Stress on the sidewalk:

The mental health costs of close proximity crime

Job market paper

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Abstract

I apply novel, extremely micro-level datasets to provide new evidence on crime's impact on mental health. I find that each reported violent and sexual crime significantly increases the stress levels of those in the vicinity for three days after the crime was committed. The temporal aspect of the effect is specifically driven by violent and sexual crimes committed two days earlier, a lag which suggests the presence of a mediator of the information–word of mouth or the media. To measure that, I scrape news data and observe significant increases in nationwide stress levels in response to the number of articles published on the topic of crime in the domestic news section of multiple daily newspapers. I measure crime's effect on stress by merging a unique daily response panel dataset that has over 75,000 responses from 2010 to 2017 in the Thames Valley region of England with secure access data containing every reported crime in the same region with exact location, time, and event characteristics. The result that violent and sexual crimes increase stress holds with extensive controls for individual fixed effects, circumstantial characteristics, and spatial fixed effects, including fixed effects for the smallest level of census geography in England that contain only an average of 250 people.

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After more than a decade of decreasing crime rates, the United Kingdom became subject to a sharp, and continuing, increase in high impact crimes recently. Compared to 2016, homicides increased by 9% [Kirchmaier and Llera, 2018], knife crimes by 22%, and rape by 31%[1] [Office for National Statistics, 2018]. In this context, estimating the total cost of social harm by crimes is particularly important. This paper contributes to that estimation by looking at crime's beyond-victim impact on the mental health of those in the neighborhood.

Crime has adverse effects on citizens beyond its impact on victims, with crime levels influencing choices about home ownership, work hours, and physical health choices, like exercising. High impact, violent crime also comes with mental health costs for the neighborhood. Specifically, I find that these crime substantially increase stress levels. Even in countries like the United Kingdom, where crime rates are relatively low, crime appears to be a top concern when making major life choices, like home ownership, and it is a topic people are eager to learn more about, based on its prevalence in the news.

In this paper, I show that committed crime has substantial immediate effects as well. Connecting highly secure data on daily crime with a daily response panel dataset on stress over a period of 8 years (2010-2017), I find that each individual violent crime event significantly increases stress levels for those in the vicinity during the coming three days after the crime was enacted. Back of the envelope calculations suggests that individuals' willingness to avoid a violent crime in the neighborhood is 80 pence per crime, leading to an approximate £200 ($250) social cost per violent crime.

Stress, 'an adverse reaction due to pressure' [Office for National Statistics, 2015], is a major contributor to productivity loss. In 2016/17, in the UK 12.5 million work days were lost due to work-related stress, which accounts for 49% of all lost work days [Health and Safety Executive, 2017]. Furthermore, stress is also a substantial contributor to physical ill health. Environmental factors that contribute to the onset of stress, however, have a limited understanding in the economic literature, due to the lack of availability of regular panel data on stress. This research bridges that gap, using a daily response panel dataset, Mappiness [MacKerron, 2012], for estimating the impact of crime on individual stress. Using crime reports over 8 years from the Thames Valley region of England, an area immediately west of London with a population of 2.1 million, I observe that crimes, specifically violent and sexual crimes, are a significant negative externality for stress.

[1] Reporting of crime has changed slightly in pursuit of improving on the vast underreporting, specifically in the case of some of these high-impact crimes, but the Office for National Statistics (ONS) notes that, regardless, there is an objective increase in these crimes.
Knife crimes are defined as possession of weapons offenses where the weapon was a knife or another sharp object.

When focusing on the temporal pattern in which violent crime impacts stress, I find the presence of a two day lag in crime's effect manifesting in stress levels, implying the possibility of a mediator. Exploring the possible mediating channel of the media, I scrape leading British news sites and find that the number of articles written on the topic of crime in the domestic news section has a significant impact on stress levels across the UK. Overall, the paper measures the effect of each committed violent or sexual crime on stress, suggesting a significant increase in stress for those nearby, and suggesting that the channel of the effect is at least in part due to news written on crime occurring locally and nationally.

Crime is one of the major diseconomies in contemporary societies. In Becker's (1968) seminal work, the social loss L generated by crime is defined as the sum of the harm caused by the crimes *H(O)*, the gain to offenders, the cost of combating, and the cost of punishing the offenses[2].

The total social harm, *H(O)*, is traditionally measured as a directly monetary function, such as the lost revenue from taxes in money laundering or lost productivity for a victim temporarily out of work due to a crime. For example, the social loss generated by violent crimes—estimated at 7.7% of the GDP —is currently calculated by summing up costs associated with policing, the justice and the prison system, and direct damage due to the crimes committed [UK Peace Index, 2013]. However, this measure is incomplete, and the "estimate for the cost of crime may be a significant understatement of the net damages to society, [...] because much of the damage is omitted" [Becker, 1968]. The current paper sets out to contribute to the completion of *H(O)* through measuring the social mental health costs due to crime.

The current paper contributes to the broad pool of works on neighborhood effects on economic and mental wellbeing [Katz and Liebman, 2001, Kling and Katz., 2007, Ludwig and Sanbonmatsu., 2012], specifically adding to literature estimating crime's adverse beyond-victim effects. As one of the early contributors to this strand of literature, looking at work as an outcome, Hamermesh [1999] finds that violent crime, in particular homicide, leads to reduced work, especially on evenings and weekends. Focusing on another behavioral outcome, walking and exercising, Janke et al. [2013] show using British data that violent crime leads to a reduction in these activities in one's home neighborhood. Violent

[2]
$$L = H(O) - G(O) + C(p,\ O) + bpfO$$
where L is the social loss function, *H(O)* is the extent of harm by the number of offenses, G(O) is the gain to offenders by the number of offenses, *C(p, O)* is the cost of combating O offenses with p probability of conviction, and *bpfO* is the total social loss from punishment (a multiplication of *bf*, the loss per offense, and pO, the number of offenses punished)

crime can also lead to pre-term births and lower birth rates, as found by Messer et al. [2006] in the US context. Crime also has an adverse effect on business activity [Greenbaum and Tita, 2004] and on house prices [Tita and Greenbaum, 2006], again predominantly driven by violent crime, while Cornaglia and Leigh [2011] using data on Australia shows that this type of crime leads to a reduction in a composite index measuring physiological wellbeing. This composite index, however, is a combination of 12 questions on mental (and sometimes physical) functioning; the decomposition suggests that crime's effect on wellbeing is mostly driven by a reduction in 'engagement in social and other daily activities due to the individual's physical or mental health,' but it is unclear whether the channel of effect is through physical heath, mental health, or the reduced activity level. Papers focusing on exceptionally severe violent acts, such as terrorism, also find significant negative wellbeing effects: Bryson and MacKerron [2018], using an event study setup, show that IRA bombings that lead to death significantly increase stress and anxiety among the population in Northern Ireland, and Metcalfe and Dolan [2011] provide evidence that the September 11th attacks in the United States even affected the British population's wellbeing.

Opposing this strand of findings are papers suggesting that the beyond-victim costs are predominantly driven by property crimes. Here, Gibbons [2004], writing specifically about London, and opposing Greenbaum and Tita [2004]'s findings, suggests that an increase in property crime leads to property prices dropping, driven specifically by criminal damage. In his interpretation, it is perception of crime through graffiti and vandalism that leads to a higher fear of crime, which then reflects in property prices. Meanwhile, Dustmann and Fasani [2016] find that property crimes significantly increase residential anxiety and depression.

The present paper contributes an unprecedented precision to the existing literature in a unique combination of three ways concurrently: (1) temporally; (2) spatially and; (3) in the definition of the y variable. The estimations by most papers, as well as those provided by the two closest papers to the present one, Cornaglia and Leigh [2011]'s and Dustmann and Fasani [2016]'s, both use annual surveys for measuring wellbeing, and annual and quarterly data on crime, respectively. Additionally, crime is generally measured at a larger regional or city level, specifically in the above two papers at the Local Government Area (in Australia) and at the Local Authority (in the UK) levels, which have an average of 215,000 and 145,000 residents. In comparison to those papers, the current paper measures crime at an area level which has an average of 250 residents. Lastly, both aforementioned papers measure their dependent variable as a composite index—one reaching key significance on a variable mixing physical and mental health and the other pooling together anxiety and depression, two different mental health conditions vastly different in severity and long-term risks—thus hindering the precise understanding how human wellbeing is impacted. This paper, on the other hand, uses a single measure of stress over a composite index, which in turn can be better policy-informing in how for example the resulting negative mental outcome can impact physical health and productivity.

While there is a growing amount of work on the effect of neighborhood-level circumstances on sexual crimes (see for example Blanes i Vidal and Kirchmaier [2017] on domestic abuse specifically), there is little work on how sexual offenses specifically impact non-victims. This might be due to a combination of the facts that sexual offenses occur less regularly than other kinds of violence overall, have an outstandingly low reporting rate, and have low perpetrator conviction rates due to insufficient evidence. Sexual offender data is public in the United States, and by making use of that information, Linden and Rockoff [2008] show that house prices fall when convicted sexual offenders are present in the area. The current study contributes to research on sexual crimes by considering non-sexual, violent against the person crimes, as well as sexual crimes, in order to understand both. While the latter category cannot be interpreted alone because of the small sample size, the inclusion of these crimes strengthens the results, suggesting that sexual crimes generate a substantial wellbeing loss at the neighborhood-level.

The article is structured as follows: Section 1 describes the measures of stress and of crime, including the underlying mechanism connecting the two, the data on news about crime in the media, and the methods for collecting this data. Section 2 discusses the empirical strategy, as well as the identification issues. Section 3 reports the results of the estimations and the robustness tests. In this section, I also benchmark the results using monetization and present results on the impact of crime news reported in the media. Finally, the last section provides a brief discussion and contains concluding remarks.

1 Background, Data, and Descriptive Evidence

1.1 Measuring crime

The high-impact, personally dangerous crimes that have been on the rise in Britain are also the ones most feared by the British population. Using data from the Crime Survey for England and Wales, I find that the two types of crimes respondents report an average higher than 3 (on a 1 to 4 scale) in terms of how afraid they are from them are being attacked (3.18) and raped (3.22)[3]. Based on these results, I focus in the analysis on two crime categories: (1) violence against the person, which excludes sexual crimes, and (2) sexual offenses.

Detailed information on crime from 2010 to 2017 is available from the Thames Valley Police Force Area. Thames Valley ranks in the middle of all police forces in England and Wales (26 of 43) in terms of its crime rate in England and Wales.[4] The force area, which has a population of 2.1 million, is directly bordered by London (Metropolitan Police), which consistently registers the highest crime rate in the country, as well as eight other forces with varying crime rates. Its mid-way ranking in terms of crime makes the region a good fit for research providing extrapolateable results. In terms of geography, Thames Valley encompasses one of the biggest territories among all forces, including both urban and rural areas. The bigger cities within this jurisdiction include Oxford and Milton Keynes, as well as Slough, which sits on the western fringes of London and has well above country-average crimes rates.

The dataset provided by Thames Valley Police contains information on each criminal offense reported to the police force, with data on the location, time, and type of the crime. Over the nearly eight years the crime data overlaps with the availability of the Mappiness data (June 2010 to December 2017), there were 1,023,841 reported crimes in Thames Valley.

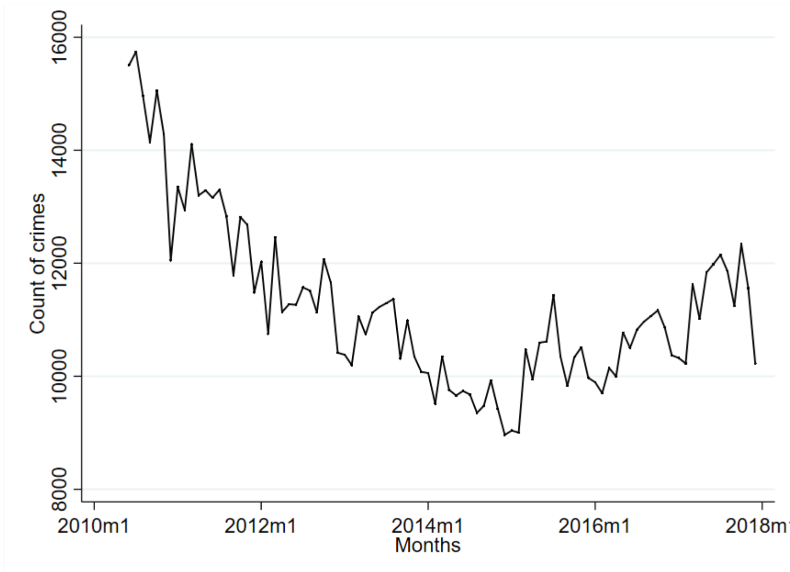
The average number of crimes per year in the region was between 120,000 and 180,000. Looking at Figure 1, we can observe the temporal cyclicality of crime, where the summers see higher rates of crime and there is an overall, slow downward trend in total crime over the decade, just like in the rest of the country. In the analysis, these trends are controlled for using a set of temporal controls: year (8 dummies), month (12 dummies), day of the week (7 dummies), and hour of the day (8 dummies, for each 3 hour block of the day) are included in all regressions as variables.

[3]The identification of most feared crimes are author calculations using the Crime Survey for England and Wales, year 2012-13 (when they were not on the rise yet, nor was a special media attention on them). In the survey there is a series of 7 questions on fear of various types of specifically victim based crimes, such as 'How worried are you about... having your home broken into and something stolen?'.

See further information on the Crime Survey here: http://www.crimesurvey.co.uk/en/index.html

[4]See more on crime rates in police forces here: https://www.ons.gov.uk/peoplepopulationandcommunity/ crimeandjustice/datasets/policeforceareadatatables

Figure 1: Distribution of monthly crime rates in Thames Valley – June 2010 - December 2017



1.1.1 Types of crime

The police forces in England and Wales work a nested system for categorizing crime, which is often referred to as the 'crime tree.'[5] Here, all crimes are categorized first into two broad categories, victim based crimes and non-victim based offenses. In the second level of categorization, nine categorizes are differentiated. Victim based crimes include violence against the person, sexual offenses, robbery, theft and burglary, and arson and criminal damage. Non-victim based crimes include drug offenses, weapons offenses, public order offenses, and miscellaneous crimes.

The two kinds of offenses this research focuses on make up 20.48% of crimes, with violence against the person constituting 18.22% of all crimes, and sexual offenses 2.26% (see Table 1 for the crime tree with a focus on these crimes, as well as the Appendix for a complete crime tree for all crimes). Violence against the person encompasses a wide range of illegal activities from assault to stalking to child abduction. The most often reported violent crimes are assault without injury, assault occasioning actual bodily harm, common assault and battery, and harassment[6] Sexual offenses are rapes in 31%

[5]See more about the crime tree here: https://www.justiceinspectorates.gov.uk/hmicfrs/crime-and-policing-comparator/about-the-data/

[6]Further violent crimes that occurred in more than 1000 cases during the observation period: Threats to kill, assault (with injury) on constable, breach of restraining order, owner or person in charge allowing dog to be dangerously out of control injuring any person or assistance dog, sending letters etc. with intent to cause distress or anxiety, wound or

of the cases and include categories such as administering a substance with intent (to commit a sexual offence), attempted rape, and exposure.

Table 1: Crime tree for violent and sexual crimes reported in Thames Valley
(June 2010 to December 2017)

	Freq.	%		Freq.	%
Violence Against the Person	185183	18.22	Homicide	131	0.01
			Violence with Injury	77336	7.61
			Violence without Injury	107716	10.6
Sexual Offences	22941	2.26	Rape	7067	0.7
			Other Sexual Offences	15874	1.56
Robbery	9440	0.93			
Theft Offences	550814	54.2			
Criminal Damage and Arson Offence	143369	14.11			
Drug Offences	44986	4.43			
Possession of Weapons Offences	6601	0.65			
Public Order Offences	38771	3.81			
Miscellaneous Crimes Against Society	14246	1.4			
Total	1016351				

When a crime is reported, the category it falls into is always determined by what the most severe aspect of the crime was. Furthermore, if both a victim based and a victimless crime with equal severity occurs, the incident is recorded with the victim based crime taking precedence. For example, if a person commits a violent act with injury using an illegal object, both violence against the person as well as possession of weapons offenses are present, and thus the crime will be categorized as a violence with injury crime, as that is the more severe of the two[7].

1.1.2 Spatial-temporal vicinity to crime

The research makes extensive use of the fact that England has compact census geographies (to a much smaller detail than the United States), and that both crime and stress data are available with fine granularity. Crime levels are measured at the so called "Output Area" level, the smallest geographical unit in the country. Output Areas (OA) have an average of only 131 households (approximately 250

inflict grievous bodily harm with or without weapon, wounding with intent to do grievous bodily harm.

[7]See more on categorization of crimes in Crime Recording General Rules, Section F, The Principal Crime Rule. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment$_{data}/file/721595/count - general - jul - 2018.pdf$

adults), which translates to about a single street. This size is around 20 times smaller than the average zip code in the United States. OAs are the very direct area around an individual, often the size that one can visually observe it in its entirety from a single vantage point.

There are 7262 OAs in Thames Valley, with an average 17.73 crimes per year in each. Looking at the median annual crime level, which was only 9.88 crimes per year per OA, it is clear that the distribution of crime in OAs is heavily left skewed (see figure in Appendix). The average number of crimes per day in the whole of Thames Valley is 378, which translates to on average 0.04 crimes per day per Output Area. This means that, on average on any given street every month, one reported crime happens. At the Output Area, using the initial dataset of offense lists, a daily crime level is then calculated for violent and sexual crimes, as well as other crimes.[8]

When controlling for neighborhood characteristics, the research also uses the area level of Lower Layer Super Output Areas (LSOAs). Thames Valley has 1423 LSOAs, which have an average of 1614 residents and take up only a city block, one neighborhood in a small town, or a tiny village. OAs are one-fifth the size of an LSOA. Using area fix effects first at the larger then at the smaller area level allows for identifying the in what vicinity crime has an impact.

1.2 Measuring stress

Stress, one of the most prevalent negative mental states, is not a mental illness itself, but measures broader ill-being that can often translate to or exacerbate illnesses. Information on stress levels are available from a daily panel dataset, Mappiness. Mappiness, a smartphone application that is freely available to download, started in 2010 and had a total of more than 30,000 participants who have logged more than 3 million responses. Individuals are free to sign up and leave at any time, which means that the data is not representative of the population (though it can be weighted to population average for all major demographic aspects, except for the poorest and the oldest deciles). On the other hand, the scale of the sample of the dataset allows for detailed identification, and has made possible

[8] Spatial vicinity is defined based on Output Areas over using exact distance from the respondent to the crime, because OAs are designated to be 'constrained by obvious boundaries such as major roads,' have similar population sizes, have 'approximately regular shapes,' be exclusively urban or exclusively rural, and be 'as socially homogenous as possible based on tenure of household and dwelling type.' The ways that OAs are delineated prove advantageous for this research, as crimes are perceived by respondents in neighborhoods where residents tend to share characteristics, rather than in areas strictly defined by exact distance from a crime, which disregards these aspects.
See more on how OA borders are designed here: https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeographyoutput-area-oa

studies on wellbeing at finer details that before (see for example [Bryson and MacKerron, 2017]).

Once an individual signs up, they are alerted twice a day at random times to report on how they're feeling; who they're with; if they're at home, at work, or elsewhere; and what of the 40 (plus Other) activities they're doing at the given moment.[9] The smartphone also notes the location of the response and the home location of the respondent, thus allowing for a precise estimation on the effects of the neighborhood a respondent lives in or spends their time in. The question on stress is worded, "How relaxed are you?," in order to frame the question positively. For the analysis, the values are inverted to measure stress (or a slightly broader combination of feelings such as stress, worry, and anxiety). The two ends are labeled 'Not at all' and 'Extremely.' A strong asset of the questions posed digitally is that it is not measured on an ordinal scale, but on a continuous one represented as a sliding scale, where each pixel available on the smartphone can be the chosen value. This leads to much higher precision and values that can be treated as intervals. Furthermore, because no actual numbers are visible, mean reversion is likely less of a methodological problem; without seeing what value one selects, it is substantially harder to fall back to the same point the next day. For the analysis, the values respondents select are scaled 0 to 100 for ease of interpretation.

Over the observed period, 5.25%, or 100,594, of all Mappiness responses come from Thames Valley and belong to 5033 individuals. Of those responses, 75996 come from 1476 individuals living in Thames Valley as well (see Appendix for a detailed table).[10] These responses, by individuals living in and responding from Thames Valley form my main sample. I find that for the expanded sample of all responses, both from those living in and those living outside of the Thames Valley, the results are fully consistent.

Among those responses that were given within Thames Valley, 52.7% were responses coming from an area that had some crime reported in the two previous weeks. In terms of individuals, 79.5% of respondents responded at least once in an area where some crime happened in the past two weeks, suggesting that most people regularly spend time in areas where crime has happened. If we look only at the day before the response, 12.6% of responses came from streets with one crime and 4.7% with more than one crime reported the day before (see Appendix).

[9] Responses that are given more than 60 minutes after the randomized beep are excluded from the analysis to effectively measure the mood and activities at prompting time.

[10] Most individuals cross administrative borders with some frequency, that is why we see three times as many respondents who responded from Thames Valley at least twice, but don't live there, than those who live there. Similarly, those living in Thames Valley gave 83.7% of their responses within it, and 16.3% outside of it.

The sample of Mappiness respondents within Thames Valley—as countrywide as well—are different in some aspects to the population average. In particular, respondents are financially better off, younger, and more likely to be employed than the average resident. On the other hand, the gender and the average household size are similar to the population overall (see Appendix for tabulated information on the demographic characteristics).

1.3 Measuring media coverage on crime using webscraping

Even when most major types of crimes were decreasing in the country (up to 2016), fear of crime remained a major concern for people in the United Kingdom. One in four to one in five people there say that it is very or fairly likely that they will become a victim of a crime in the coming year, when actual victimization rates are around one in eight people [Office for National Statistics, 2017]. This difference between perception and reality is substantial and causes persistent problems for policy makers [Duffy et al., 2008]. Along with the likelihood of becoming the victim of a crime, individuals also over-predict the prevalence of crime itself. People slightly overestimate how much crime happens in their own neighborhood and vastly overestimate how much crime happens nationally. Based on the Crime Survey for England and Wales conducted since 2009, more than 80% of residents said they thought crime has been rising in the year prior to responding, when that has not been true in any year up until 2017. Those who perceived local crime to be on the rise mostly credited personal experience, word of mouth, and local newspapers as sources that informed their opinion, while those who felt national crime to rise cited tabloids, TV, radio, and the Internet as their sources. Therefore, it is possible that the channel of effect between crime and stress is at least partially through mediated information.

To test whether national reporting on crime can impact social stress, I collect information on the number of news articles written on the topic of crime in two leading British newspapers, *The Sun* and *The Guardian*. The former is the most widely circulated newspaper in the country,[11] while *The Guardian* is one of the highest regarded UK dailies, having most often been named National Newspaper of the Year in the British Press Awards,[12] as well as the only Britain-based newspaper having won a Pulitzer Prize (shared with The Washington Post) since the turn of the century.[13] *The Sun* is widely

[11] https://www.abc.org.uk/report/newsbrands
[12] pressawards.org.uk
[13] https://www.pulitzer.org/prize-winners-by-category/204

considered to be a tabloid, while *The Guardian* is thought to offer more substantial writing, so these provide two differing voices to test the hypothesis.

Newspaper websites are not designed predominantly to be searched on a per-day basis going back years, therefore I use the Nexis database,[14] which is a leading online compilation of printed news articles collected from most large publications in Britain and the United States. Nexis is searchable by date, and the search methods are identical for all news outlets, therefore making it a better candidate for obtaining information on the population of articles on crime than individual publication websites would be.

Nexis also categorizes the printed articles based on whether they were in the news section or other sections. Making use of this, I limit my search to news articles. In the case of *The Guardian*, domestic and foreign news are also differentiated,[15] and I only keep news articles on domestic crimes. In the case of *The Sun*, this domestic-foreign distinction is not available, so results here might be less clear due to the sample being somewhat inflated by pieces on foreign crime, which likely interact with stress differently, if at all.

To identify the number of articles about crime in an outlet per day, I apply a searching method called indexing. Indexing associates topics with each article in the database based on the words used in it. Thus, indexing can search for a concept and finding all articles that belong to this concept.[16] Furthermore, Nexis' indexing not only associates a term with the article, but also provides a percentage showing how strongly linked the article is to the index term, along with providing the length of the article, the author of it, and the section it was published in. In Nexis, the index word 'crime' has a list of 68 sub-indexes associated with it, from 'Bribery' through 'Cybercrime' to 'Vandalism.' Articles associated with any of these sub-indexes are searched for when implementing an indexing search on

[14] https://www.nexis.com
Nexis is a service most universities in the UK and US subscribe to, making the pay-for service freely accessible to academics.

[15] The Guardian is the national newspaper with the highest circulation for which Nexis provides this distinction.

[16] According to Nexis' information provided to the author the association of articles with topics was initially created through machine learning and natural language processing, and now all incoming articles are indexed based on the preexisting data.

'crime.'[17] [18]

As seen above, Nexis is ideal for identifying articles about crime events; however, it has severe limitations on the amount of data downloadable with one query. Therefore, I opt to automate the process through webscraping. Using the scraper tool Kantu, I define my search query and am able to access and download the list of articles on crime each month for each of the two newspapers between 2010 and 2017.[19] Each month's CSV file contains information on the date the article was published, the author, the title, the page it was published on, the length in words, and the section it was published in.

Looking at the descriptive statistics, the number of articles written on the topic of crime is vastly different for the two publications. While only 0.8% of days pass without *The Sun* publishing at least one piece on crime, 24.26% of days contain no crime reporting in *The Guardian*. A large portion of *The Sun*'s articles about crime are very short and consist only 100 to 200 words. Additionally, these short crime blurbs don't have a prominent place in the newspaper, but hinder identifying the connection between news and stress, as with them there are practically no days 'untreated.' Therefore, in the analysis, I exclude articles in *The Sun* below 250 words and present results based on the longer pieces.

2 Empirical strategy

My estimation is based on the following simple set up. For individual i in locality l at time t

$$S_{ilt} = \beta_{0i} + \beta_1 C_{lt-1} + \beta_2 W_{lt} + u_{ilt}$$

[17] See more about the concept of indexing at: http://help.lexisnexis.com/tabula-rasa/lninexis/indexterms_cpt-concept?lbu=GB&locale=en_US&audience=business
See more on indexing specifically in Nexis, and Nexis' LexisNexis SmartIndexing Technology at: http://help.lexisnexis.com/tabula-rasa/lninexis/smartindexing_cpt-concept?lbu=GB&locale=en_US&audience=business
Further details on indexing are at: http://help.lexisnexis.com/tabula-rasa/lninexis/selectsearchtopics_ref-reference?lbu=GB&locale=en_US&audience=business
Some broad information on how Nexis implements the indexes is available here: https://www.lexisnexis.com/en-us/about-us/about-us.page
Lastly, to learn more about sub-indexes, go to 'Power Search,' on the page go to 'Add Index Terms,' and there to 'Advanced index term look-up.'

[18] An alternative method like searching articles explicitly for a keyword, for example 'crime', would not accurately locate articles about criminal offenses unless the word 'crime' happens to appear in the text of the article.

[19] See more about scraping with Kantu here: https://a9t9.com/kantu

where S, the dependent variable, is the measure of stress for individual i responding in locality l at time t. β_0 captures the individual fixed effects, C_{lt-1} measures the impact of crime in the most recent 3 days (t-1 to t-3), while W_l captures the weather and population characteristics of the locality-time.

In practice, if I only observed two localities, and crime changed over time in one but not the other, that would be a difference-in-differences problem. This can be thought of as situation where there are a multitude of moving differences, both in terms of the number of change-periods and in terms of various levels of treatment.

The estimates this way also make use of the availability of information on the location of not only the respondent's home, but various other locations they spend time in or pass through. With 54.2% of responses given while the person is within their home (and a further small portion, 0.4% from the home LSOA, but not at home), the crime rate of the home neighborhood is heavily considered in the specification. But instead of treating it as the single influential variable, as often is the case in the literature, this setup allows for a more refined estimation.

Weather and population characteristics Wlt are air temperature, sunlight, rain, cloud cover, and wind speed, available through the MET Office's Integrated Data Archive System (MIDAS) Land and Marine Surface Stations Data, and are based on most recent hour or most recent day estimates from the nearest or nearest three measurement towers.[20] Daylight information is from R's *StreamMetabolism* package. Furthermore, I include the annual total population for each OA as a control.

Lastly, I apply both two-way fixed effects and two-way clustering of the standard errors, in both cases at the level of the individual and at the Output Area. Two-way fixed effects control for the innate characteristics of both the individual and the area (for example, that it's generally a stressful location or not), while two-way clustered standard errors help correctly acknowledging the fact that some individuals provide more responses than others and some locations have more responses coming from them than others.

[20] http://catalogue.ceda.ac.uk/uuid/220a65615218d5c9cc9e4785a3234bd0

3 Results

3.1 Violent and sexual crimes' effect on stress

Results on how crime effects stress are visible in Table 2. The dependent variable is the individual's stress level measured on a 0 to 100 scale, while the key independent variable is a dummy variable measuring if there was at least one violent or sexual crime in the past three days in the OA the respondent is in at the time of the response.[21] Model (5), the preferred specification, includes fixed effects at the individual level, controls for the uniqueness of each month of each year,[22] controls for the characteristics of the weather at the time and location of the response (including sun, rain, could cover, wind speed, and temperature), and controls for the characteristics of the time of the response (day of the week, hour of the day, daylight or night time). Furthermore, the Model also has fixed effects at the Output Area, controlling for the uniqueness of the street, square, or park. Using OA fixed effects controls for the characteristics of the neighborhood, and in that for the impact of generally ongoing crime on stress. With this complete set of controls (along with standard errors also being clustered two ways—at the individual and the OA), it is possible to estimate the impact of a specific crime. Doing so, I find that violent and sexual crimes significantly increase stress with 1.08 percentage points.[23] [24]

These results are robust to various tests. First, a falsification test imputing the crime levels of 5, 15, 30, and 90 days in the future all prove insignificant, thus suggesting that the findings causally link violent and sexual crime levels to societal stress (see results in Appendix). Secondly, I exclude temporally or spatially extreme crime and find that the results are identical. In terms of temporally extreme crime, I retest my results excluding responses from August 2011, because that month saw the largest riots in recent British history, which spread nationwide and had their own substantial negative

[21]Estimates with the independent variable set up as categorical, measuring the exact level of crime provide very similar results. This is due to the fact that the vast majority of treated responses were treated with exactly one violent or sexual crime in the last 3 days.

[22]I test whether the results are consistent if controlling for the uniqueness of each month of each year in each locality using Year * Month * Local Authority (a broader geographical area) controls, and find consistent results.

[23]It is noteworthy that the significance on other crimes persist with the majority of the controls already in place (as in Model (3)), and it is the introduction of the LSOA (approximately the size a city block, on average 5 OAs make up an LSOA) level fixed effects where other crimes become insignificant. It is thus possible that, even with the full set of prior controls the impact of how dangerous or safe the neighborhood appears in general is conflated with the effect of the recent level of non-violent, non-sexual crimes. The paper thus contributes to identifying how precisely it is important to control for the uniqueness of the locality to identify a likely causal relationship.

[24]If I further decompose violent and sexual crimes according to the third level of the crime tree, I find that it is violent crimes with injury and sexual crimes that drive the results, while violent crimes without injury appear to have no effect. This result is however only significant at the 10% level, possibly due to sample size limitations. (See results in Appendix.)

Table 2: The effect of at least one violent or sexual crime or in the past three days

	(1)	(2)	(3)	(4)	(5)
Violent or sexual crime at t-1 to t-3	1.614***	2.342***	1.905***	0.961***	1.083***
	(0.364)	(0.498)	(0.446)	(0.361)	(0.368)
Other crime at t-1 to t-3	3.053***	2.458***	1.698***	0.0578	0.0288
	(0.220)	(0.381)	(0.305)	(0.267)	(0.297)
Individual fixed effects		Yes	Yes	Yes	Yes
Standard errors clustered at individual		Yes	Yes	Yes	Yes
Year*Month		Yes	Yes	Yes	Yes
Circumstnatial controls			Yes	Yes	Yes
LSOA fixed efects				Yes	
OA fixed effects					Yes
Standard errors clustered at OA					Yes
Constant	34.51***				
	(0.0946)				
N	73670	73670	73670	73670	73670

Constant is lost due to two-way clustering in Model (5), and due to applying the same code for consistency beforehand. Constant is provided in Model (1) to anchor the size of the effect.

Respondent sample size in Model (5): 1378.

Regressions with the full set of controls are available from author upon request.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

wellbeing cost [Bencsik, 2018]. In terms of spatially extreme crime, I find that one particular OA has three days every year with exceptionally high crime, because it is the site of the annual Reading Rock Festival.[25] I exclude all responses from this OA and the results hold.

Third, I redefine the period for which the crime level is considered, and if a Mappiness response is given past noon, the crime level of t to t-3 is considered (that is, I add the level of crime on the day of the response). If the response arrives before noon, the original t-1 to t-3 period is applied. Rerunning the regressions using these independent variables, the coefficients are nearly as large as in the key table, here significant at the 5% level. Next, I test whether the sample's demographic differences from the population might be concerning, specifically, whether the respondents are unrepresentatively financially well off. I exclude those in the top 10% of the income distribution in Britain and find that the results hold up on the truncated sample. Lastly, because Doleac and Sanders [2015] show a consistent relationship between criminal activity and moving into and out of Daylight Savings Time, I create a set of dummies for the spring and fall clock change dates and, adding these as independent

[25] Of those OA-days that register more than 20 crimes between 2010 and 2017 80.5% happened at the time and site of the festival.

variables, I find the results to be unchanged.

Next, I decompose the temporal effect of the treatment to explore what channels might contribute to stress' effect on crime. In my key results, I find that crime in the last three days matters, and here I show that it is crimes committed two days ago that drive the results. This is shown in Table 3, which estimates crime's cumulative effect over the past week. Looking at Column 1, the crime level yesterday alone shows no significant effect; it is the cumulative crime over the past two or more days that matters. However, the result could still be due to the problem of small treated sample size in the first column, so I retest my model looking at each previous days' crime level one by one. Results here are bound to be weak due to the small treated sample size, but I find that the only day that is significant (at the 10% level) in its effect alone is two days prior to the response.[26] [27] This lag effect is noteworthy, because if it were crimes committed yesterday that created the effect, one could argue that the impact is (predominantly) direct exposure either to the crime itself or to crime-related responses like police cars on the street. However, the significance coming from two days ago suggests that part of the effect comes through an additional channel, such as word of mouth or the media.

Table 3: Temporal pattern of violent and sexual crime's impact on stress –Past 1 to 7 days

	(1) 1 day	(2) 2 days	(3) 3 days	(4) 4 days	(5) 5 days	(6) 6 days	(7) 7 days
Violent or sexual crime	0.413	1.073*	1.083***	1.063***	0.887**	0.837**	0.894**
in the last...	(0.575)	(0.574)	(0.368)	(0.350)	(0.350)	(0.383)	(0.367)
Other crime	-0.443	-0.130	0.0288	0.165	-0.0261	-0.0395	-0.0682
in the last...	(0.305)	(0.305)	(0.298)	(0.260)	(0.255)	(0.248)	(0.260)
N	73670	73670	73670	73670	73670	73670	73670

Models defined as Table 2 Model (5).

Model (3) is identical to Table 2 Model (5).

* p<0.10, ** p<0.05, *** p<0.01

3.2 Monetized cost of crime

Whether mental health costs can be expressed as an approximate monetary cost has been debated, with the conclusion usually being that a back of the envelope calculation is useful for contextualizing the

[26]The fact that adding the response day's crime level to the treated time frame weakened the results in an above robustness test also supports the idea that it is not crimes of the last 24 hours that drive the results.

[27]Collapsing the week into two time units, t-1 to t-3 and t-4 to t-7, I find that the latter has no significance (see results in Appendix), suggesting that crime's externality on stress is present for two to three days.

impact (see most recently Corry [2018] arguing against, and in response to that, Frijters [2018] arguing for the sensibility of monetization). Monetizing stress costs deduced from a daily panel, however, is complex due to the lack of comparability with results from annual surveys. In a daily panel, respondents' income does not change, so the classic approach of comparing the impact of change in income versus the variable of interest on wellbeing cannot function.

I approach the problem using an intermediary step: looking at the wellbeing benefits of reasonably clearly priced activities. In particular, I find that that among those living in Thames Valley responding from outside the home[28], 'Watching TV, film" (such as being at the movies) decreases respondent stress, on average, with 6.3 points; "Theatre, dance, concert" has a -5.1 point effect on stress; while "Exhibition, museum, library" has -6.4 points (see Appendix results along with the effects of other activities).

These cultural activities vary greatly in their cost, for example a theater ticket in the UK in 2013 (mid-way through the survey) cost £22.66 on average[29], while a cinema ticket was £6.53[30], and a museum ticket was £5.63[31]. Overall, the average household expenditure on recreation and culture was £64 per week[32], suggesting that entertainment is a popular activity among Britons, thus serving as a reasonable comparison group.

Using a crude, linear calculation, and accepting that the question is approached as a willingness to pay question, when it would ideally be a willingness to avoid question, one could say that both in the case of cinema and museums on average individuals pay £1 for 1 point of decreased stress, while in the case of theater and concerts (the latter lacks overall consumer statistics) it is slightly higher.

Given that people are willing to pay £1 for 1 point decrease in stress, and the impact of violent crime is 1.08 points, that would lead to an approximate cost of £1.08 ($1.25) per violent crime committed for the 131 households (with approximately 250 adult residents). A lower bound cost of each violent crime then would be £270 ($300). With on average 2187 violent crimes per month in the whole of Thames Valley, the total, beyond-victim (and police and judiciary) cost of crime per month is £590,000.

[28] I exclude responses from home, because it is harder to know the price of watching a film at home or seeing a theater piece broadcasted than when out of the house, likely enjoyed in an entertainment space.

[29] https://uktheatre.org/theatre-industry/guidance-reports-and-resources/sales-data-reports/

[30] https://www.cinemauk.org.uk/the-industry/facts-and-figures/uk-cinema-industry-economics-and-turnover/average-ticket-price/

[31] Based on 2016, as earlier is not available. https://www.aim-museums.co.uk/wp-content/uploads/2017/03/Successfully-Setting-Admissions-Policy-and-Pricing-.pdf

[32] https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/expenditure/bulletins/familyspendingintheuk/financialyearending2017

3.3 Perceived crime's effect

The two day lag between a crime being reported and it having an effect on stress levels suggests the presence of a mediator. Messer et al. [2006] explicitly theorizes that 'crimes often are well-publicized neighborhood events, making them a potentially proximate and salient form of neighborhood stress.' However, there are no studies showing that the connection between crime and stress would run (partially) through crime's 'publicity.' To explore this, I collect news articles on crime. Looking at *The Sun* and *The Guardian* newspapers, I find that the number of news articles written on the topic of crime the day before the individual responds to the survey significantly affects stress levels nationwide.

In *The Guardian*, any level of crime news has a negative effect, with the size of the effect being largely linearly related to the number of articles. In *The Sun*, the results are less consistent (possibly because foreign crime news couldn't be separated, and are counted for this outlet here), but the general direction is similar.

Table 4: The stress effect of news articles on crime

	(1) The Guardian		(2) The Sun
Baseline article number: 0		Baseline article number: 0-1	
Number of articles		Number of articles	
1	0.109**	2-3	0.423*
	(0.0514)		(0.255)
2	0.165***	4-5	0.370
	(0.0554)		(250)
3	0.346***	6-7	0.531**
	(0.0607)		(0.246)
4+	0.151**	8+	0.351
	(0.0623)		(0.242)
Constant	35.05		35.65
N	1667044		1198585

To obtain comparable results, the categories are created along the distribution that split the number of pieces per day into approximate quintiles. For The Guardian this is 0, 1, 2, 3, and 4 or more articles; while for The Sun it is 0-4, 5-6, 7-8, 9-11, and 12 or more pieces.
Note: For The Sun only articles of at least 250 words considered.
Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

4 Conclusion

In this article, I analyze the effect of crime on individual stress levels. Looking at the region of the Thames Valley Police Force Area, I use data on every crime reported in the region with a population of more than 2 million between 2010 and 2017. I combine this with a daily response panel dataset on stress, Mappiness. Connecting crime and subsequent stress outcomes at the temporal specificity of each day and the spatial specificity of the Output Area (the smallest geographical area in the UK, 20 times smaller than the zip code in the United States), I provide unprecedentedly precise estimates.

I find that violent and sexual crimes significantly increase stress for those in the Output Area if such a crime occurred in the past 3 days. Decomposing the effect by day, I find that the results are driven by violent and sexual crimes committed two days ago that drive the effect, suggesting a lag between treatment and outcome. I hypothesize that this lag is due to one of the channels of effect between crime and stress being mediated information consumption, namely news articles on crime. To test this, I scrape news websites to access data on each day's print version and find that, both for *The Guardian* and for *The Sun*, the number of news articles on crime has a significant effect in increasing stress levels nationwide.

Additionally, while previous studies focused on the individual's home neighborhood, I show that it is not required for someone to live in a given neighborhood, but only to be present in it, for the negative impact to materialize. This suggests that the negative impact reaches further than assumed before, and cities with a few crime-ridden districts can have individuals residing anywhere in the city experience a mental health cost from visiting those districts. This cost is significantly present for each crime committed in the last few days, compared to none, and is driven by violent crimes.

Recent research has highlighted how crime's externalities go well beyond procedural costs and the impact on the victim. With long-term changes like migration out of increasingly crime-heavy cities [Cullen and Levitt, 1999], slower business growth [Greenbaum and Tita, 2004] and lower birth rates in crime-heavy locales, [Messer et al., 2006] neighborhood crime has various negative consequences. Adding to this literature, I find that mental health is strongly negatively impacted, contributing to a more precise estimation of crime's externalities.

Some of these earlier studies (such as Messer et al. [2006]) explicitly argued that 'the mechanisms through which neighborhood crime environments might influence [physical] health are largely unknown,' and that 'a threatening environment can produce physiologic responses that may impair health in several ways.' I bridge the gap between these two statements, finding that recent crime levels significantly increase stress for individuals in the Output Area. This stress can then often translate into physical health problems. For example, stress significantly increases the odds of obesity [Cnop et al., 2012], as well as the odds of heart attack (both for those with and without coronary heart disease) [Wilbert-Lampen et al., 2008], and day-to-day environmental factors are more common among those with depression [Herane-Vives and Cleare, 2018]. Considering that England currently spends more per year on treatment of obesity and diabetes than on policing, the fire service, and the judicial system combined, it is important to recognize how the mental and physical health costs of crime intertwine with and increase each other [Public Health England, 2017].

Overall, this study contributes to a more complete estimation of the social harm caused by crime and does so by focusing on mental health, an outcome that then also can become a driver for additional negative effects. I conclude that crime's mental health externality is large and has economics costs associated with it. This implies that reduction in crime levels could have further benefits beyond the ones considered before.

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Appendix

Table 5: Crime tree for crimes reported in Thames Valley (June 2010 to December 2017)

	Freq.	%		Freq.	%		Freq.	%
Victim based crimes	911747	89.71	Violence Against the Person	185183	18.22	Homicide	131	0.01
						Violence with Injury	77336	7.61
						Violence without Injury	107716	10.60
			Sexual Offences	22941	2.26	Rape	7067	0.70
						Other Sexual Offences	15874	1.56
			Robbery	9440	0.93	Robbery		
			Theft Offences	550814	54.20	Domestic Burglary	43167	4.25
						Non Domestic Burglary	55801	5.49
						Residential Burglary	6238	0.61
						Business and Community Burglary	2674	0.26
						Vehicle Offences	103923	10.23
						Theft from the Person	23459	2.31
						Bicycle Theft	42926	4.22
						Shoplifting	106082	10.44
						All Other Theft Offences	166544	16.39
			Criminal Damage and Arson Offence	143369	14.11	Criminal Damage	136753	13.46
						Arson	6616	0.65
Non victim based crimes	104604	10.29	Drug Offences	44986	4.43	Trafficking of Drugs	6156	0.61
						Possession of Drugs	38830	3.82
			Possession of Weapons Offences	6601	0.65	Possession of Weapons Offences		
			Public Order Offences	38771	3.81	Public Order Offences		
			Miscellaneous Crimes Against Society	14246	1.40	Miscellaneous Crimes Against Society		
						Total	1016351	

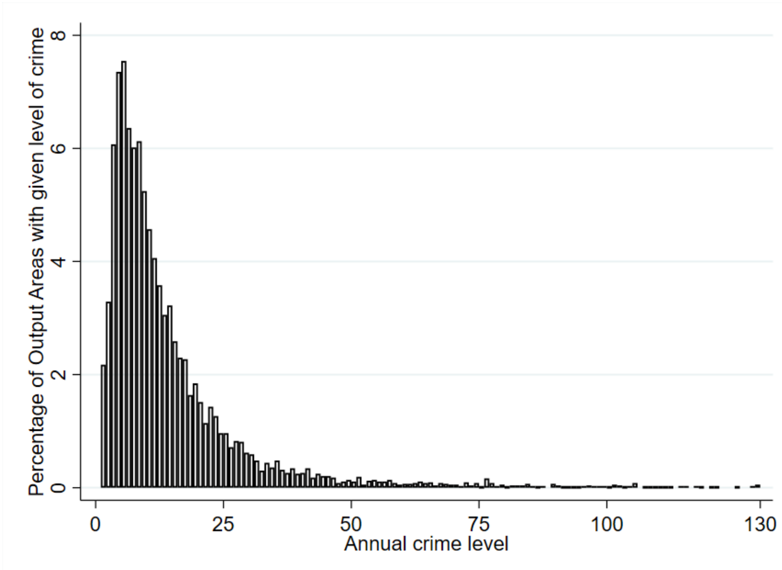
Previous to the current line-out of the crime tree there was a separate category of fraud (now labeled 'Fraud (historic)') with a total of 7490 reported crime during the period. This category is not listed on the tree.

Table 6: Mappiness sample in Thames Valley

	Freq.	%		Freq.	%
Response not in TV	1815729	94.8			
Response in TV	100594	5.25	From respondent living in TV	75996	75.5
	(5033)			(1476)	
			From respondent living outside of TV	14812	14.7
			Unknown home location	9786	9.7
Total	1916323			100594	

Respondent sample size in brackets underneath.

Figure 2: Distribution of the level of crime in Output Areas



Note: The annual average crime level in the top 1% of most crime-heavy OAs are not pictured for sensible visual representation. These 75 OAs' crime ranges from 130 to 1859, with some of the particularly high levels being due to the OA being a location where annual festivals or other mass events happen.

Table 7: Demographic characteristics of Mappiness participants and the population

	(1) Respondents who responded from TV	(2) Respondents living in TV	(3) Population characteristics
Female	49.1	51.8	55.9
Average age	34	34	48
Average number of adults in household	2.16		2.26
Average household income	57,955	59,075	22,375
Employed	81.5		59
Married	35.1		55.3
At least one child in household	29.2	34.75	32.3

Population characteristics are calculations by the author (except for income, see below), using the Understanding Society dataset, year 2011-2012.

Police Force Areas have different geographic borders to the nested statistical geography system of England, therefore demographic characteristics are not available at a level to contain only, and just only the exact area with a PFA. PFAs are however nested within regions, therefore these statistics are available at the level to represent the whole of the South East, which contains Thames Valley, alongside with Hampshire, Kent, Surrey, and Sussex.

Household income per head for the South East available from here: https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome/bulletins/ regionalgrossdisposablehouseholdincomegdhi/1997to2016

Table 8: Individual responses' exposure to crime in the response OA yesterday

	Violence	Sexual offenses	Robbery	Theft, burglary	Arson, criminal damage	Drugs	Weapons offenses	Public order offenses	Misc.
%									
No crime	97.4	99.7	99.8	91.0	98.2	99.2	99.9	98.5	99.7
1 crime	2.09	0.28	0.22	6.03	1.72	0.70	0.14	1.14	0.29
2 crimes	0.33	0.0080	0.015	1.50	0.088	0.099		0.24	0.0070
3 or more	0.14	0.0020		1.47	0.013	0.025		0.13	0.0040
Freq.									
No crime	98010	100305	100362	91539	98758	99761	100457	99070	100287
1 crime	2107	279	217	6065	1735	708	137	1147	296
2 crimes	336	8	15	1512	89	100		246	7
3 or more	141	2		1479	13	25		131	4
Total	100594	100594	100594	100595	100595	100594	100594	100594	100594

Table 9: Decomposition of violent and sexual crimes based on the presence of injury

	(1)
Violence with injury or sexual crime	1.009*
	(0.587)
Violence without injury	1.083
	(1.005)
Other crime	-0.862
	(1.018)
N	73670

Sexual crimes are not decomposed further, but considered an equally severe category to violence with injury. Excluding sexual crimes would result in identical estimates.
Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 10: Falsification test – Future crime's impact on current stress with crime measured at 5, 15, 30, and 90 days in the future

	(1)	(2)	(3)	(4)
	5	15	30	90
Violent or sexual crime	0.295	-0.479	0.207	0.194
	(0.388)	(0.420)	(0.516)	(0.370)
Other crimes	-0.0660	-0.152	-0.174	0.0435
	(0.259)	(0.247)	(0.236)	(0.254)
N	73670	73670	73670	73670

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 11: Violent and sexual crime in past 1 to 3 days and 4 to 7 days

	(1)
	feel_str
Violent or sexual crime at t-1 to t-3	1.109***
	(0.373)
Other crime at t-1 to t-3	0.0225
	(0.297)
Violent or sexual crime at t-4 to t-7	0.496
	(0.405)
Other crime at t-4 to t-7	-0.0302
	(0.260)
N	73670

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 12: Violent, sexual, and other crime in each of the past 7 days

	(1)
Violent or sexual crime at t-1	0.401
	(0.607)
Other crime at t-1	-0.456
	(0.304)
Violent or sexual crime at t-2	1.129*
	(0.591)
Other crime at t-2	-0.0254
	(0.357)
Violent or sexual crime at t-3	0.639
	(0.500)
Other crime at t-3	0.0284
	(0.301)
Violent or sexual crime at t-4	0.637
	(0.443)
Other crime at t-4	0.205
	(0.369)
Violent or sexual crime at t-5	-0.0402
	(0.582)
Other crime at t-5	-0.350
	(0.351)
Violent or sexual crime at t-6	0.465
	(0.446)
Other crime at t-6	0.198
	(0.296)
Violent or sexual crime at t-7	0.768
	(0.622)
Other crime at t-7	0.188
	(0.321)
N	74083

Standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 13: Activities' effect on individual stress levels

	(1)
Working, studying	4.022**
	(0.448)
In a meeting, seminar, class	1.901**
	(0.516)
Travelling, commuting	2.013**
	(0.387)
Cooking, preparing food	-0.751
	(1.664)
Housework, chores, DIY	2.031
	(1.693)
Waiting, queuing	2.667**
	(0.656)
Admin, finances, organising	2.030+
	(1.008)
Childcare, playing with children	-2.020*
	(0.838)
Pet care, playing with pets	-6.299**
	(1.222)
Carr or help for adults	5.738
	(3.550)
Sleeping, resting, relaxing	-6.190**
	(0.855)
Sick in bed	15.29**
	(3.145)
Talking, chatting, socalising	-4.136**
	(0.411)
Making love, intimacy	-7.910**
	(2.506)
Eating, snacking	-2.278**
	(0.486)
Drinking coffee, tea	-2.079**
	(0.318)
Drinking alcohol	-4.787**
	(0.766)
Watching TV, film	-6.314**
	(0.627)
Listening to music	-3.856**
	(0.714)
Reading	-3.222**
	(0.813)
Theatre, dance, concert	-5.104**
	(1.179)
Exhibition, museum, library	-6.366+
	(3.396)
Constant	33.70**
	(8.145)
N	26842

Model defined as Table 4, Model (5).

The full set of activities list is available upon request.