witnesses fundamentally reshapes the measurement of the social costs of crime: (i) the unit social costs of crime rise by 25% relative to conventional methods once witnesses are accounted for; (ii) the total social costs of crime rise over time remain flat, despite sustained falls in victimization rates – that can help explain why 90% of individuals do not perceive crime rates to be falling – either nationally or locally. This helps unlock a puzzle that has long been considered across many economies: the wedge between actual and perceived crime.

Our analysis opens up multiple directions for future work.

First, a wider set of experiences should be considered in the economics of crime literature beyond victimization. Our analysis starts to build a bridge towards work in criminology where there has long been a distinction between direct victimization and indirect (*vicarious*) victimization [Tyler 1980, Hale 1996]. As a preliminary step in this direction, we exploit the fact that in some years the CSEW asks about vicarious experiences of crime – through knowing a victim of burglary or assault (in the 12 months preceding the survey). Panel A of Table A6 shows how direct experiences of witnessing or being a victim of these crime types associate with perceptions. Panel B does the same for these two vicarious experiences. We see that: (i) vicarious experiences are associated with perceptions of institutions to the same extent as direct experiences; (ii) for local and personal perceptions, vicarious experiences shift perceptions in the same direction as direct experiences, but the partial correlations are generally smaller than for witnessing the same crime types (which are in turn weaker than for being a victim).

These results highlight that distinguishing the mediating effect of witnessing crime and other indirect experiences can help advance a growing literature on how exposure to crime and violence – say through families, neighbors, coworkers or classmates – propagates across individuals [Monteiro and Rocha 2017, Bindler and Ketel 2019, Ang 2021, Cabral *et al.* 2025]. Moreover, the increased aggregate social costs of crime we document taking into account witnessing effects still underestimate the true social costs if other vicarious experiences – especially hearing about crime through social media – have also increased over time.

Second, by considering perceptions across domains, we broaden out a small literature examining trust in institutions of the criminal justice system. In criminology, such perceptions have long been argued to be important to understand why individuals obey the law – because they believe the system is legitimate rather than fear punishment [Tyler and Huo 2002, Tyler 2006]. In economics, there has been a growing focus on whether direct citizen-police interactions impact trust in law enforcement institutions [Desmond *et al.* 2016, Blattman *et al.* 2021, Ang *et al.* 2025, Facchetti

2024]. Given we find witnessing crime has a stronger association with perceptions of institutions in the justice system than being a victim of crime, we start to open the black box of understanding the far broader issue of how experiences unrelated to interactions with state actors, still translate into views towards the state, and thus potentially a wider set of behaviors including compliance with the law.

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.[26]

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

[26] 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.

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

A.2.1 Experiences of Crime

Witnessing 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.

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.

Victimization For victims, 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% 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 quality 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

Suppose the true model linking crime-related experiences (W_i, V_i) and crime-related perception domain d is given by (5) where $\widetilde{R}_i$ denotes a single latent index capturing unobserved risks of exposure to crime-related experiences. This risk factor is unobserved to the researcher, who estimates (6) where $\varepsilon_{id} = \lambda_d \widetilde{R}_i + u_{id}$. We use this set-up to: (i) derive the omitted-variable bias in the witness and victim coefficients; (ii) study how these biases affect comparisons across domains; (iii) consider the interaction between witnessing and victimization.

As the regression includes only V_i and W_i, excluding $\widetilde{R}_i$ generates omitted-variable bias in $(\tilde{\beta}_{Wd}, \tilde{\beta}_{Vd})$. As the regression model includes an intercept that absorbs unconditional means, the omitted-variable-bias derivation is naturally written after partialling out the constant. The resulting first-order conditions can therefore be expressed in centered-moment form:

$$\lambda_d Cov(W_i, \widetilde{R}_i) = (\tilde{\beta}_{Wd} - \beta_{Wd}) Var(W_i) + (\tilde{\beta}_{Vd} - \beta_{Vd}) Cov(W_i, V_i), \quad (12)$$

$$\lambda_d Cov(V_i, \widetilde{R}_i) = (\tilde{\beta}_{Vd} - \beta_{Vd}) Var(V_i) + (\tilde{\beta}_{Wd} - \beta_{Wd}) Cov(W_i, V_i). \quad (13)$$

Define the biases $b_{Wd} = \tilde{\beta}_{Wd} - \beta_{Wd}$ and $b_{Vd} = \tilde{\beta}_{Vd} - \beta_{Vd}$. Solving (12) and (13) for b_{Wd} and b_{Vd}:

$$b_{Wd} = \tilde{\beta}_{Wd} - \beta_{Wd} = \lambda_d \frac{Var(V_i)Cov(W_i, \widetilde{R}_i) - Cov(W_i, V_i)Cov(V_i, \widetilde{R}_i)}{Var(W_i)Var(V_i) - Cov(W_i, V_i)^2}, \tag{14}$$

$$b_{Vd} = \tilde{\beta}_{Vd} - \beta_{Vd} = \lambda_d \frac{Var(W_i)Cov(V_i, \widetilde{R}_i) - Cov(W_i, V_i)Cov(W_i, \widetilde{R}_i)}{Var(W_i)Var(V_i) - Cov(W_i, V_i)^2}. \tag{15}$$

When $Cov[W_i, V_i] > 0$, it is convenient to parameterize $Cov[\widetilde{R}_i, V_i] = \gamma Cov[\widetilde{R}_i, W_i]$, with $\gamma > 0$.[27] Substituting this into the expressions above yields:

$$\begin{aligned} b_{Wd} &= \lambda_d \frac{Var[V_i]Cov[W_i, \widetilde{R}_i] - Cov[W_i, V_i]\gamma Cov[W_i, \widetilde{R}_i]}{Var[W_i]Var[V_i] - Cov[W_i, V_i]^2} \\ &= \lambda_d Cov[W_i, \widetilde{R}_i] \frac{Var[V_i] - \gamma Cov[W_i, V_i]}{Var[W_i]Var[V_i] - Cov[W_i, V_i]^2} \\ &= \lambda_d \phi_W. \end{aligned} \tag{16}$$

$$\begin{aligned} b_{Vd} &= \lambda_d \frac{Var[W_i]Cov[V_i, \widetilde{R}_i] - Cov[W_i, V_i]Cov[W_i, \widetilde{R}_i]}{Var[W_i]Var[V_i] - Cov[W_i, V_i]^2} \\ &= \lambda_d Cov[W_i, \widetilde{R}_i] \frac{\gamma Var[W_i] - Cov[W_i, V_i]}{Var[W_i]Var[V_i] - Cov[W_i, V_i]^2} \\ &= \lambda_d \phi_V. \end{aligned} \tag{17}$$

The magnitude and direction of the biases (16) and (17) depend on: (i) the covariance between the omitted factor and witnessing, $Cov[\widetilde{R}_i, W_i]$; (ii) the covariance between the omitted latent risk factor and victimization via γ; (iii) the correlation between the two regressors, $Cov[W_i, V_i]$; (iv) the domain-specific loading λ_d. Provided that W_i and V_i are not perfectly collinear, the denominator of the expressions is strictly positive, so the sign of the biases are determined by the numerators.

The key point is ϕ_W and ϕ_V do not vary across perception domains. All domain-specific variation in omitted-variable bias comes through λ_d. Hence an implication of the bias formulae is:

$$\frac{b_{Wd}}{b_{Vd}} = \frac{\phi_W}{\phi_V}, \tag{18}$$

so the relative bias in the witness and victim coefficients does not depend on domain d. At the same time, as the overall scale of the bias still depends on λ_d, the absolute size of the bias may differ across domains.

[27] In the special case where $Cov(W_i, V_i) = 0$, these expressions reduce to the single-regressor OVB formulae, with each bias depending on the covariance between the experience and the latent risk factor, scaled by the variance of that experience.

Zero-effect Null Suppose the true causal effects of witnessing and victimization are zero in every perception domain, so that $\beta_{Wd} = \beta_{Vd} = 0$ for all d. The zero-effect null yields two testable implications.

First, under this hypothesis, the estimated coefficients are then entirely driven by omitted-variable bias, $\widetilde{\beta}_{W_d} = b_{W_d}$ and $\widetilde{\beta}_{V_d} = b_{V_d}$. This implies the observed coefficient ratio must equal the bias ratio in (18). Using (16) and (17), it follows that $r_d \equiv \widetilde{\beta}_{W_d}/\widetilde{\beta}_{V_d} = b_{W_d}/b_{V_d} = [Var(V_i) - \gamma Cov(W_i, V_i)]/[\gamma Var(W_i) - Cov(W_i, V_i)]$. Solving for the value of γ implied by each perception domain gives:

$$\gamma_d = \frac{[Var(V_i) + r_d Cov(W_i, V_i)]}{r_d Var(W_i) + Cov(W_i, V_i)}. \tag{19}$$

Since γ describes the relative covariance of the latent risk factor with victimization and witnessing, it is not domain-specific under the single-factor omitted-variable model. Therefore, under the zero-effect null, a common value of γ should rationalize the estimated coefficient ratios across all perception domains. We compute the implied values of γ_d for each domain in Table A3, using the outcome-specific residualized variance-covariance matrix of W_i and V_i. The implied values range from .42 to 1.04, and we reject equality of multiple pairs of implied γ values across domains.

The second restriction concerns the victim-witness gap. Defining the true and estimated gaps in domain d as $\Delta_d \equiv \beta_{Vd} - \beta_{Wd}$ and $\tilde{\Delta}_d \equiv \tilde{\beta}_{Vd} - \tilde{\beta}_{Wd}$, subtracting (16) from (17) gives $\tilde{\Delta}_d = \Delta_d + \lambda_d(\phi_V - \phi_W)$, so under the zero-effect null, the observed gap is bias alone:

$$\tilde{\Delta}_d = \lambda_d(\phi_V - \phi_W). \tag{20}$$

The term $(\phi_V - \phi_W)$ is a single scalar common to all domains, so the sign of $\tilde{\Delta}_d$ is governed by the sign of λ_d. If the latent factor affects all crime-related perceptions in the same direction, then the sign of $\tilde{\Delta}_d$ cannot switch across domains, unless the latent factor itself affects different perception domains in opposite directions or the single-factor structure is violated.

As documented in Table 4, witnessing has a larger negative association than victimization for domains of perception related to institutions and neighborhoods, while victimization has a larger negative association for more personal domains. Under the single-factor omitted-variable model, this pattern cannot arise if the true causal effects of both experiences are zero, unless the latent factor affects perception domains in opposite directions. That is a less natural form of confounding, because the latent factor captures unobserved exposure to crime-related risk, which should worsen rather than improve crime-related perceptions across domains.

Interactions of Experiences Consider now extending the true and estimated model with an interaction between V_i and W_i, defined as $I_i \equiv V_i W_i$. The true model is:

$$Y_{id} = \alpha_d + \beta_{Wd} W_i + \beta_{Vd} V_i + \beta_{Id} I_i + \lambda_d \widetilde{R}_i + u_{id}, \qquad \mathbb{E}[u_{id} \mid W_i, V_i, I_i, \widetilde{R}_i] = 0, \tag{21}$$

where $\widetilde{R}_i$ again denotes the unobserved risk factor introduced in (6). Suppose instead the researcher estimates:

$$Y_{id} = \tilde{\alpha}_d + \tilde{\beta}_{Wd}W_i + \tilde{\beta}_{Vd}V_i + \tilde{\beta}_{Id}I_i + \varepsilon_{id}, \qquad \varepsilon_{id} = \lambda_d\widetilde{R}_i + u_{id}, \tag{22}$$

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

By the Frisch-Waugh theorem, the coefficient on the interaction in the restricted regression is obtained by regressing the residualized outcome r_{Yid} on the residualized interaction r_{Ii}:

$$\tilde{\beta}_{Id} = \frac{\mathbb{E}[r_{Ii}r_{Yid}]}{\mathbb{E}[r_{Ii}^2]}, \tag{23}$$

Substituting in (21) and using $\mathbb{E}[r_{Ii}u_{id}] = 0$, the bias of the interaction coefficient is:

$$b_{Id} = \tilde{\beta}_{Id} - \beta_{Id} = \lambda_d \frac{\mathbb{E}[r_{Ii}r_{\widetilde{R}_i}]}{\mathbb{E}[r_{Ii}^2]}. \tag{24}$$

The bias in the interaction coefficient depends on whether the latent risk factor predicts *joint* exposure to witnessing and victimization beyond what is already implied by its separate relationships with each experience. More precisely, since $\mathbb{E}[r_{Ii}^2] > 0$, the sign and magnitude of the bias are determined by $\mathbb{E}[r_{Ii}r_{\widetilde{R}i}]$. If $\mathbb{E}[r_{Ii}r_{\widetilde{R}_i}] = 0$, the omitted factor generates no bias in the interaction coefficient, even though it may still bias the estimated main effects of witnessing and victimization.

To determine the direction of bias, recall that all perception outcomes are coded so that higher values correspond to more favorable perceptions. If greater latent crime-related risk worsens perceptions, then the natural case is $\lambda_d < 0$. Suppose first that higher latent risk is disproportionately concentrated among individuals who are both witnesses and victims, so that $\mathbb{E}[rIir_{\widetilde{R}i}] > 0$. Then equation (24) implies $b_{Id} < 0$. Omitted-variable bias would therefore bias the interaction downward, amplifying rather than offsetting the combined adverse association of witnessing and victimization. This natural form of confounding cannot explain the positive interaction documented in Panel C of Figure 3. Rather, it works in the opposite direction.

Conversely, under the null of no true interaction, $\beta_{Id} = 0$, explaining the positive estimated interaction entirely through omitted-variable bias in (24) would require $\mathbb{E}[r_{Ii}r_{\widetilde{R}_i}] < 0$. The covariance would also need to be sufficiently large in absolute value to match the magnitude of the estimated interaction. In other words, after accounting for the separate relationships of latent risk with witnessing and victimization, individuals experiencing both would need to have lower latent risk than predicted. This is the opposite of the more natural concern that latent crime-related risk is especially high among those exposed to both experiences.[28]

A.4 Robustness of Post-victimization Experience Effects

The results on post-victimization experiences are predicated on individuals reporting the crime to the police. The estimated recovery on some perception margins might reflect those with greater latent confidence in the justice system and police to begin with are more likely to report crimes, and so positive post-victimization experiences aid their recovery more 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 A5 shows the results are largely similar across these reporting groups.[29]

We also examine whether the impact of post-victimization experiences differ by gender and type of crime. Figure A6 summarizes results by gender. On no margin of perceptions can we reject impacts statistically differ by gender, but we note that in terms of quality of life, the impacts on women are more negative than on men. Figure A7 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.

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 borne 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 $i \in$

[28] Moreover, as our analysis is restricted to single-victim and single-witness experiences, scenarios involving repeated or overlapping crime-related events, or a high concentration of multiple experiences within particular networks or locations, are less central in our estimation sample. This also makes it less natural for omitted risk to generate a large residual relationship with joint exposure.

[29] 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.

$\mathcal{I}$ 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 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 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:

$$V_i^k = \sum_h \omega_{hk} V_i^h, \tag{25}$$

where V_i^h are the component-specific per-incident unit costs reported by Heeks *et al.* for crime type h. Table A7 summarizes the crime type mapping, showing the frequency weights of each crime type (Column 2), and the resulting average unit cost when we aggregate the unit costs from the disaggregated crime types in Heeks *et al.* (Column 3) to our 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 costs borne by victims, 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:

$$\text{Unit Social Cost}^k = V^k + W^k, \tag{26}$$

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 only borne by victims. For each cost component 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:

$$W^k = \sum_{i \in \mathcal{I}_W} V_i^k. \tag{27}$$

The unit social cost of crime type k becomes:

$$\text{Unit Social Cost}_{(1)}^k = V^k + W^k = V^k + \sum_{i \in \mathcal{I}_W} V_i^k. \tag{28}$$

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 A7. 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 average cost of witnessing crime (£3617) is around 60% 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 $\widehat{B}_v^{k,i}$ 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 (8), with weights given by their respective shares among victims (60% and 40%). $\widehat{B}_w^{k,i}$ 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 (8), 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:

$$m_i^k = \frac{\widehat{B}_w^{k,i}}{\widehat{B}_v^{k,i}}. \tag{29}$$

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 A8. 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:

$$W_i^k = m_i^k V_i^k, \quad \text{for } i \in \mathcal{I}_W, \tag{30}$$

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

$$\text{Unit Social Cost}_{(2)}^k = V^k + W^k = V^k + \sum_{i \in \mathcal{I}_W} m_i^k V_i^k. \tag{31}$$

Columns 7a to 8b of Table A7 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 58% using the lower bound estimate (from £3617 to £1532). The average cost of witnessing crime is around a quarter of the costs to victims. 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

Approach Our findings show that favorable post-victimization outcomes in the justice system can potentially mitigate some of the negative impacts of 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 post-victimization outcomes, namely cases in which an offender is found and charged.

We adopt the same mapping of cost components used in our calculations of the witness-inclusive costs. 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 $\hat{\delta}_3^{k,i} - \hat{\delta}_1^{k,i}$ 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 (10).

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

$$\nu_i^k = \max\left\{0,\ 1 - \frac{\hat{\delta}_3^{k,i} - \hat{\delta}_1^{k,i}}{|\widehat{B}_v^{k,i}|}\right\}, \tag{32}$$

so capturing 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 $\nu_i^k = 0$ to avoid assigning negative costs. If instead the most favorable post-victimization outcome worsens perceptions, ν_i^k can be greater than one. Estimates of the multipliers ν_i^k are reported in Columns 5 to 8 of Table A8.

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 $V_{i,pos}^k = \nu_i^k V_i^k$, for $i \in \mathcal{I}_V$. The victim unit cost becomes:

$$\tilde{V}_i^k = (1-\pi^k)V_i^k + \pi^k V_{i,pos}^k, \text{ for } i \in \mathcal{I}_V, \tag{33}$$

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 given by:

$$\text{Unit Social Cost}_{(3)}^k = \tilde{V}^k = \sum_i \tilde{V}_i^k. \tag{34}$$

Columns 9a to 10b of Table A7 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 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.

Results The results are in Table A9, where for completeness, Columns 1 to 3 show the earlier estimates based on our two approaches. Columns 4 and 5 show 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 Panel D of Figure 3, such experiences: (i) have little impact on improving perceptions of neighborhoods, and while they do offset initial falls in confidence in institutions, these perceptions play no role in the social cost calculation based on the 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 13-15%, 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 6 and 7 of Table A9 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 justice system – or any channel through which the likelihood of victims experiencing favorable post-victimization outcomes increases. 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 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.[30]

A.5.4 Aggregate Social Costs and Their Decomposition

To trace aggregate social costs over time, we combine the fixed unit costs with annual counts of victims and witnesses from the CSEW. In survey year t, let $N^V_{k,t}$ denote the number of single-incident victims of crime type k, and let $N^W_{k,t}$ denote the number of single-incident witnesses experiencing crime type k. Define $N^V_t = \sum_k N^V_{k,t}$ and $N^W_t = \sum_k N^W_{k,t}$, and the corresponding crime-type shares as $s^V_{k,t} = N^V_{k,t}/N^V_t$ and $s^W_{k,t} = N^W_{k,t}/N^W_t$. As V^k is a cost per victimization

[30] The results are 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 in Table A9), the returns to investing in *ex ante* prevention is generally higher for most crime types, but the opposite is true for violent crime.

incident and W^k is a cost per individual witnessing experience, the two components are first aggregated separately and then added:

$$SC_t = SC_t^V + SC_t^W = \sum_k N_{k,t}^V V^k + \sum_k N_{k,t}^W W^k = N_t^V \bar{V}_t + N_t^W \bar{W}_t, \tag{35}$$

where $\bar{V}_t = \sum_k s_{k,t}^V V^k$ and $\bar{W}_t = \sum_k s_{k,t}^W W^k$. The unit costs are held fixed at 2015-16 prices, so $\bar{V}_t$ and $\bar{W}_t$ vary only through changes in the crime-type composition of victimization and witnessing, respectively. The victim and witness components are constructed from separate count series. Victim counts are restricted to individuals with a single victimization incident and are available for every year in the study period. Witness counts are drawn from our main estimation sample and are available only in waves in which the witness module was administered: 2003-04 to 2007-08 and 2011-12 to 2014-15. Within each year, we rescale the CSEW sampling weights to account for observations excluded during sample construction. This ensures that the crime-type distribution reflects the population represented in our analysis and remains consistent with the construction of the witness-cost multipliers.

Between 2003-04 and 2014-15, the number of victimization reports falls by 20.4%, while the victim average unit cost rises by 3.8%. The victim component therefore falls by 17.4%, from approximately £25.2 billion to £20.8 billion. Over the same period, the number of witness reports rises by 9.6%, while the witness average unit cost rises by 23.6%. The witness component therefore rises by 35.5%, from approximately £9.1 billion to £12.3 billion. Combining the two components, witness-inclusive aggregate social costs fall from approximately £34.2 billion to £33.1 billion, a decline of 3.4%. Hence accounting for witnesses offsets almost all the decline in the victim-only social cost series. We plot this witness-only component in Panels A and B of Figure 4 (red series).

To construct the alternative scenario in Panel B of Figure 4, we hold the total number of witness reports fixed at its 2003-04 level, while allowing the crime-type composition of witnessing and the victim component to evolve as observed:

$$SC_t^B = N_t^V \bar{V}_t + N_{2003}^W \bar{W}_t. \tag{36}$$

Under this alternative, the witness component rises by 23.6% because of the changing composition of witnessing, while the full victim-and-witness total falls by 6.5% between 2003-04 and 2014-15.

A.5.5 Social Costs by Age Subgroups

The unit-cost and aggregate calculations can be reproduced for subgroups. We do so for age subgroups (16-25, 26-45, 46+). For each subgroup we recompute the witness-adjusted unit social cost $(V + W)/V$ from our second approach. The victim unit costs V^k are the Heeks *et al.* [2018] values, common to all groups; only the witness component W_g^k varies, through a subgroup-specific multiplier. As the age subgroup regressions (Table A5) report only the main witness and victim experience effects, without the victim×witness interaction, the subgroup multiplier is the simple ratio of the two, $\widehat{\beta}_W/\widehat{\beta}_V$, rather than the overlap-weighted decomposition used for the entire sample.

For subgroup g, the aggregate social cost is computed by separately scaling the victim and witness unit costs by their corresponding subgroup counts:

$$SC_{g,t} = \sum_k N^V_{g,k,t} V^k + \sum_k N^W_{g,k,t} W^k_g. \tag{37}$$

In Panel C of Figure 4, we plot the changes between 2003-04 and 2014-15 in the subgroup-specific costs for victims only, witnesses only, and the two combined. Although the calculations are conducted for all three age groups, for expositional ease Panel C displays only the youngest 16-25 and oldest 46+ groups to highlight the contrast across age groups.

References

[1] ADDA.J, B.MCMONNELL AND I.RASUL (2014) "Crime and the Depenalization of Cannabis Possession: Evidence from a Policing Experiment," *Journal of Political Economy* 122: 1130-202.

[2] ADUKIA.A, B.FEIGENBERG AND F.MOMENI (2025) "From Retributive to Restorative: An Alternative Approach to Justice in Schools," *American Economic Review* 115: 2722-54.

[3] ALTONJI.J.G, T.E.ELDER AND C.R.TABER (2005) "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools," *Journal of Political Economy* 113: 151-84.

[4] ANG.D (2021) "The Effects of Police Violence on Inner-City Students," *Quarterly Journal of Economics* 136: 115-68.

[5] ANG.D, P.BENCSIK, J.BRUHN AND E.DERENONCOURT (2025) "Community Engagement with Law Enforcement After High-profile Acts of Police Violence," *AER: Insights* 7: 124-40.

[6] AUGENBLICK.N, E.LAZARUS AND M.THALER (2025) "Overinference from Weak Signals and Underinference from Strong Signals," *Quarterly Journal of Economics* 140: 335-401.

[7] BARBERIS.N, R.GREENWOOD, L.JIN AND A.SHLEIFER (2015) "X-CAPM: An Extrapolative Capital Asset Pricing Modelm" *Journal of Financial Economics* 115: 1-24.

[8] BENJAMIN.D (2019) "Errors in Probabilistic Reasoning and Judgment Biases", in B.D.Bernheim, S.DellaVigna and D.Laibson (eds.) *Handbook of Behavioral Economics: Applications and Foundations* Vol. 1, North-Holland: Elsevier.

[9] BESLEY.T.J AND H.MUELLER (2012) "Estimating the Peace Dividend: The Impact of Violence on House Prices in Northern Ireland," *American Economic Review* 102: 810-33.

[10] BINDLER.A, R.HJALMARSSON, N.KETEL AND A.MITRUT (2024) "Discontinuities in the Age-victimisation Profile and the Determinants of Victimisation," *Economic Journal* 134: 95-134.

[11] BINDLER.A AND N.KETEL (2022) "Scaring or Scarring? Labor Market Effects of Criminal Victimization," *Journal of Labor Economics* 40: 939-70.

[12] BLATTMAN.C, D.P.GREEN, D.ORTEGA AND S.TOBON (2021) "Place-based Interventions at Scale: The Direct and Spillover Effects of Policing and City Services on Crime," *Journal of the European Economic Association* 19: 2022-51.

[13] BORDALO.P, N.GENNAIOLI AND A.SHLEIFER (2020) "Memory, Attention, and Choice," *Quarterly Journal of Economics* 135: 1399-442.

[14] BORDALO.P, J.J.CONLON, N.GENNAIOLI, S.Y.KWON AND A.SHLEIFER (2023) "Memory and Probability," *Quarterly Journal of Economics* 138: 265-311.

[15] BORDALO.P, G.BURRO, K.KOFFMAN, N.GENNAIOLI AND A.SHLEIFER (2025) "Imagining the Future: Memory, Simulation, and Beliefs," *Review of Economic Studies* 92: 1532-63.

[16] CABRAL.M, B.KIM, M.ROSSIN-SLATER, M.SCHNELL AND H.SCHWANDT (2025) "Trauma at School: The Impacts of Shootings on Students' Human Capital and Economic Outcomes," forthcoming, *Review of Economic Studies*.

[17] CAMPEDELLI.G.M, G.DANIELE, A.F.M.MARTINANGELI AND P.PINOTTI (2023) "Organized Crime, Violence and Support for the State," *Journal of Public Economics* 228, 105029.

[18] CARD.D AND G.B.DAHL (2011) "Family Violence and Football: The Effect of Unexpected Emotional Cues on Violent Behavior," *Quarterly Journal of Economics* 126: 103-43.

[19] CHALFIN.A, B.HANSEN AND R.RYLEY (2023) "The Minimum Legal Drinking Age and Victimization," *Journal of Human Resources* 58: 1141-77.

[20] COHEN.M.A (2005) *The Costs of Crime and Justice*, Routledge, New York.

[21] COHEN.M.A (2008) "The Effect of Crime on Life Satisfaction," *Journal of Legal Studies* 37: S325-53.

[22] CORNAGLIA.F, N.E.FELDMAN AND A.LEIGH (2014) "Crime and Mental Well-being," *Journal of Human Resources* 49: 110-40.

[23] DESMOND.M, A.V.PAPACHRISTOS AND D.S.KIRK (2016) "Police Violence and Citizen Crime Reporting in the Black Community," *American Sociological Review* 81: 857-76.

[24] DOLAN.P, G.LOOMES, T.PEASGOOD AND A.TSUCHIYA (2005) "Estimating the Intangible Victim Costs of Violent Crime," *British Journal of Criminology* 45: 958-76.

[25] DUFFY.B, R.WAKE, T.BURROWS AND P.BREMNER (2008) "Closing the Gaps – Crime and Public Perceptions," *International Review of Law, Computers & Technology* 22: 17-44.

[26] DUSTMANN.C AND F.FASANI (2016) "The Effect of Local Area Crime on Mental Health," *Economic Journal* 126: 978-1017.

[27] DUSTMANN.C AND M.MERTZ (2024) Victims of Crime, mimeo, UCL.

[28] ESBERG.J AND J.MUMMOLO (2018) Explaining Misperceptions of Crime, mimeo, Princeton.

[29] FACCHETTI.E (2024) Police Infrastructure, Police Performance, and Crime: Evidence from Austerity Cuts, mimeo, Tor Vergata.

[30] FREEMAN.R.B (1999) "The Economics of Crime," in O.Ashenfelter and D.Card (eds.) *Handbook of Labor Economics* Vol. 3, Elsevier.

[31] FUSTER.A, D.LAIBSON AND B.MENDEL (2010) "Natural Expectations and Macroeconomic Fluctuations," *Journal of Economic Perspectives* 24: 67-84.

[32] GARLAND.D (2001) *The Culture of Control: Crime and Social Order in Contemporary Society*, University of Chicago Press.

[33] GIULIANO.P AND A.SPILIMBERGO (2025) "Aggregate Shocks and the Formation of Preferences and Beliefs," *Journal of Economic Literature* 63: 542-97.

[34] HALE.C (1996) "Fear of Crime: A Review of the Literature," *International Review of Victimology* 4: 79-150.

[35] HEEKS.M, S.REED, M.TAFSIRI AND S.PRINCE (2018) *The Economic and Social Costs of Crime* (2nd ed.) Home Office Research Report.

[36] HJALMARSSON.R, S.MACHIN AND P.PINOTTI (2024) "Crime and the Labor Market," in C.Dustmann and T.Lemieux (eds.) *Handbook of Labor Economics* Vol. 5, North Holland.

[37] JANSSON.K (2008) *British Crime Survey: Measuring Crime for 25 Years*, Home Office: London.

[38] JOHNSTON.D.W, M.A.SHIELDS AND A.SUZIEDELYTE (2017) "Victimisation, Well-being and Compensation: Using Panel Data to Estimate the Costs of Violent Crime," *Economic Journal* 128: 1545-69.

[39] KETEL.N, A.BINDLER, A.MITRUT AND R.HJALMARSSON (2020) "Costs of Victimization," in K.F.Zimmermann (ed.) *Handbook of Labor, Human Resources and Population Economics*, Springer.

[40] KOZLOWSKI.J, L.VELDKAMP AND V.VENKATESWARAN (2020) "The Tail that Wags the Economy: Beliefs and Persistent Stagnation," *Journal of Political Economy* 128: 2839-79.

[41] KROSNICK.J.A AND D.F.ALWIN (1989) "Aging and Susceptibility to Attitude Change," *Journal of Personality and Social Psychology* 57: 416-25.

[42] LINDEN.L AND J.E.ROCKOFF (2008) "Estimates of the Impact of Crime Risk on Property Values from Megan's Laws," *American Economic Review* 98: 1103-27.

[43] LUDWIG.J AND P.J.COOK (2001) "The Benefits of Reducing Gun Violence: Evidence from Contingent-valuation Survey Data," *Journal of Risk and Uncertainty* 22: 207-26.

[44] MALMENDIER.U (2021) "Exposure, Experience, and Expertise: Why Personal Histories Matter in Economics," *Journal of the European Economic Association* 19: 2857-94.

[45] MALMENDIER.U AND L.S.SHEN (2024) "Scarred Consumption," *AEJ: Macroeconomics* 16: 322-55.

[46] MALMENDIER.U AND J.A.WACHTER (2024) "Memory of Past Experiences and Economic Decisions," in *Oxford Handbook of Human Memory*, *Two Volume Pack: Foundations and Applications*, OUP.

[47] M.A.MASTEN AND A.POIRIER (2026) "The Effect of Omitted Variables on the Sign of Regression Coefficients," *American Economic Review*, forthcoming.

[48] MASTROROCCO.N AND L.MINALE (2018) "News Media and Crime Perceptions: Evidence from a Natural Experiment," *Journal of Public Economics* 165: 230-55.

[49] MONTEIRO.J AND R.ROCHA (2017) "Drug Battles and School Achievement: Evidence from Rio de Janeiro's Favelas," *Review of Economics and Statistics* 99: 213-28.

[50] NISBETT.R.E AND L.D.ROSS (1980) *Human Inference: Strategies and Shortcomings of Social Judgment*, Englewood Cliffs, NJ: Prentice Hall.

[51] OSTER.E (2019) "Unobservable Selection and Coefficient Stability: Theory and Validation," *Journal of Business Economics and Statistics* 37: 187-204.

[52] PEW RESEARCH (2024) What the Data says About Crime in the US [https://www.pewresearch.org/short-reads/2024/04/24/what-the-data-says-about-crime-in-the-us/]

[53] PINKER.S (2012) *The Better Angels of Our Nature: Why Violence Has Declined*, London: Penguin.

[54] POPE.D.G AND J.C.POPE (2012) "Crime and Property Values: Evidence from the 1990s Crime Drop," *Regional Science and Urban Economics* 42: 177-88.

[55] POPE.J.C (2008) "Fear of Crime and Housing Prices: Household Reactions to Sex Offender Registries," *Journal of Urban Economics* 64: 601-14.

[56] ROSEN.S (1974) "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition", *Journal of Political Economy* 82: 34-55.

[57] SHEM-TOV.Y, S.RAPHAEL AND A.SKOG (2024) "Can Restorative Justice Conferencing Reduce Recidivism? Evidence From the Make-it-Right Program," *Econometrica* 92: 61-78.

[58] THALER.M (2024) "The Fake News Effect: Experimentally Identifying Motivated Reasoning Using Trust in News," *AEJ: Microeconomics* 16: 1-38.

[59] TYLER.T.R (1980) "Impact of Directly and Indirectly Experienced Events: The Origin of Crime-related Judgments and Behaviors," *Journal of Personality and Social Psychology* 39: 13-28.

[60] TYLER.T.R (2006) *Why People Obey the Law*, Princeton University Press.

[61] TYLER.T.R AND Y.J.HUO (2002) *Trust in the Law: Encouraging Public Cooperation with the Police and Courts*, Russell Sage Foundation.

[62] ZAWITZ.M ET AL. (1993) Highlights From 20 Years of Surveying Crime Victims: The National Crime Victimization Survey, 1973-92, NCJ-144525 Bureau of Justice Statistics, US Department of Justice, Washington, DC.

Table 1: Sources Used to Form Crime-related Perceptions

Means

	(1) Criminal justice system	(2) Police	(3) National crime rate	(4) Local crime rate
Number of respondents	37,227	16,783	38,125	34,596
Experiences				
Personal	.170	.191	.175	.378
Indirect	.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 to the questions "(...) which sources would you say [were the most influential/provided you with the most information] about the Criminal Justice System?" for survey waves 2003-04 to 2007-08. Column 2 consists of responses to the question "Thinking about the police in the country as a whole, which (...) sources provide you personally with the most information?" for survey waves 2004-05 to 2007-08. Columns 3 and 4 consist of responses to the questions "(...) which of these sources would you say have given you the impression that crime has [answer to previous Question] in [the country as a whole/your local area] over the past [two/few] years?" for survey waves 2011-12 to 2014-15. For all questions respondents were asked to code all answers that apply from a list, so the response categories are not mutually exclusive. Indirect experiences combines answer categories "Relatives' and/or friends' experiences" and "Word of mouth/information from other people". 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

	(1) Non-victims Non-witness	(2) Non-victims Witness	(3) Victims Non-witness	(4) Victims Witness	Victim-Witness Gap (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	-.026**
Confidence in the police	.069	-.071	-.057	-.194	-.014
Neighborhood problems	.129	-.369	-.241	-.617	-.127***
Feel safe walking alone after dark	.032	.043	-.045	-.053	.087***
Worried about being victimized	.015	-.102	-.196	-.254	.094***
Quality of life affected by crime	.088	-.110	-.312	-.404	.202***

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 differences, 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 Rates, by (

Sample: 2003-2007, 2011-2014

Means

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

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 witnessing and victimization rates by year (where witness rates exclude witnessing antisocial behavior). Panel B decomposes witnessing and victimization rates 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
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)
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
Observations (both panels)	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, 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: Perceptions and Crime-related Experiences, Robustness

Sample: 2011-2014 and 2017

OLS regression estimates, robust standard errors

			Selection on Unobservables				Matching		Neighborhoods		
		(1) Baseline	(2a) Oster β at δ=1	(2b) Oster |δ| at β=0	(2c) MP |δ| for β>0	(2d) MP |δ| for β>0	(3a) Witness	(3b) Victim	(4a) LA FE	(4b) LSOA FE	(4c) LSOA Crime Rate
					Max OVB = 2β	Max OVB = 10β					
Confidence in the criminal justice system	**Witness**	-.179***	-.190	21	21	2.66	-.177***		-.179***	-.190***	-.180***
		(.012)					(.012)		(.012)	(.015)	(.012)
	Victim	-.091***	-.093	54.9	54.9	36.9		-.090***	-.089***	-.072***	-.090***
		(.016)						(.016)	(.016)	(.021)	(.016)
Confidence in the police	**Witness**	-.184***	-.188	367	21.8	1.57	-.180***		-.183***	-.171***	-.185***
		(.008)					(.008)		(.008)	(.009)	(.008)
	Victim	-.143***	-.141	35.7	34.5	5.58		-.144***	-.142***	-.138***	-.145***
		(.011)						(.011)	(.011)	(.012)	(.011)
Problems in neighborhood	**Witness**	-.506***	-.469	5.88	4.39	1.45	-.492***		-.504***	-.458***	-.487***
		(.015)					(.015)		(.015)	(.019)	(.015)
	Victim	-.252***	-.210	5.3	5.3	4.47		-.254***	-.252***	-.222***	-.244***
		(.020)						(.020)	(.019)	(.025)	(.020)
Feel safe walk in dark	**Witness**	-.158***	-.190	4.97	4.97	4.97	-.154***		-.154***	-.124***	-.146***
		(.010)					(.010)		(.010)	(.012)	(.010)
	Victim	-.133***	-.145	12.4	12.4	12.4		-.134***	-.125***	-.103***	-.119***
		(.013)						(.013)	(.013)	(.016)	(.014)
Worried to become victim	**Witness**	-.133***	-.138	49.9	49.9	7.23	-.130***		-.134***	-.140***	-.130***
		(.016)					(.016)		(.016)	(.027)	(.016)
	Victim	-.156***	-.151	22.1	22.1	12.6		-.154***	-.149***	-.160***	-.148***
		(.022)						(.022)	(.022)	(.038)	(.022)
Crime on quality of life	**Witness**	-.214***	-.209	15.8	11.9	2.04	-.211***		-.220***	-.269***	-.219***
		(.021)					(.022)		(.021)	(.044)	(.021)
	Victim	-.392***	-.380	14.8	10.8	2.11		-.396***	-.390***	-.351***	-.386***
		(.033)						(.033)	(.033)	(.064)	(.033)
Individual characteristics		Yes	Yes				Yes	Yes	Yes	Yes	Yes
Interview month and year fixed effects		Yes	Yes				Yes	Yes	Yes	Yes	Yes
Police force area fixed effects		Yes	Yes				Yes	Yes			
Local authority fixed effects									Yes		Yes
LSOA fixed effects										Yes	
LSOA crime rate control											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 2a reports selection on unobservables bounds for proportionality parameter 0 and 1, Column 2b reports the proportionality parameter needed for the estimated effect to equal zero following Oster [2019], and 2c and 2d report the proportionality parameter needed for the effect to switch sign assuming bounds on OVB ranging from 2 to 10 following Masten and Poirier [2026]. Columns 3a and 3b report the estimated witness and victim effects respectively from entropy balancing, using the same set of covariates and FE's. For the witness effect victimization status is included in the balancing set of covariates and vice versa. Column 4a replaces police force area fixed effects (42 levels) with local authority district (LAD) fixed effects (347 levels). Column 4b shows estimates from the regression with all individual characteristics and month of interview fixed effects, but uses LSOA fixed effects instead of police force area fixed effects or local authority district fixed effects. Column 4c retains the LAD FE and adds a control for the crime rate of the respondent's Lower-layer Super Output Area (LSOA), taken from officially recorded data on crime from the police.

Table 6: 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	-.159***	-.141***	-.432***	-.128***	-.139***	-.208***
	(.007)	(.006)	(.007)	(.006)	(.007)	(.016)
Victim	-.121***	-.114***	-.291***	-.144***	-.191***	-.393***
	(.010)	(.010)	(.011)	(.009)	(.011)	(.027)
Witness x victim [dissimilar experience]	.036**	-.014	.033*	.036**	.065***	.075
	(.017)	(.016)	(.019)	(.015)	(.017)	(.046)
Witness x victim [similar experience]	.135***	.074**	.313***	.060**	.033	.189**
	(.030)	(.030)	(.034)	(.027)	(.031)	(.086)
Total Effect = Witness + Victim + Interaction						
Dissimilar experiences	-.244***	-.269***	-.690***	-.236***	-.265***	-.527***
	(.013)	(.013)	(.015)	(.012)	(.013)	(.036)
Similar experiences	-.145***	-.181***	-.410***	-.212***	-.296***	-.413***
	(.028)	(.028)	(.032)	(.026)	(.029)	(.081)
Witness = Victim [p-value]	[.001]	[.008]	[.000]	[.095]	[.000]	[.000]
Total effect dissimilar = similar [p-value]	[.001]	[.003]	[.000]	[.391]	[.322]	[.196]
Year, month of interview and police force area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.060	.037	.156	.234	.110	.061
Observations	181,868	236,473	170,443	200,790	169,876	32,923

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 7: Unit Social Costs of Crime

Crime type	Approach 1 Witnesses (1)	Approach 2 Witness-adjusted costs (2) Lower bound	 (3) Upper bound
Average unit cost	1.59	1.25	1.26
Violent crime	1.69	1.28	1.28
Burglary	1.33	1.15	1.18
Theft	1.29	1.14	1.19
Criminal damage	1.26	1.27	1.29

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 Column 1, witnesses are assigned the same unit cost as victims for selected cost components from Heeks et al. [2018]. In Columns 2 and 3, we use perception-based multipliers to scale victim costs into witness costs. The lower- and upper-bound estimates are based on alternative sets of multipliers.

Table 8: Perceptions of Recent Changes in Crime Rates

Sample: 2003-2007 and 2011-2014

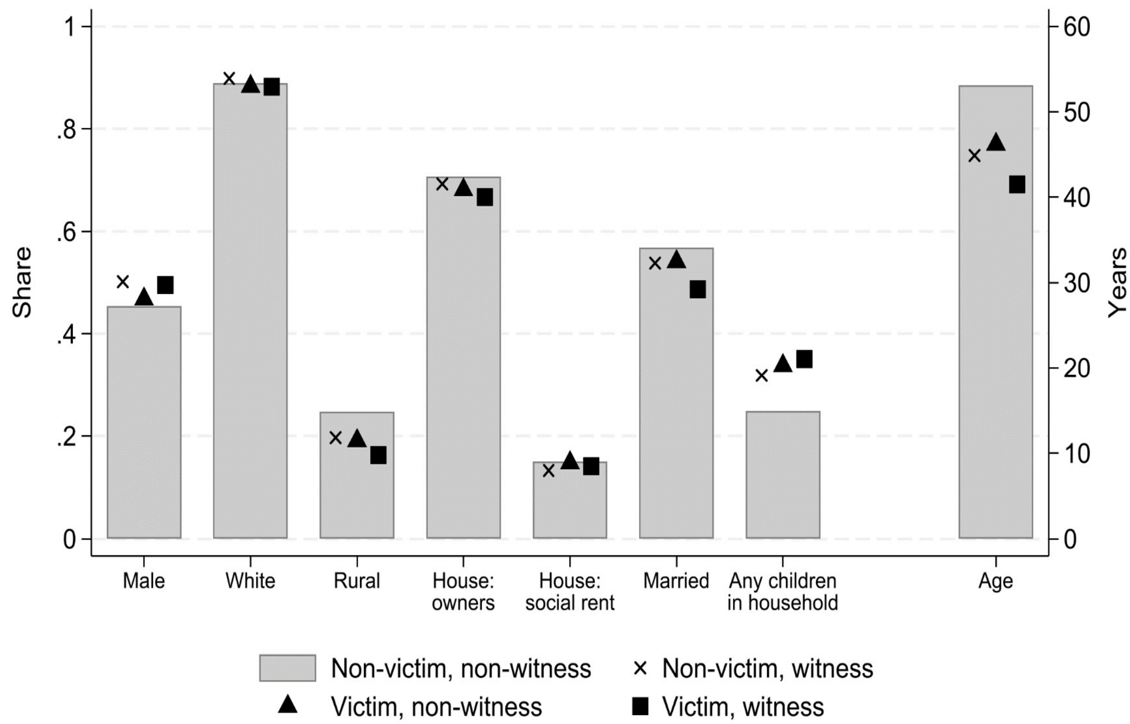
OLS regression estimates, robust standard errors

	(1) National crime rate has increased	(2) Local area crime rate has increased
Panel A: baseline		
Witness	.043***	.088***
	(.004)	(.003)
Victim	.033***	.094***
	(.005)	(.004)
Panel B: by crime type		
Witness=criminal damage	.040***	.092***
	(.015)	(.011)
Witness=theft	.044***	.075***
	(.009)	(.007)
Witness=burglary	.010	.157***
	(.023)	(.019)
Witness=violent	.044***	.058***
	(.007)	(.005)
Witness=ASB	.044***	.102***
	(.005)	(.004)
Victim=criminal damage	.035***	.100***
	(.009)	(.007)
Victim=theft	.029***	.079***
	(.007)	(.006)
Victim= burglary	.043***	.152***
	(.012)	(.011)
Victim=violent	.035**	.079***
	(.015)	(.012)
P-values:		
A: Witness = Victim	[.096]	[.207]
B: Witness crime types equal	[.676]	[.000]
B: Victim crime types equal	[.754]	[.000]
Year, month of interview and police force area fixed effects	Yes	Yes
Observations (both panels)	107,467	185,826

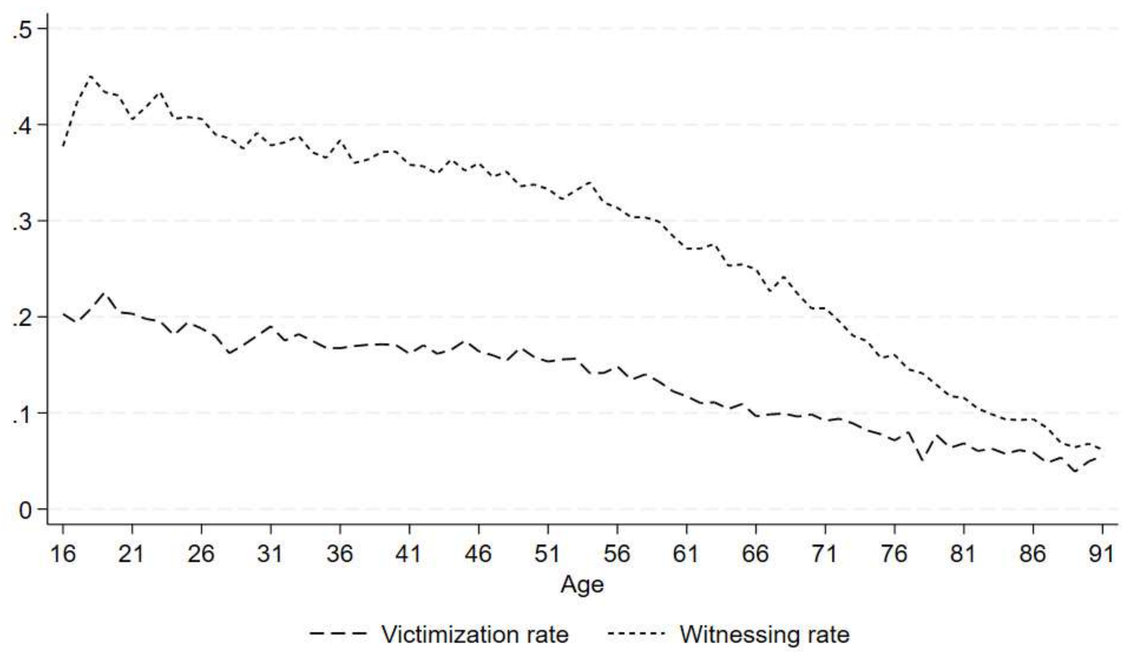
Notes: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. The sample consists of individual responses from pooling the 2003-04 to 2007-08, 2011-12 to 2014-15 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social 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 that the crime rate increased in the past two or few years (with there being slight variation in the wording of the survey question). 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

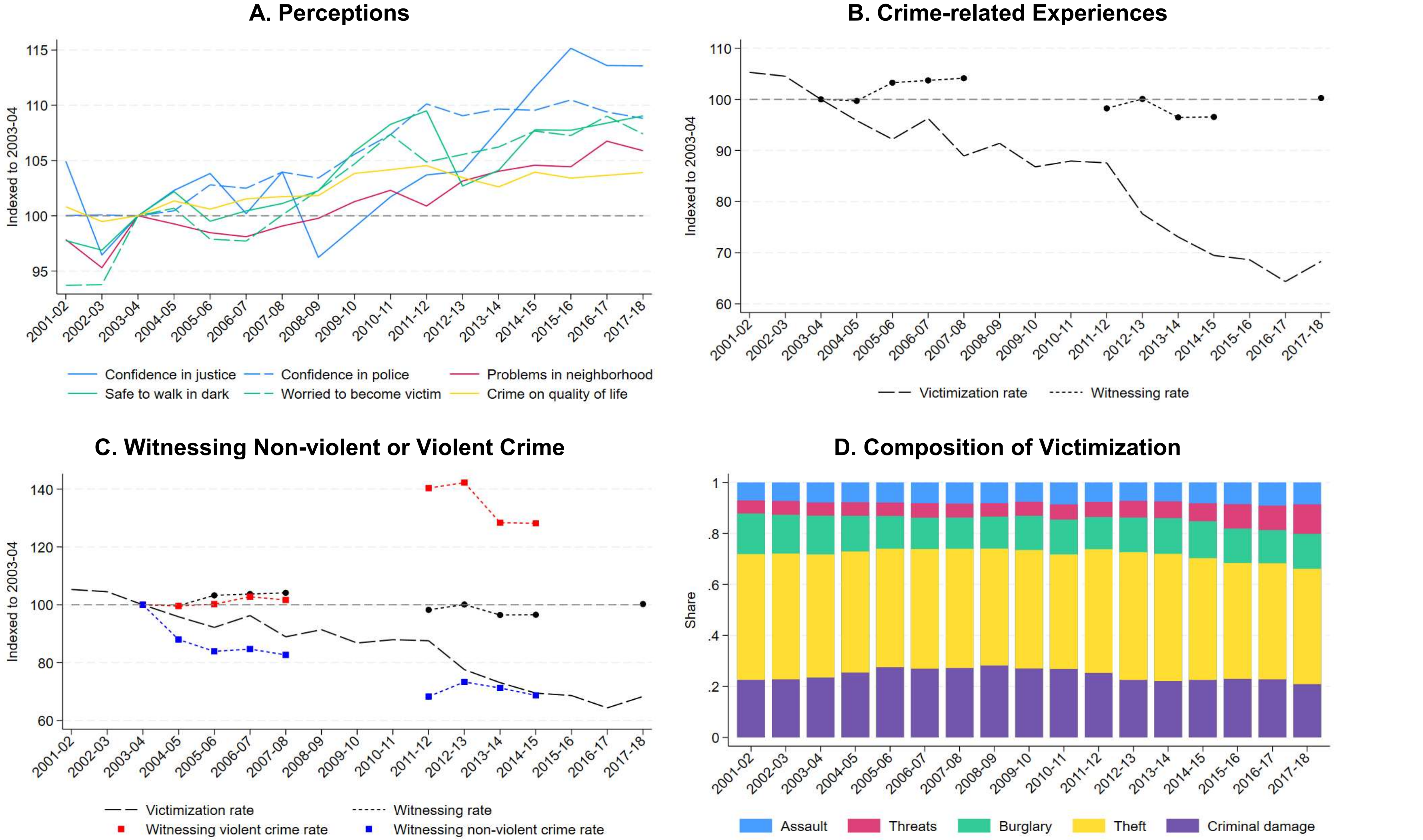


B. Victimization and Witnessing Age Profiles



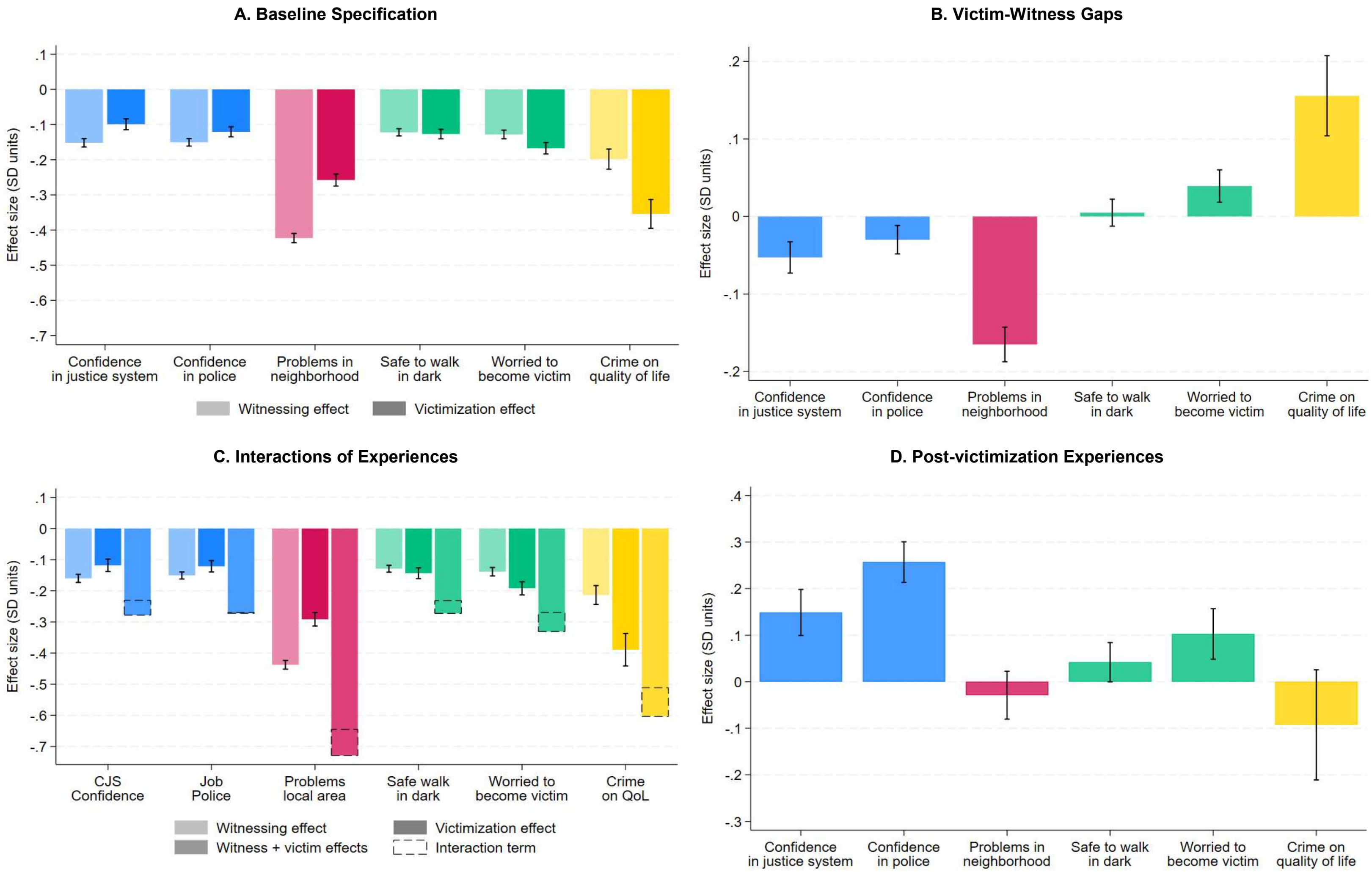
Notes: The sample consists of individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW survey waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. Observations are weighted by individual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

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



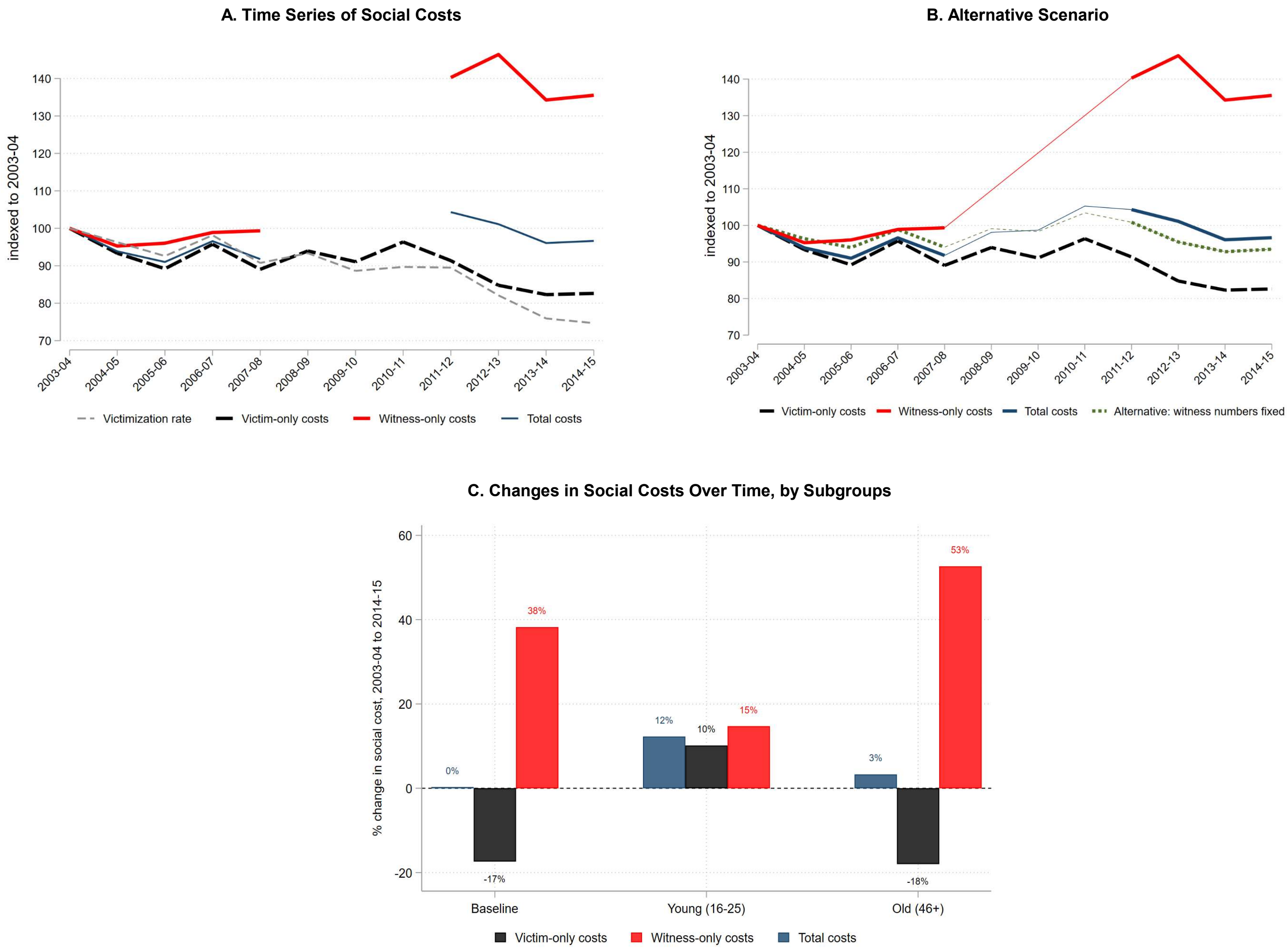
Notes: The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW survey waves, excluding individuals with multiple victimizations. Data on witnessing is available in 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18, but not by crime type in 2017-18. Observations are 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



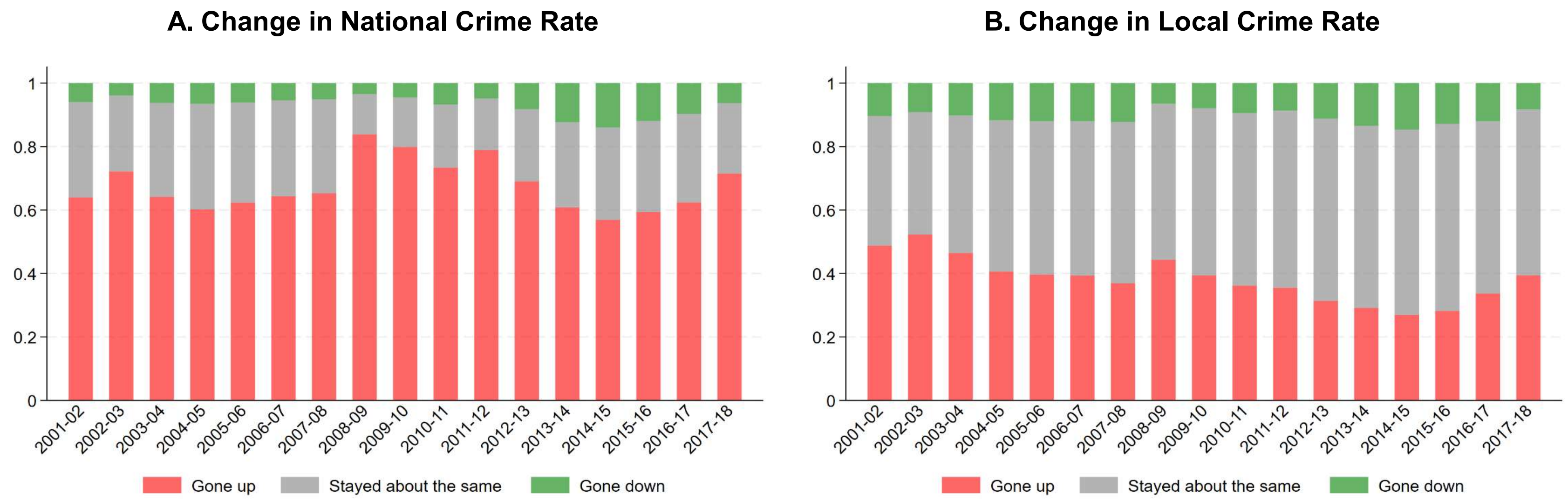
Notes: In Panel A we show estimates of witnessing effects (lighter bars) and victimization effects (darker bars) across six perception outcomes, and panel B shows the difference between the two effects. On Panel C, we also show their combined effect and highlights in the dashed box the size of their interacted effect. For panels A-C 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. Panel D reports effects of having 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, but the offender not found. The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW waves, excluding individuals with multiple victimizations. 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. 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. Panel D in addition controls 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 4: Aggregate Social Costs of Crime



Notes: The figure shows trends in victimization rates and aggregate social costs of crime between 2003–04 and 2014–15, with series normalized to 100 in 2003–04. Panel A compares trends in the victimization rate (in gray), victim-only costs (in black), witness-only costs (in red), and total costs (in blue) . The victimization rate uses the rate of single-incident victims who are also single-incident witnesses; for the three years in which the witness rate is unavailable, it is imputed by applying the year-on-year percentage change in the broader single-incident victimization rate. Victim-only social costs are calculated following Heeks et al. [2018], while witness-only social costs include the costs borne by witnesses alone. Total social costs incorporate both components. Annual unit social costs are constructed using item-level cost components from Heeks et al. [2018], aggregated into four crime categories and weighted by annual crime-type shares derived from the CSEW. Witness counts are drawn from our main estimation sample for the waves in which the witness module was administered. Panel B reproduces thevictim-only, witness-only and total costs series and adds a counterfactual that holds witness numbers fixed at their 2003–04 level (in green). Witness counts for 2008–09 to 2010–11, when the witnessing module was not administered, are linearly interpolated. Panel C reports the percentage change from 2003–04 to 2014–15 in victim-only costs, witness-only costs, the total social costs, and a counterfactual holding subgroup-specific witness numbers fixed at their 2003–04 levels. The age comparison reports respondents aged 16–25 and 46+.

Figure 5: Perceptions of Changes in National and Local Crime Rates



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 responses to two similar questions on national crime rate changes: "I would like to ask whether you think that the level of crime in the country as a whole has changed over the past two years. would you say there is more crime, less crime or the same amount?" and "What do you think has happened to crime in the country as a whole over the past few years?". Panel B combines responses to two similar questions on local crime rates: "How much would you say the crime rate here has changed since two years ago? In this area, would you say there is more crime or less crime?" and "What do you think has happened to crime in your local area over the past few years?". All four questions were asked on a 5-level Likert scale. 'Gone up' combines responses "Gone up a lot" and "Gone up a little", and 'Gone down' combines responses "Gone down a lot" and "Gone down a little".

Table A1: Perceptions and Crime-related Experiences

Sample: 2003-2007, 2011-2014 and 2017

OLS regression estimates, t-statistics in parantheses, p-values in brackets

	(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***
robust	(-25.0)	(-27.9)	(-63.6)	(-23.6)	(-20.3)	(-13.6)
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
clustering by police force area	(-31.6)	(-27.1)	(-28.9)	(-20.9)	(-13.7)	(-16.1)
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
no controls	-.096***	-.139***	-.477***	0.008	-.106***	-.180***
	(-15.8)	(-26.6)	(-71.4)	-1.37	(-16.5)	(-12.6)
no weights	-.156***	-.153***	-.439***	-.132***	-.141***	-.214***
	(-30.8)	(-33.7)	(-82.6)	(-30.3)	(-27.8)	(-17.3)
spatial correlation across police force areas	-.181***	-.182***	-.485***	-.147***	-.134***	-.214***
	(-15.7)	(-22.4)	(-33.6)	(-15.3)	(-8.63)	(-11)
Romano-Wolf adjustment for MHT	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Victim	-.099***	-.121***	-.258***	-.127***	-.167***	-.354***
robust	(-12.5)	(-16.4)	(-29.4)	(-18.3)	(-20.4)	(-16.9)
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
clustering by police force area	(-12.8)	(-9.38)	(-27.3)	(-12.9)	(-12.8)	(-12.3)
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
no controls	-.061***	-.125***	-.321***	-.084***	-.187***	-.360***
	(-7.48)	(-17.2)	(-35.4)	(-11)	(-21.6)	(-17)
no weights	-.101***	-.110***	-.267***	-.122***	-.175***	-.369***
	(-15.3)	(-18)	(-38.2)	(-21.1)	(-26.3)	(-20.7)
spatial correlation across police force areas	-.088***	-.143***	-.241***	-.126***	-.154***	-.379***
	[-5.94]	[-11.4]	[-13]	[-10.8]	[-7.33]	[-11.3]
Romano-Wolf adjustment for MHT	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
P-values witness = victim:						
baseline	[.000]	[.001]	[.000]	[.576]	[.000]	[.000]
clustering by police force area	[.000]	[.011]	[.000]	[.585]	[.006]	[.000]
no controls	[.001]	[.125]	[.000]	[.000]	[.000]	[.000]
no weights	[.000]	[.000]	[.000]	[.181]	[.000]	[.000]
spatial correlation	[.000]	[.010]	[.000]	[.164]	[.451]	[.000]

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. Spatially correlated (Conley) standarr errors allow for correlation across police force areas. These specifications use only the 2011-12 to 2014-15 and 2017-18 CSEW survey waves. 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 t-statistics in parentheses. p-values adjusted for Romano-Wolf multiple hypothesis testing are also reported. Unless stated otherwise, 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. Unless stated otherwise, observations are weighted by individual probability weights provided by the CSEW, adjusted for the number of observations per wave.

Table A2: 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 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. 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 A3: Implied Gamma Under Zero-true Experience Effect Scenarios

OLS estimates and residualized variance-covariance terms

	(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
β_W witness	-.152	-.150	-.423	-.122	-.128	-.198
β_V victim	-.099	-.121	-.258	-.127	-.167	-.354
r = β_W / β_V	**1.54**	**1.24**	**1.64**	**.961**	**.766**	**.559**
Var(V)	.124	.120	.124	.124	.124	.120
Var(W)	.202	.201	.201	.202	.201	.200
Cov(W,V)	.011	.011	.011	.011	.011	.009
Implied gamma	**.439**	**.512**	**.419**	**.655**	**.803**	**1.04**
	(.034)	(.030)	(.014)	(.040)	(.048)	(.092)

Notes: We report the implied value of gamma required to rationalize the observed witness-to-victim coefficient ratios a zero effect null hypothesis. The implied value of gamma is defined in (19). Variance and covariance terms are computed from the residualized witness and victim indicators using the outcome-specific estimation sample, after partialling out the controls and fixed effects in the baseline specification. A common single latent omitted factor implies that gamma should not vary across perception domains. Standard errors in parentheses are computed with delta method.

Table A4: 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 A5: 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+						
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.

Table A6: Crime-related Perceptions and Vicarious Experiences

Sample: 2003-2007

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 = burglary	-.094**	-.087**	-.338***	-.159***	-.252***	-.308***
	(.038)	(.037)	(.042)	(.032)	(.040)	(.108)
Victim = burglary	-.122***	-.087***	-.219***	-.190***	-.259***	-.626***
	(.021)	(.020)	(.023)	(.019)	(.022)	(.063)
Witness = violent	-.110***	-.105***	-.260***	-.057***	-.122***	-.172***
	(.011)	(.010)	(.013)	(.009)	(.012)	(.026)
Victim = violent	-.081***	-.126***	-.215***	-.182***	-.239***	-.386***
	(.025)	(.023)	(.028)	(.022)	(.025)	(.062)
B: Vicarious Experiences						
Know anyone burgled past 12 months	-.112***	-.093***	-.140***	-.094***	-.159***	-.187***
	(.024)	(.024)	(.023)	(.020)	(.020)	(.032)
Know anyone assaulted past 12 months	-.128***	-.081***	-.144***	-.070***	-.082***	-.144***
	(.028)	(.029)	(.026)	(.024)	(.025)	(.040)
P-values:						
Witness = Vicar burglary	[.685]	[.876]	[.000]	[.083]	[.035]	[.279]
Victim = Vicar burglary	[.761]	[.847]	[.015]	[.001]	[.001]	[.000]
Witness = Vicar assault	[.547]	[.437]	[.000]	[.606]	[.141]	[.553]
Victim = Vicar assault	[.202]	[.229]	[.065]	[.000]	[.000]	[.001]
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 CSEW waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/antisocial behavior types. Observations are weighted by individual probability weights provided by the BSC/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 table shows estimates of the effect of witnessing, victimization, and personally knowing a victim across six perceptions. Panel A shows the baseline specification by crime type on the main regression sample which covers 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18. Panel B additionally includes indicators for a respondent personally knowing someone who became a victim to burglary or public assault in the past 12 months and covers 2003-04, 2004-05, 2006-07 and 2007-08. All columns report OLS estimates with robust standard errors in parentheses. Each specification 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.

Table A7: Mapping Crime Types from Heeks et al. [2018] and Cost Calculations

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	Approach 1: Accounting for witnesses (5) Witness	Approach 1: Accounting for witnesses (6) Total	Approach 2: Witness-adjusted costs – Witness (7a) Lower bound	Approach 2: Witness-adjusted costs – Witness (7b) Upper bound	Approach 2: Witness-adjusted costs – Total (8a) Lower bound	Approach 2: Witness-adjusted costs – Total (8b) Upper bound	Post-victimization adjustment – Victims with post-victimization outcomes (9a) Lower bound	Post-victimization adjustment – Victims with post-victimization outcomes (9b) Upper bound	Post-victimization adjustment – All victims (10a) Lower bound	Post-victimization adjustment – All victims (10b) Upper bound
Average unit cost				6,081	3,617	9,699	1,532	1,595	7,613	7,677	7,730	7,947	6,303	6,326
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	1,672
	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	1,286	1,480	1,480
	Criminal damage – other	0.98	1,330											

Notes: This table 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 A8: Multipliers

Cost component from Heeks et al. [2018]	Perception outcome	Approach 2: Witness-adjusted costs (1) Violent crime	(2) Burglary	(3) Theft	(4) Criminal damage	Post-victimization adjustment (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 5 in the main text 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 5 in the main text 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.

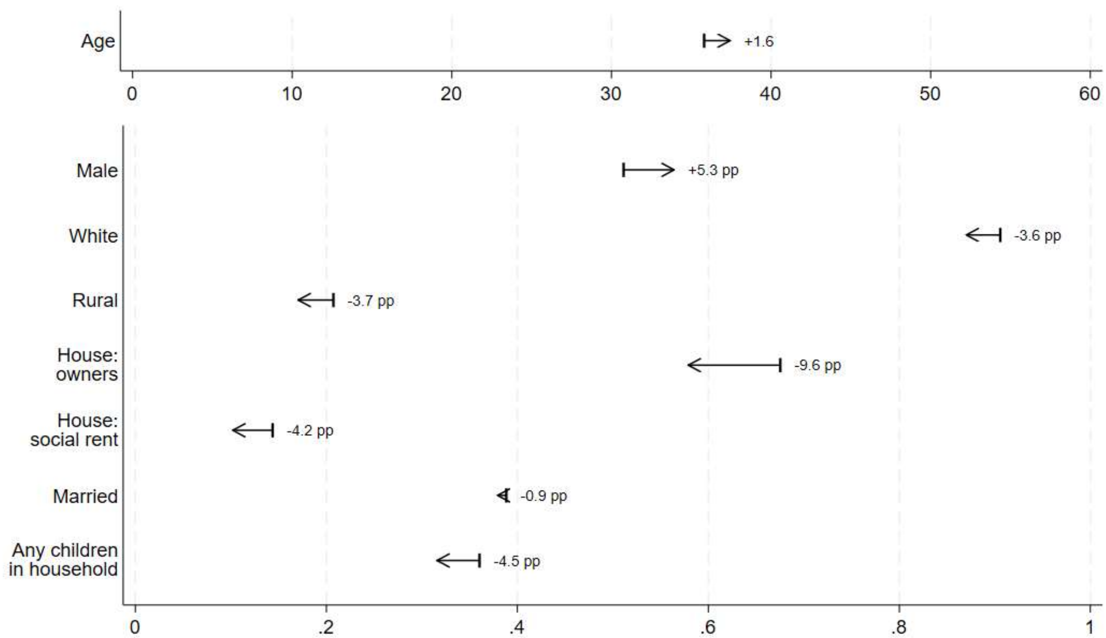
Table A9: Post-victimization Outcomes and Unit Social Costs of Crime

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	1.31	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	0.87	1.00	1.00

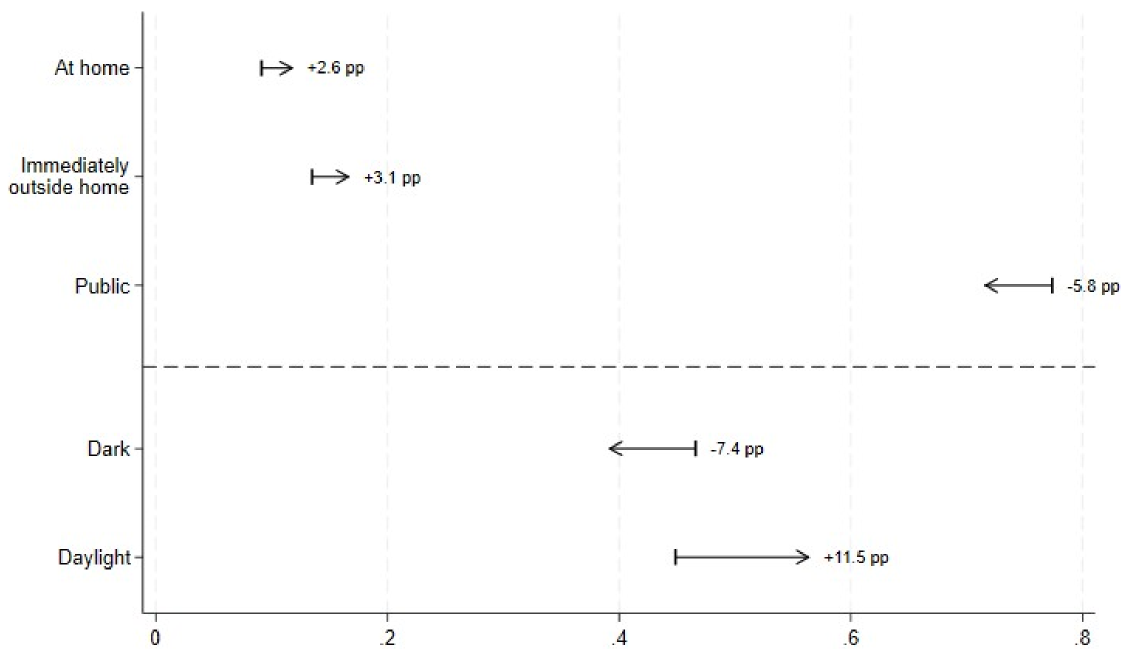
Notes: We report ratios of unit social costs of crime that account for both victims and witnesses relative to the victim-only benchmark of Heeks et al. [2018]. The first row reports the average ratio of unit social costs, across crime categories. In Column 1, witnesses are assigned the same unit cost as victims for selected cost components from Heeks et al. [2018]. In Columns 2 and 3, 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 show adjusted costs for victims with positive post-victimization outcomes. Columns 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.

Figure A1: Changing Nature of Violent Crime

A. Changes in Characteristics of Witnesses to Violent Crime

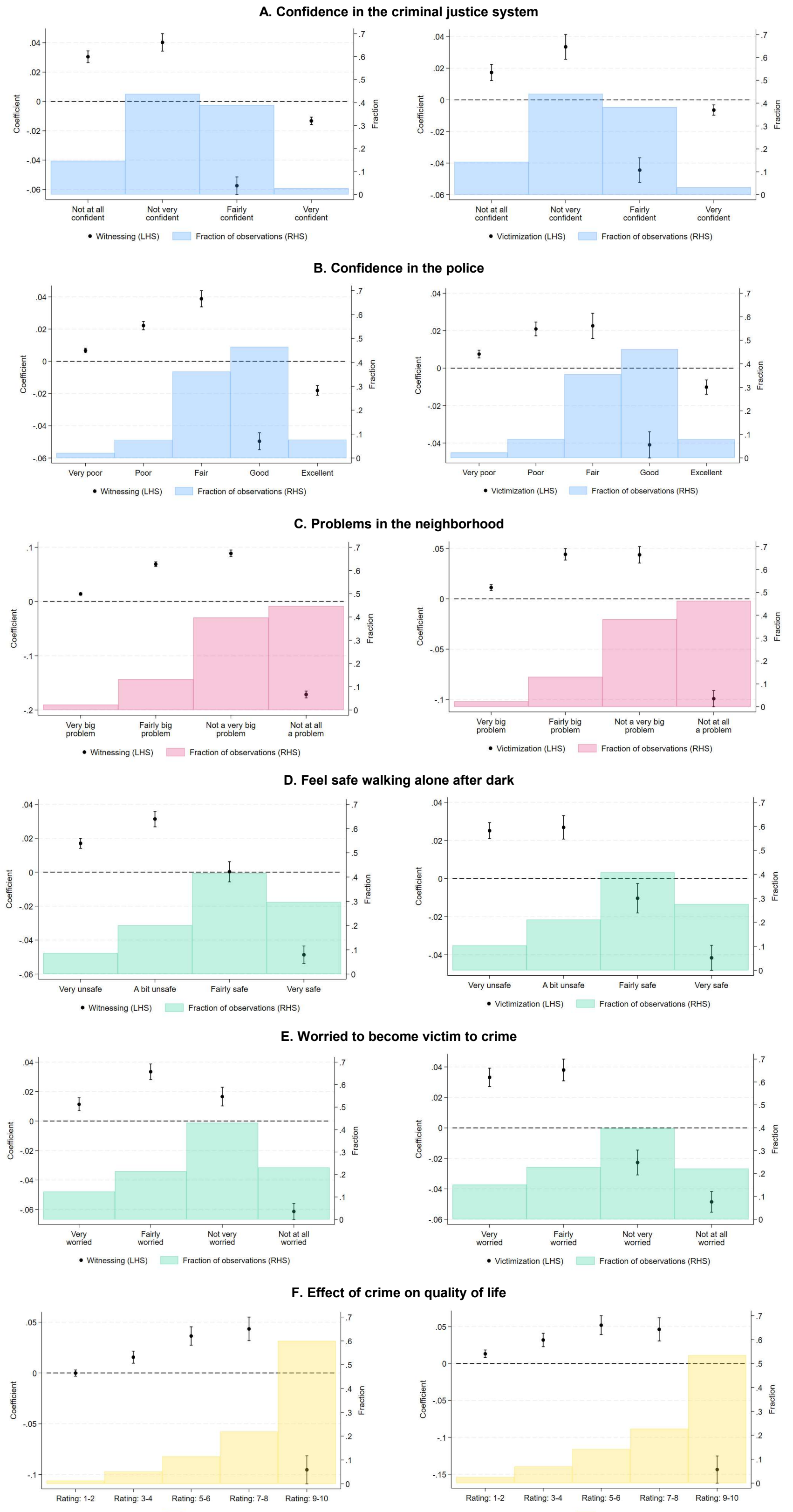


B. Changes in Location and Time of Violent Crime



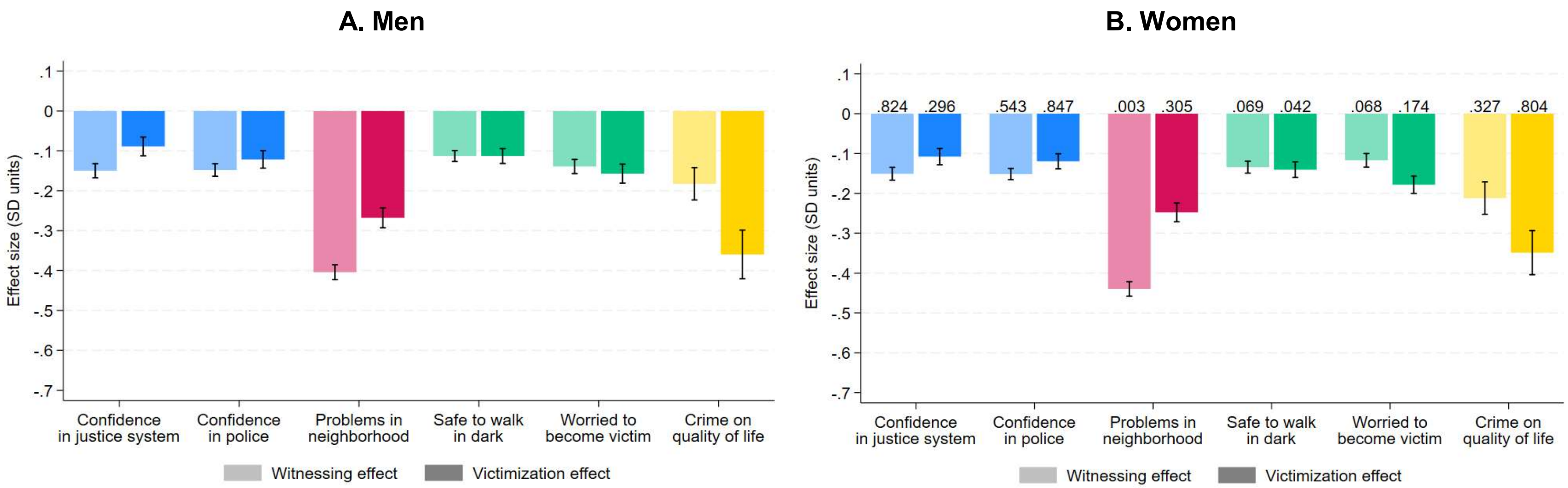
Notes: Panel A shows changes in characteristics of violent crime witnesses from 2003-04 to 2014-15. The category public combines a number of locations including transport, commerical locations, public entertainment, sports clubs, parks and pubs. Panel B displays changes in the location and time of violent crimes, from 2001-02 to 2017-18. This panel omits a third category for 'dusk/dawn'. Both panels exclude individuals with multiple victimizations. Observations are weighted by individual probability weights provided by the CSEW adjusted for the number of observations per wave.

Figure A2: Perceptions and Victimization Experiences, Detailed Outcomes



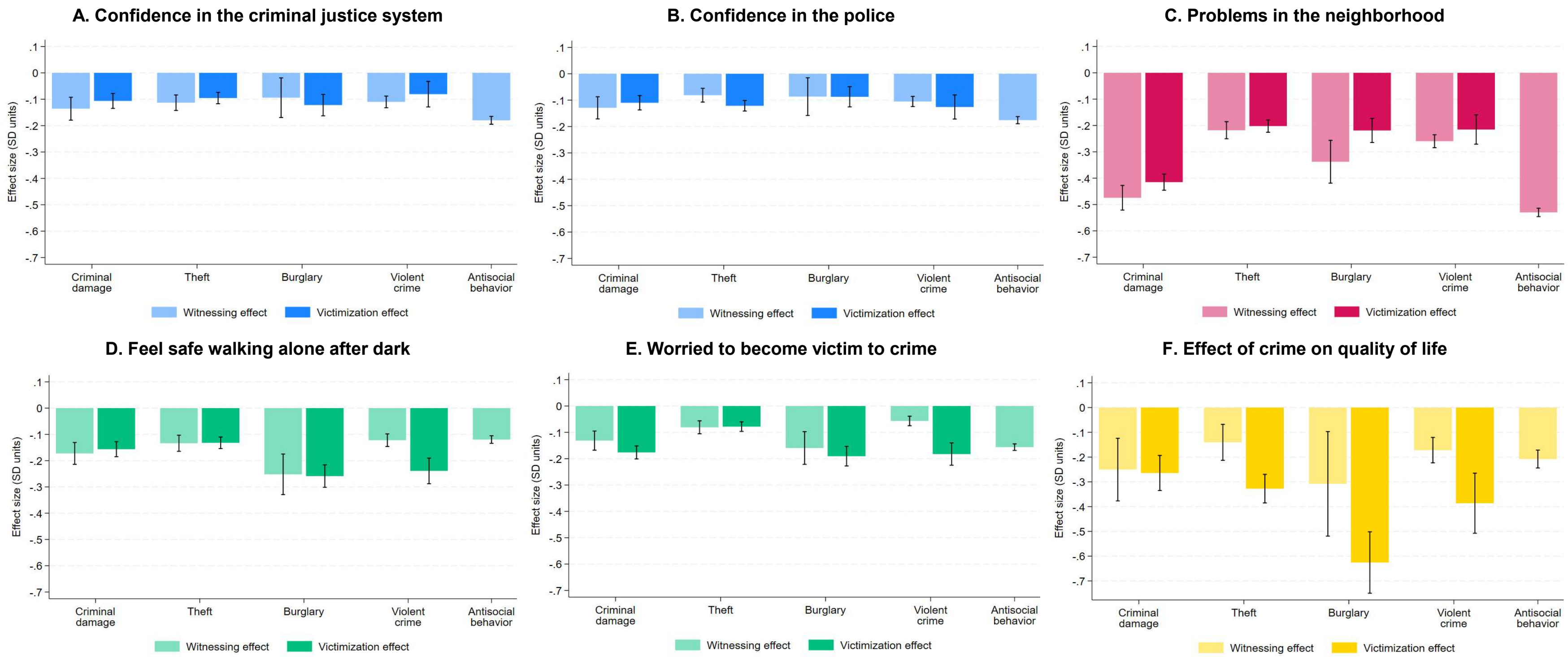
Notes: The sample consists of individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. The first Column of Panels show the estimates 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. 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 point markers report OLS estimates of the witnessing and the victimization effect. 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 A3: Perceptions and Victimization Experiences, by Gender



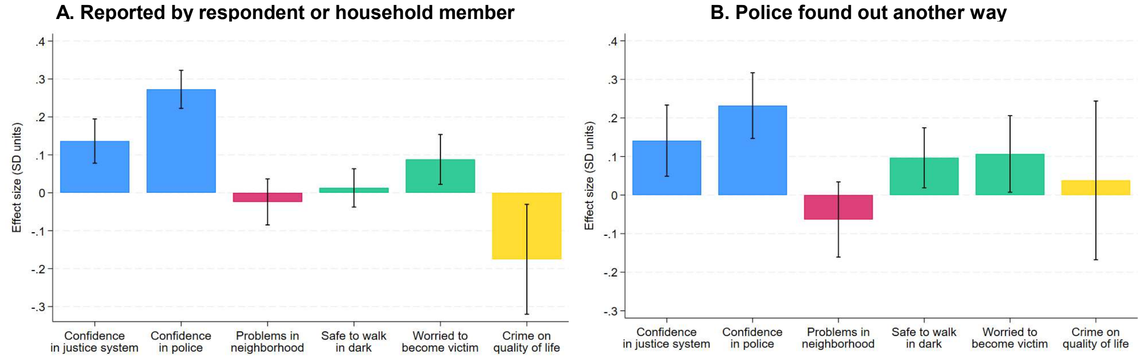
Notes: The sample consists of individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. We show estimates of witnessing effects (lighter 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



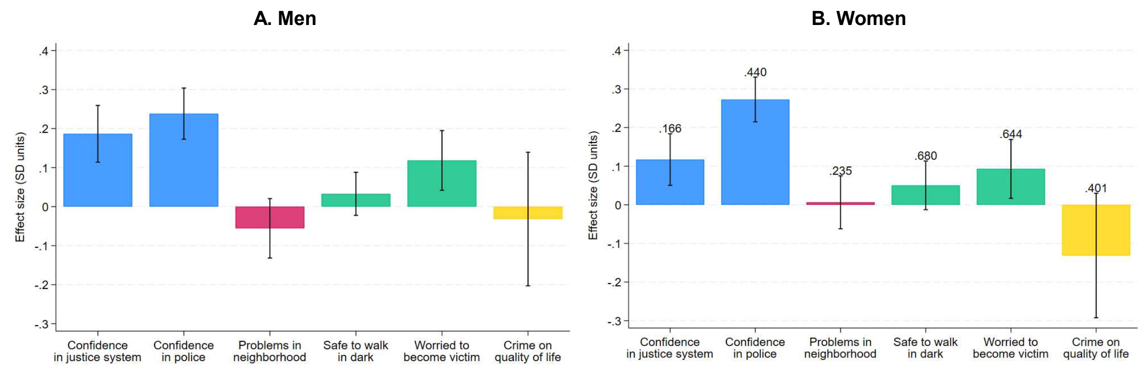
Notes: The sample consists of individual responses from pooled data of the 2003-04 to 2007-08, 2011-12 to 2014-15 and 2017-18 CSEW waves, excluding individuals with multiple victimizations or witnessing more than one of seven crime/anti-social behavior types. We show estimates of witnessing effects (lighter 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 Post-victimization Experiences, Robustness



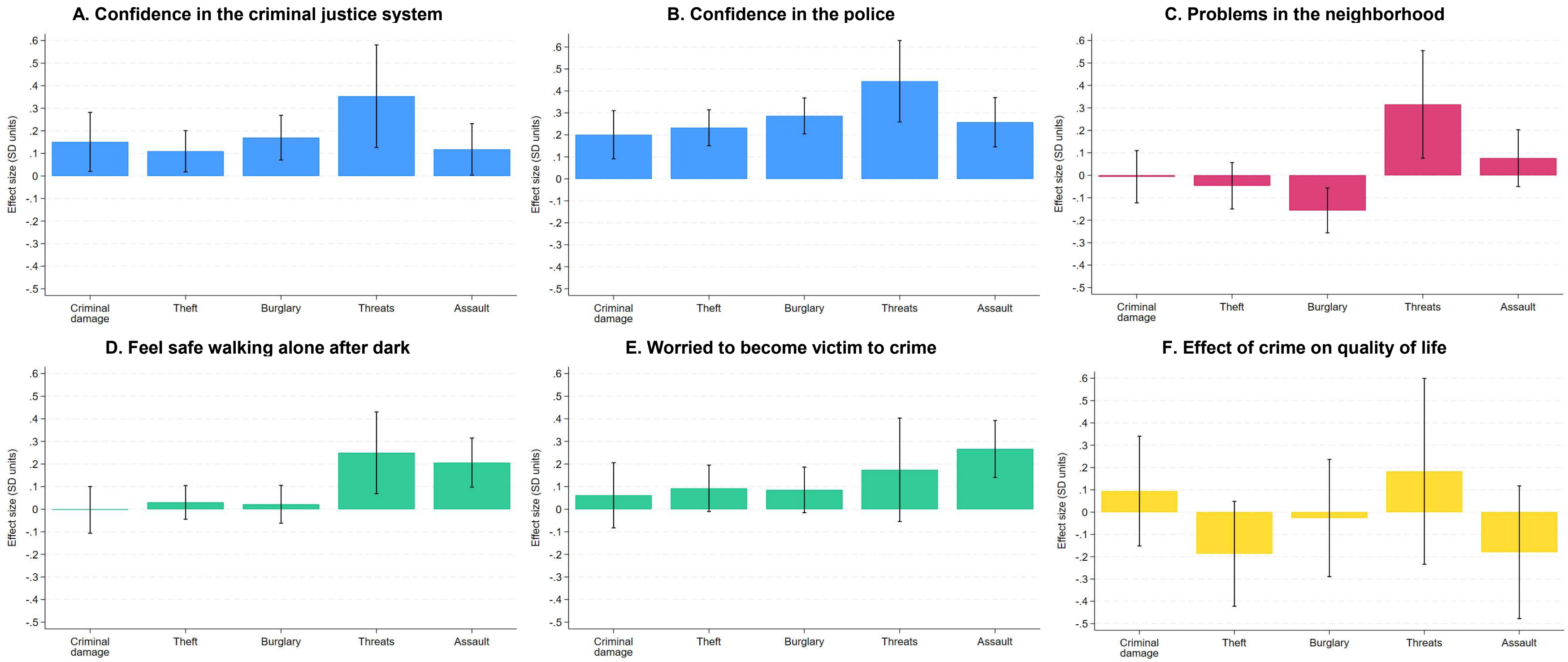
Notes: The sample consists of individual responses from pooled data of the 2001-02 to 2017-18 CSEW waves, excluding individuals with multiple victimizations. For each perception outcome variable, the bars report OLS estimates of a favorable post-victimization outcome, namely the victim-respondent's offender 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'). 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 A6: 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 A7: 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.