DISCUSSION PAPER SERIES

IZA DP No. 7545

Does Violent Crime Deter Physical Activity?

Katharina Janke
Carol Propper
Michael A. Shields

August 2013

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

Does Violent Crime Deter Physical Activity?

Katharina Janke
University of Bristol

Carol Propper
University of Bristol
and Imperial College London

Michael A. Shields
Monash University
and IZA

Discussion Paper No. 7545
August 2013

IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

IZA Discussion Paper No. 7545
August 2013

ABSTRACT

Does Violent Crime Deter Physical Activity?

Crime has been argued to have important externalities. We investigate the relationship between violent crime and an important type of behaviour: individuals' participation in their local area through walking and physical activity. We use a sample of nearly 1 million people residing in over 320 small areas in England between 2005 and 2011. We show that concerns about personal safety co-move with police recorded violent crime. To identify the causal effect of recorded violent crime on walking and other physical activity we control for individual-level characteristics, non-time varying local authority effects, national time effects and local authority-specific trends. In addition, we exploit a natural experiment that caused a sudden increase in crime – the 2011 England riots – to identify the causal impact of a large exogenous crime shock on physical activity in a triple difference framework. Our results show a substantive deterrent effect of local area violent crime on walking, pointing to important effects of violent crime on non-victims. The adverse effect of an increase in local area violent crime from the 25th to the 75th percentile on walking is equivalent in size to a 6°C fall in average minimum temperature.

JEL Classification: I12, I18, R23

Keywords: violent crime, walking, physical activity, riots

Corresponding author:

Carol Propper
University of Bristol
Bristol BS8 1TX
United Kingdom
E-mail: Carol.Propper@bristol.ac.uk

1 Introduction

It has been long recognised that crime can have externalities (Ayres and Levitt 1998). One important concern is the impact of crime on neighbourhood quality and community. Established negative externalities on neighbourhood include flight to the suburbs (Cullen and Levitt 1999, Ellen and O'Regan 2010), declining property values (Gibbons 2004), a reduction in the creation of new retail and personal service businesses (Greenbaum and Tita 2004) and geographical sorting of local businesses (Rosenthal and Ross 2010). In this paper we examine whether violent crime (which includes murder, manslaughter, knife attacks and aggravated assault) impacts on individuals' daily lives and their participation in the most common form of physical activity undertaken in their local area, walking. We also investigate the effect of violent crime on other forms of physical activity.

This is a substantive issue. First, violent crime is not uncommon. In our country of study, England, there are on average 730 police recorded offences of violent crime with injury per 100,000 local inhabitants each year during our sample period and violent crime accounts for approximately 10% of all recorded crime. Moreover, individuals tend to overestimate their chances of being a victim of violent crime.[1] Individuals get information about crime from the media (Duffy et al. 2008) and media reporting has been shown to be highly selective, focusing overwhelmingly on the most serious examples of crime and victimisation. In contrast, the lower-level property offences that make up the significant majority of recorded crime are given sparse attention, if not ignored altogether (Greer 2007).[2]

Second, walking is an important form of exercise. The importance of walking and other physical activity as a determinant of good health has been well established (U.S. Department of Health and Human Services 1996, World Health Organization 2002). Despite this, walking has been decreasing in many industrialised countries and this fall has been linked to the rise in obesity and obesity related diseases, many of which impose substantial costs on individuals and health care systems (Bassett et al. 2008, Lindström 2008).[3] Walking also has important externalities: individuals who walk in their local neighbourhood contribute to a sense of community (du Toit et al. 2007). But while concerns about personal safety are commonly cited in research as a barrier to local walking (Foster and Giles-Corti 2008), the literature to date has not found clear results for the relationship between crime and walking or physical engagement in the community. A detailed review concluded that this was partly as a result of non-causal design and small data sets (Foster and Giles-Corti 2008).

[1] For example, the United Kingdom Home Office reports that a survey in 2009/10 found that 15% of respondents said that they were 'very likely' or 'fairly likely' to be a victim of violent crime in the next 12 months, while according to the same survey only 3% of adults were victims of violent crime (Home Office 2010b).

[2] For example, from a detailed study of local print media in Australia, Cornaglia and Leigh (2011) found that over the period 2001 to 2006 there were 600 media mentions of violent crime in local papers each year, compared to 230 mentions for property crime.

[3] According to the UK's National Travel Survey the average number of walking trips was 292 trips per year in 1995/97, around 245 in the early 2000s and 222 in 2011 (Department for Transport 2012).

Our paper seeks to overcome these problems. We use a sample of nearly 1 million people in 323 small areas in England over six years. We match this to quarterly police recorded crime data at the small area level to examine the effects of recorded crime on walking and other types of common physical activity. England is a good test bed for several reasons. First, as noted above, violent crime is not uncommon in England. Second, walking is an important and common form of activity - in 2009, for example, 41% of individuals said they made walks of 20 minutes or more at least 3 times a week and an additional 22% said they did so at least once or twice a week. Walking is also often the only form of exercise that individuals do (NHS Information Centre 2011). Third, crime statistics are available at the small area (local authority) level and the six-year period covered by our data provides considerable variation in crime rates across time and space. Fourth, the English government collects information on physical activity on a consistent basis for a very large sample of adults every year, giving us a very large sample at the small area level.

These data provide an identification strategy in which we can control for small area effects, small area specific time trends, national time effects and a number of potential time-varying confounders such as small area unemployment and weather.[4] This enables us to capture contextual effects, general time effects and changes to the local infrastructure or policing that might confound the association between local crime rates and walking. To complement this analysis we exploit a natural experiment that caused a sudden increase in crime at the local level. In August 2011 riots spontaneously erupted in a small number of English urban areas. We use a triple difference design which exploits the fact that these crimes were very localised and occurred only for a few days during the summer of 2011.

We show that individuals' concerns regarding their personal safety positively co-move with recorded violent crime. An increase in recorded crime within a local area is statistically significantly associated with increased worry about being mugged or attacked and individuals equate increases in police recorded crime with their own assessment of crime changes. This supports our modelling assumption that increases in recorded violent crime in a local area induce greater concerns about personal safety, which in turn lead to individuals changing their physical activity behaviour. Our results show that increased violent crime in the local area leads to a statistically significant reduction in walking. In particular, individuals reduce walking at the intensive, rather than extensive margin, and reduce non-leisure walking more than leisure walking. This fits with a response to crime for an activity that takes place in the individual's local area and where crime or fear of it can be avoided by using alternative means of transport (public transport or a car). The adverse effect of an increase in local area violent crime from the 25^{th} to the 75^{th} percentile on walking is equivalent in size to the effect of a 6 °C fall in average minimum temperature at the local level. Our analysis of the riots supports these results, showing that physical activity falls following the sudden increase in local area crime. But we find interesting gender differences: females decrease participation while men

[4]For the relationship between weather and crime see, for example, Cohn (1990) and Jacob et al. (2007).

increase theirs.

Our analysis contributes to the literature on the wider detrimental impacts of crime on non-victims. Our paper is closest to a small number of papers that have examined the effect of crime risk on individuals' daily activities. Kling et al. (2001) found that parents living in areas of high crime tried to keep their children indoors to avoid them becoming victims of violence. Hamermesh (1999) found that victimisation risk affects working time patterns in the USA. Braakmann (2012) looked at responses to victimisation from crime in Mexico and at measures individuals take to protect themselves, such as stopping going out, changing routes or modes of transportation or starting to carry a weapon. He found that individuals do respond, but also that women respond differently from men. Women were more likely to change their mode of transport and adopt other avoidance strategies, whilst men were more likely to carry a weapon and to go out more. We also link to studies which have found an impact of crime on health, both physical and mental. Sundquist et al. (2006) report an association between area-level violent crime and coronary heart disease and Messer et al. (2006) find an association with preterm birth and low birth weight. For Australia, Cornaglia and Leigh (2011) find there are significant effects of both recorded violent crime and media reports of violent crime on reductions in mental wellbeing. For Britain, Dustmann and Fasani (2012) identify a substantive effect of both property crime and violent crime on mental distress. Finally, there are also a number of papers that estimate subjective wellbeing and behavioural impacts of high profile acts of violence, including the September 11 terrorist attacks (Metcalfe et al. 2011) and the London bombings in 2005 (Rubin et al. 2005, Dustmann and Fasani 2012).

The paper is structured as follows. In Section 2 we describe our data and also provide an analysis of the relationship between changes in police recorded violent crime and individuals' concerns about their own personal safety. Section 3 presents our main empirical identification strategy. Section 4 presents our main estimates, sub-group analyses and robustness tests. Section 5 describes our analysis of the impact of the 2011 English riots. Section 6 concludes.

2 Data

2.1 The sample and our physical activity measures

Our data are from the Active People Survey (APS), a cross-sectional survey of adults in England designed explicitly to measure levels of participation in sport and active recreation at the local level (data sources are in Appendix Table A-1). The survey contains detailed measures of participation in physical recreation and sport undertaken in the last four weeks prior to interview as well as a wide range of individual and household level demographic and socio-economic characteristics.[5]

[5]The survey is commissioned by Sport England. Interviews are spread evenly across the 12 months of each survey period and are conducted by telephone using Random Digit Dialling. The CATI system randomly selects one person aged 16 or over from the eligible household members. The average response rate is 25%. Various piloting stages ensure quality data.

To date, five waves of data have been released for analysis, covering the period October 2005 to October 2011.[6] The first four waves of the survey cover all 354 local authorities in England. These are the primary unit of local government , responsible for provision of a range of services, including education, public housing, social services and leisure and recreation services.[7] The number of local authorities was reduced to 326 in 2009 following local government reorganisation and we match the 354 authorities into their 326 counterparts (most local authorities did not change). This gives us a total pooled sample of 1,104,155 individuals aged 16 and above residing in 326 areas.

We undertake various deletions. We omit three local authorities (the Isles of Scilly and the City of London because of their small populations and the London Borough of Westminster because of its very high crime rate, which is due to the difference between the resident and the daytime population, a high proportion of whom are tourists). We exclude respondents falling into the age group 16 to 24 (as many of these are students who tend to live away from home during term time, making assigning the correct crime measure difficult) and respondents aged 75 or over (as their walking ability might be low). After eliminating respondents with missing values for our outcome variables, we are left with a working sample of 893,075 adults in 323 local authorities over a period of 22 quarters.

Our main outcome variable is the number of days in the last four weeks the respondent has walked for at least 30 minutes. At the start of the interview respondents are asked about their recent walking activities: "I would like you to think about all the walking you have done. Please include any country walks, walking to and from work or the shops and any other walks you may have done. Please exclude time spent walking around shops. In the last four weeks, that is since ... have you done at least one continuous walk lasting at least 5 minutes?" This question also identifies individuals who are unable to walk (1.4% of respondents). Next, the interviewer asks "In the last four weeks, that is since ... have you done at least one continuous walk lasting at least 30 minutes?" followed by "On how many days in the last four weeks have you walked for at least 30 minutes?". We use the responses to these two last questions to construct a variable indicating the number of days in the last four weeks on which the respondent has walked for 30 minutes or more.[8]

We also split the 30 minute variable into leisure and transport walking. After a question about usual walking pace, the interviewer asks "Can I ask, on how many of those days were you walking for the purpose of health or recreation not just to get from place to place?" We define the number of days given in response to the question about walking for health or

[6](The survey did not run October 2006 to October 2007). APS1 (October 2005 to October 2006), APS2 (2007 to 2008), APS3 (2008 to 2009), APS4 (2009 to 2010) and APS5 (2010 to 2011). APS1, n = 363,724; APS2, n = 191,325; APS3, n = 193,947; APS4, n = 188,354 and APS5, n = 166,805. APS5 differed to APS1-4 in that certain questions about socio-economic status are randomly asked of 50% of the sample, including household income and car ownership.

[7]Local authorities vary in population but most have populations of 60,000 to 300,000.

[8]Ideally, we would have information about walks of shorter duration, such as at least 10 or 20 continuous minutes of walking. However, the only alternative measure in APS is the yes/no response to the question listed above about any continuous walking lasting at least 5 minutes in the last four weeks.

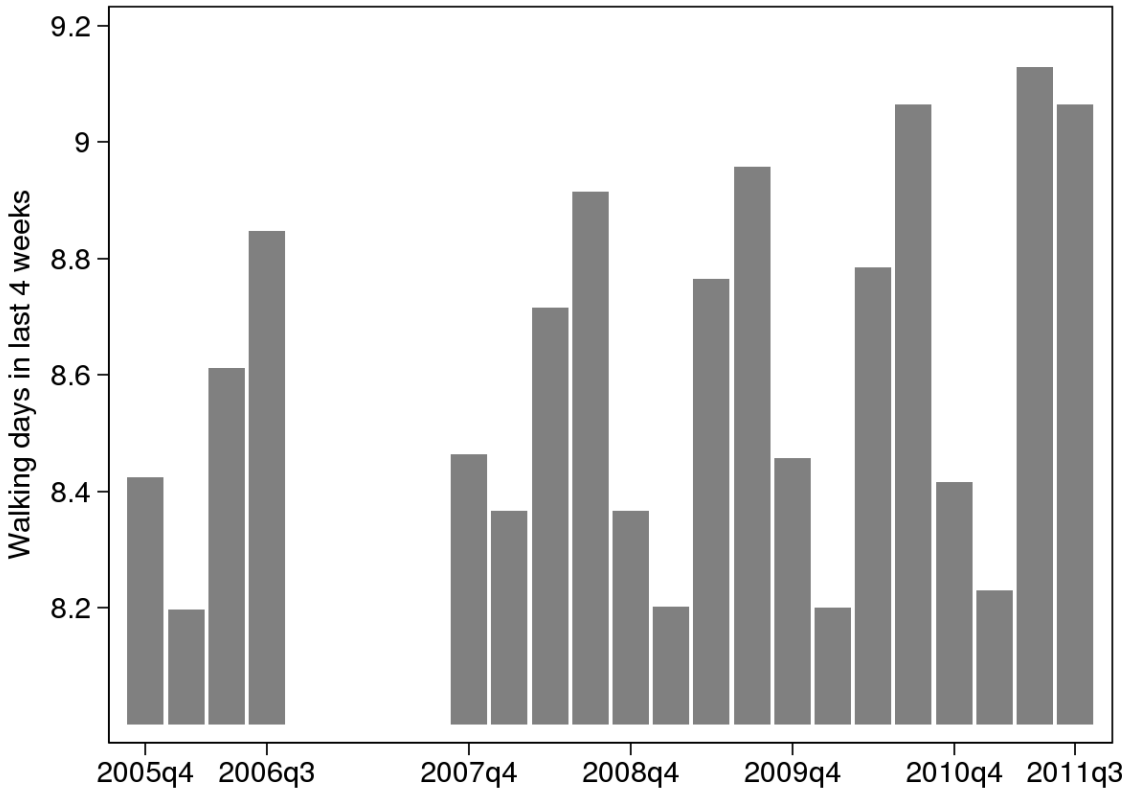

Figure 1: Quarterly means of walking days in last 4 weeks

recreation purposes as leisure walking days and construct a measure of transport walking days by subtracting leisure walking days from all walking days.[9]

Table 1 shows that the sample average is 8.6 days of walking for at least 30 minutes over the past four weeks, with more walking for leisure (5.8 days) than for transport (2.8 days). A significant number of individuals report not to have walked continuously for at least 30 minutes in the last four weeks, which highlights the health concerns arising from the sedentary nature of the English population. Figure 1 shows the quarterly distribution of mean walking days over the whole sample period. We see a strong seasonal pattern: walking is lowest in the winter months (the last and first quarters of the year) and highest in the summer (quarter 3). There is also an upward trend in the amount of walking.

The APS also collects data on other types of sport and physical recreation that respondents have participated in over the last four weeks. The survey records over 400 different activities although, for many of these, very few respondents report participation. The most common activities are cycling, swimming, going to the gym, football, aerobics and racket sports. Individuals report on how many days in the last four weeks they undertook each type

[9]Respondents might interpret "for the purpose of health or recreation" in a way that counts transport walking as leisure walking.

of activity. There is no minimum participation time (unlike the 30 minutes for the walking measure), with the exception of cycling, which is reported only for spells of 30 minutes or more. We summed the number of days across all types of activity to obtain a measure of other physical activity excluding walking. Table 1 shows the mean of this variable is 5.4 episodes in the past four weeks.

Table 1: Descriptive statistics

Variable	Mean	St. dev.	25^{th} perc.	Median	75^{th} perc.
Outcome variables (N = 893,075)					
Walking days in last 4 weeks					
All	8.59	9.9	0	4	14
Transport	2.83	6.2	0	0	2
Leisure	5.77	8.6	0	2	8
Other physical activity episodes	5.42	9.1	0	0	8
Local authority variables					
(N = 7,093, n = 323, $\bar{t}$ = 21.96)					
Number of offences per 1,000 population					
Violent crime with injury	7.32	3.3	4.8	6.8	9.3
Between		3.0			
Within		1.4			
Remaining offences	71.81	27.6	51.5	65.7	86.9
Between		25.5			
Within		10.4			
Unemployment rate	5.8	2.3	4.1	5.4	7.1
Between		1.9			
Within		1.3			
Weather variables					
(N = 376,918, n = 323, $\bar{t}$ = 1,166.9)					
Rainfall (mm)	2.1	1.3	1.1	1.8	2.7
Maximum temperature (°C)	14.1	5.8	9.0	14.6	19.0
Minimum temperature (°C)	6.5	4.5	2.5	6.5	10.5

2.2 Police recorded crime

Our crime measures are derived from quarterly police recorded crime data at local authority level. The data contain the number of offences notifiable to the Home Office in 10 major categories (violence against the person, sexual offences, robbery, burglary, offences against vehicles, other theft offences, fraud and forgery, criminal damage, drug offences, other miscellaneous offences). We create quarterly rates per 1,000 population using National Statistics mid-year population estimates. We then assign to each APS survey respondent the sum of the quarterly rates in the four quarters preceding the interview quarter. As most people expe-

rience crime only indirectly, updating of beliefs about crime prevalence is likely to take longer than one quarter. Additionally, changes in the quarterly crime rate may be due to chance rather than systematic changes in crime prevalence, increasing measurement error. Summing over the previous four quarters cancels out random errors. In Section 4.4.1 we examine the robustness of our results to alternative definitions of the crime measurement period.

As our crime variable we use police recorded violent crime with injury.[10] Violence against the person with injury includes homicide, causing death by dangerous driving, grievous bodily harm and actual bodily harm. For most people the main information source on crime is the local and national media and as noted in the Introduction, violent crime dominates media reporting on crime (Williams and Dickinson 1993, Chermak 1994, Cornaglia and Leigh 2011). It seems reasonable to assume that individuals focus more on this type of crime, rather than on violent crime without injury or property crime, when evaluating the security aspects of their walking decision. Violent crime has also been shown to have the most effect on mental illness by Cornaglia and Leigh (2011) for Australia and to have similar effects to property crime in Dustmann and Fasani (2012) study of crime and mental ill health in English urban areas. We use all other crime as a control to capture changes in recording practices, technological change in crime fighting and changes in policing practices at local authority level that might confound the relationship between violent crime and walking.[11]

2.3 The relationship between recorded violent crime and concerns about personal safety

The number of police recorded violent offences with injury can affect individuals' walking decisions only if it affects their perceived probability of becoming a victim of crime in their local area. To test this key assumption, we examine the relationship between police recorded crime and survey data on perception of crime and worry about crime. As the APS does not contain any information on respondents' concerns about personal safety in their local area we analyse the relationship between police recorded violent crime and perception of and worry about crime using data from the British Crime Survey (BCS).

The BCS is a household survey conducted annually of around 45,000 respondents. Respondents are asked:

- "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?" with answers on a five point

[10] A common criticism leveled at police recorded crime is that it does not reflect the true extent of crime as it contains only crimes that have been discovered, reported to the police and then recorded by the police (Coleman and Moynihan 1996). However, for the crimes that we expect to determine individuals' perceived probability of becoming a victim of crime while walking - violence against the person with injury - police recorded crime provide reasonable coverage (Coleman and Moynihan 1996).

[11] For example, the Police Reform Act 2002 introduced Police Community Support Officers (PCSOs), who have limited powers and whose main role is to provide a visible and reassuring presence on the streets. Employment of PCSOs varies across police force areas. The Metropolitan Police Service (responsible for law enforcement in Greater London) recruited the first PCSOs in September 2002 and still has the highest contingent of PCSOs (Johnston 2006).

scale running from "A lot more crime" to "A lot less crime". We construct a binary variable that takes the value 1 if the respondent answers "a lot more crime" or "a little more crime" and 0 otherwise.

- "How worried are you about being mugged and robbed?" and "How worried are you about being physically attacked by strangers?" with answers on a four point scale from "very worried" to "not at all worried". We construct a binary variable that takes the value 1 if the respondent answers very worried or fairly worried and 0 otherwise.

We use the 2005-06, 2006-07 and 2007-08 waves of the BCS as these identify the 38 police force areas of residence of the respondent. We assign to each respondent the violent crime with injury rate in the police force area of residence over the four quarters preceding their interview quarter.

Table 2: Linear probability models of relationship between police force area rate of violent crime with injury and perception of crime

	Crime up	Worry mugged	Worry attack
Without area effects	0.012	0.141***	0.117***
	(0.031)	(0.037)	(0.033)
With area effects	0.097***	0.045***	0.047**
	(0.029)	(0.013)	(0.018)
Mean of dependent variable	0.40	0.35	0.34
Areas	38	38	38
Observations	84,050	103,000	102,995

Coefficient on log violent crime with injury shown, with robust standard errors in brackets, clustered by police force area. All coefficients from separate regressions. All regressions include individual-level controls for gender, age, ethnicity, highest educational attainment, employment status, an indicator for a limiting long-standing illness or disability, family structure, household income, an indicator for living in social rented housing and an indicator for car in household. *Significant at 10%, **significant at 5%, ***significant at 1%

To examine the relationship between recorded crime and concern about crime we estimate linear probability models of the relationship, at police force area level, between our recorded violent crime with injury variable and perception of and worry about crime. We condition on a similar set of individual-level demographic and socio-economic controls to those in the APS (discussed in Section 2.4: the means of BCS controls are in Table A-3 in the Appendix). The coefficients on the (log of the) violent crime rate are presented in Table 2. The results in the first row are without police force area effects, while those in the second row include police force area effects. The first column shows that cross-sectionally there is no association between the violent crime rate and a perceived increase in crime but, within police force area, there is a strong association between violent crime and the perception of crime. Respondents do not, therefore, confuse living in a high crime area with a rise in crime in their area. A rise in reported crime in the local area from the 25^{th} to the 75^{th} percentile increases the

probability of reporting an increase in crime by 3 percentage points ($0.35 * 0.097 = 0.034$). Both variables measuring worry about crime are correlated cross-sectionally and within police force areas with recorded crime. These results provide empirical support for our assumption that the perceived probability of becoming a victim of crime depends on the number of police recorded offences in the local area.

2.4 Individual and household level controls

The APS collects information about a wide range of individual and household-level characteristics. When selecting controls we wished to control for individuals' time and income constraints. As proxies for time endowment we use dummy variables indicating the respondent's employment status (working full-time, working part-time, unemployed less than 12 months, unemployed more than 12 months, retired, not working because of children, not working because of disability, student, other) and family structure (single adult, children aged 0 to 4, 5 to 10, 11 to 15). Dummies for household income in six bands and an indicator for living in public (social rented) housing serve as proxies for the respondent's budget.

Education is likely to affect the demand for walking, either through its relationship with time preference or through its effect on the efficiency of the health production process (Grossman 2006). We therefore control for the respondent's highest educational attainment, gender and ethnicity. Car ownership is likely to be another important determinant of walking, so we include a dummy indicating whether a car is available for use by the respondent or other members of the household. We also control for respondents' age (in five ten-year bands beginning at age 25) and for a dummy variable indicating whether the respondent had a limiting long-standing illness or disability. Finally, we control for the day of the week the interview took place.

Where there are missing values for the covariates we include indicator variables to control for this non-response. We add a separate dummy variable indicating missingness due to certain questions not being asked in APS5. Summary statistics for these controls are in Appendix Table A-2.

2.5 Area-level controls

To capture local economic conditions that might be correlated with local crime and potentially make the local environment more or less attractive for walking, we use unemployment rates for the four quarters preceding the interview. We also control for weather conditions. Using data from the UK Meteorological Office we calculate the inverse-distance weighted mean of daily maximum temperature, daily minimum temperature and daily precipitation measured at the weather stations within a 30 km radius (20 km for precipitation) around the local authority's centroid over the four week period preceding the interview.[12] Descriptive statistics for these

[12]For details, see Appendix Table A-1

variables are presented in Table 1.

3 Empirical strategy

3.1 Estimation equation

To identify the causal effect of violent crime on walking we exploit quarterly within area variation in our data. We estimate:

$$Physical\ activity_{iat} = \beta \sum_{j=1}^{4} crime_{a(t-j)} + \boldsymbol{X}'_{at} + \boldsymbol{Z}'_{iat}\boldsymbol{\theta} + \lambda_t + \alpha_a + \delta_a t + \varepsilon_{iat} \qquad (1)$$

Our main measure of physical activity is the number of days in the last four weeks on which individual i in local authority a interviewed in time period t has walked continuously for at least 30 minutes. We also analyse walking days separated into leisure and transport walking days and the total number of physical activity episodes other than walking (e.g. cycling, swimming, gym, aerobics, golf, tennis) in the last four weeks. Time period t is a calendar quarter. The explanatory variable of interest is $\sum_{j=1}^{4} crime_{a(t-j)}$, police recorded crime in local authority a in the previous four quarters. A full set of time effects, λ_t, provides non-parametric control for trends in crime and walking that are national in scope. Local authority effects α_a control for non-time varying unobserved differences between local authorities and local authority-specific time trends $\delta_a t$ parametrically control for deviations from national time effects. $\boldsymbol{X}'_{at}$ and $\boldsymbol{Z}'_{iat}$ are vectors of local authority and individual-specific controls, respectively, as discussed in Sections 2.4 and 2.5. We estimate robust standard errors that allow for clustering at the local authority level.

3.2 Test of difference-in-difference estimation strategy

As deviations in the violent crime rate from the quarterly national average, the local authority average and the local authority specific trend are unlikely to be correlated with omitted factors, our design should recover the causal effect of violent crime on walking. We examine this further here. Our estimation method is akin to a difference-in-difference strategy. Formally, Equation 1 would be the same as a difference-in-difference if we had only two periods (first difference) and two areas (second difference). In our implementation we have 22 quarters and 323 local authorities, which increases our ability to identify the causal effect of crime on walking. To test whether the difference-in-difference assumptions are satisfied, we examine the relationship between the observed baseline conditions and subsequent changes in the violent crime rate. An association between crime growth rates and baseline conditions after controlling for local authority effects, year-quarter effects and local authority-specific time trends may indicate that local authorities that differ in terms of crime growth also differ in terms of time-variant

Table 3: Association between growth rate of violent crime and lagged level of covariates, lagged walking and lagged violent crime rate. Dependent variable is quarterly growth rate of violent crime with injury rate.

	Lagged covariates			Walking and crime variables			
	Individual controls	Local authority controls	All controls	Lagged walking days	Change in walking days	Lagged violence with injury	Change in violence with injury
	(1)	(2)	(3)	(4)	(5)	(6))	(7)
F-statistic	0.75	1.02	0.78				
p-value	0.89	0.39	0.87				
Coefficient				0.001	0.001	−0.273	0.006
				(0.001)	(0.000)	(0.008)	(0.013)
Observations	6,447	6,447	6,447	6,447	6,124	6,447	6,124

Each column reports results from a separate regression of the growth rate of violent crime $[log(crime_{a(t+1)}) - log(crime_{at})]$ on the relevant variables. Columns 1, 2 and 3 report tests for the joint significance of lagged covariates $[\boldsymbol{X}'_{a(t-1)}$ and $n^{-1}\sum_{i=1}^{n}\boldsymbol{Z}'_{ia(t-1)}]$. Column 4 reports the coefficient on $n^{-1}\sum_{i=1}^{n} walking_{ia(t-1)}$, Column 5 the coefficient on $\overline{walking}_{a(t-1)} - \overline{walking}_{a(t-2)}$, Column 6 the coefficient on $log(crime_{a(t-1)})$ and Column 7 the coefficient on $log(crime_{a(t-1)}) - log(crime_{a(t-2)})$. Standard errors in brackets. All regressions include local authority effects, year-quarter effects and local authority-specific trends. 323 local authorities in all regressions.

unobserved factors.

Table 3, Columns 1 to 3, presents the regressions of crime growth between $(t+1)$ and t on blocks of the individual and local authority covariates, separately and jointly, in $(t-1)$. As crime growth is measured at local authority level, we aggregate the individual-level data to local authority-quarter level. The results show no significant association between the baseline conditions (separately or jointly) and crime growth. In Columns 4 and 5 we check for any association between future crime growth and levels and changes in past local authority-quarter means of reported walking days. We see that neither are statistically significantly associated with subsequent crime growth. In Column 6 we examine the relationship between crime growth and the past level of crime. The coefficient on the lagged level of crime is negative and statistically significantly different from zero, suggesting that in local authorities with higher baseline levels of crime the crime rate dropped more sharply. However, Column 7 shows that lagged crime growth is not associated with subsequent crime growth. In sum, these tests provide support for our identification strategy.

4 Results

4.1 Preliminary data description

We begin by presenting patterns in the data. We map the sample means of our two key variables, number of days walking continuously for at least 30 minutes in the last four weeks and violent crime with injury rates in the preceding four quarters, at local authority level. The left hand side of Figure 2 maps crime, with areas with least crime in white and most crime in black. The map shows that crime is higher in urban areas (the darker areas in the central parts of the country) but also in several local authorities along the south coast of England. The right hand side map shows walking, with areas with more walking in white and least walking in black. It shows that walking is higher in rural areas (the extreme North of England, the South West peninsular and the rural local authorities on the Welsh border). The maps also provide some pictorial evidence that areas with higher crime rates have lower walking rates (visually mainly in the northern half of England).

4.2 Main results

To examine this relationship more robustly, we begin by estimating the simple correlation between the local authority rate of violent crime with injury and the number of days walking continuously for at least 30 minutes in the last four weeks (essentially what is seen by comparing the maps in Figure 2). Column 1 in Table 4 presents the coefficient on the log of the violent crime rate in an OLS regression with no controls. This shows a statistically significant negative association.

Columns 2 to 4 present results from regressions that sequentially add individual-level controls, local authority and time effects, and local authority controls and local authority-specific

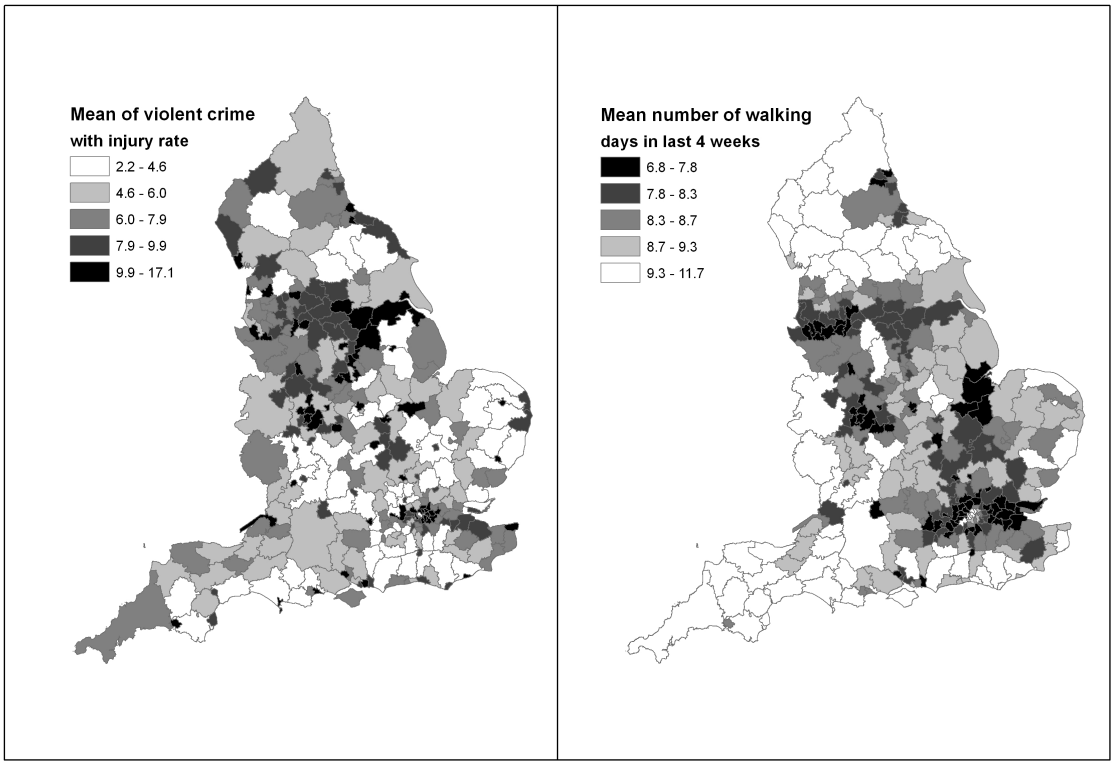

Figure 2: Local authority means of violent crime with injury rate and number of walking days in last 4 weeks

Table 4: Estimates of the effect of local authority rate of violent crime with injury on number of days walking in last four weeks

	1	2	3	4
Log(violent crime with injury)	-0.708^{***}	-0.584^{***}	-0.296^{***}	-0.487^{***}
	(0.090)	(0.085)	(0.106)	(0.168)
Log(other crime)				0.259
				(0.276)
Log(unemployment)				0.039
				(0.139)
Rainfall				-0.043^{***}
				(0.011)
Maximum temperature				0.022^{*}
				(0.012)
Minimum temperature				0.048^{***}
				(0.015)
Individual controls	No	Yes	Yes	Yes
Local authority effects	No	No	Yes	Yes
Time effects	No	No	Yes	Yes
LA-specific trends	No	No	No	Yes
R-squared	0.001	0.026	0.033	0.034

Robust standard errors in brackets, clustered by local authority. Individual-level controls are gender, age, ethnicity, highest educational attainment, employment status, an indicator for a limiting long-standing illness or disability, family structure, household income, an indicator for living in social rented housing and an indicator for car in household. 893075 observations in 323 local authorities in all regressions. *Significant at 10%, **significant at 5%, ***significant at 1%

trends. Adding individual-level controls reduces the coefficient on the crime rate by around 20%. Controlling for local authority and time effects nearly halves the coefficient. Adding local authority controls and local authority-specific trends in Column 4 – the specification in Equation 1 – increases the coefficient on the crime rate by 60% to 0.49. The effect of the controls is as follows. Neither the local authority unemployment rate or the all other crime rate is statistically significant, suggesting that our time and local authority effects control for unobserved factors that may be associated with both overall crime levels and unemployment. However, the weather controls are statistically significant. Rainfall reduces walking while temperature rises (in both the lowest and the highest temperatures) increase walking. Both of these accord with intuition: walking in the rain and the cold is less pleasant.

To gauge the economic significance of our results, we calculate the predicted change in the number of days walking as a result of a fall in the crime rate from the 75^{th} to the 25^{th} percentile. This is equal to a fall of 0.66 points in the log crime rate, so a fall of this size leads to a fall of 0.32 walking days (= 0.66 x 0.487). This is equivalent to a 4% increase at the sample mean of 8.6 walking days. In comparison, an increase in the average minimum temperature from the 25^{th} to the 75^{th} percentile results in a predicted increase in walking days of 0.38. For the average maximum temperature the predicted increase is 0.22 walking days.[13] Therefore, the impact of violent crime on the number of walking days is comparable to the impact of temperature.

In Table 5 we look separately at the effects of violent crime on transport and leisure walking. We use the specification of Equation 1. Row 1, column 1, reproduces our baseline estimate from the final column of Table 4. Row 1, columns 2 and 3 separately examine transport and leisure walking. The crime coefficient in the transport walking regression is twice the size of the coefficient in the leisure walking regression. Moreover, it is statistically significant at the 1% level in the transport walking regression but insignificant in the leisure walking regression. It seems sensible that transport walking is more affected by the local violent crime rate, as people are likely to walk for leisure both in and away from their local area, whilst transport walking takes place locally from place of residence. The predicted increase in transport walking days as a result of a drop in the violent crime rate from the 75^{th} to the 25^{th} percentile is 0.21 days, a 7% increase at the mean of 2.83 transport walking days.

We also explore whether the effects of violent crime occur at the extensive (any walking) or the intensive margin (the amount of walking, conditional on walking for 30 minutes on at least one day in the last four weeks). Row 2 of Table 5 presents results for a linear probability

[13] As previously noted, in addition to the question about the number of days on which respondents walked continuously for at least 30 minutes in the last four weeks, respondents were first asked if they have walked continuously for 5 minutes (yes or no) in the last four weeks. We have estimated a linear probability model for this binary measure of walking using the main specification in Equation 1. The coefficient on log(violent crime with injury) is –0.001 (s.e. = 0.004). We have also estimated the main model in Column 4 of Table 4 excluding respondents that indicated they are unable to walk. Our results are not substantively changed since we control for having a limiting health condition in our main specification. The coefficient on log(violent crime with injury) is –0.497 (s.e. = 0.171, N = 880,622).

Table 5: Estimates of the effect of local authority rate of violent crime with injury on physical activity by type and margin

	All walking	Transport walking	Leisure walking	Other phys. act.
No. of days/episodes	−0.487***	−0.325***	−0.164	−0.051
	(0.168)	(0.095)	(0.153)	(0.138)
Extensive (0,1)	−0.006	−0.021***	0.008	−0.004
	(0.007)	(0.007)	(0.008)	(0.008)
Intensive (1-28/200)	−0.590***	−0.455*	−0.421*	0.008
	(0.188)	(0.240)	(0.219)	(0.230)
	[643,588]	[281,231]	[507,146]	[429,611]

Coefficient on log violent crime with injury shown, with robust standard errors in brackets, clustered by local authority. 893,075 observations in 323 local authorities in all regressions in Rows 1 and 2, observations for regressions in Row 3 in [square brackets]. All walking, transport walking and leisure walking are number of respective walking days in last four weeks, other physical activity is number of episodes doing physical activities other than walking in last four weeks. All regressions include local authority effects, year-quarter effects and local authority-specific trends as well as controls for all other crime, unemployment, rainfall, daily maximum and minimum temperature and individual-level controls for gender, age, ethnicity, highest educational attainment, employment status, an indicator for a limiting long-standing illness or disability, family structure, household income, an indicator for living in social rented housing and an indicator for car in household. *Significant at 10%, **significant at 5%, ***significant at 1%

model with the full set of controls used in Row 1 in which the dependent variable takes the value 1 if the respondent reports one or more walking days and 0 otherwise. Overall, the crime rate does not seem to affect the extensive margin for all types of walking. However, the coefficient is negative and statistically significant for transport walking, though small in magnitude. Row 3 shows that the main impact of crime is at the intensive margin. We find statistically significant negative effects at the intensive margin for all walking and transport and leisure walking separately. Using the 75^{th} to 25^{th} percentile contrast, the predicted increase in walking is 0.4 days, which is a relatively large increase of 3.4% at the mean of 11.9 walking days for those individuals who do walk. The percent change in walking days is similar to the predicted increase of 4% for the full sample. Overall, these results suggest that violent crime affects walking mainly at the intensive margin, with some evidence for an effect also at the extensive margin for transport walking.

The last column of Table 5 investigates the relationship between violent crime and other types of physical activity excluding walking. All coefficients – for the total number of activity episodes in the last four weeks, the extensive and the intensive margin – are close to zero. As much of this activity is either indoors (gym, swimming) or in activities which may be located away from the local area of residence (cycling) the smaller impact of the local crime rate makes sense.

4.3 Sub-group analyses

The literature suggests that individuals differ systematically in their perceptions of crime in their neighbourhood. Women and individuals with children have been shown to perceive more crime than their neighbours (Hipp 2010) and older individuals to perceive less crime (Hipp 2010, Sampson et al. 1997). Thus there may be heterogeneity in responses to local crime rates. To examine this we re-estimate our main model for a number of sub-groups. The results are presented in Table 6.

We examine splits by gender, age, age of children in household, being in public housing, having a car in the household, urban and rural location, and by living in Greater London or outside Greater London. The results show differences across sub-groups. Males react more strongly than females, the coefficient for males being around twice the size of that for females; there is a clear gradient in age; respondents with teenage children respond more to violent crime than respondents without children; those in public housing are more affected than those in other forms of housing; those without access to a car react more than those without; those who live in urban areas react more than those in rural areas and those who live in Greater London react more than those who live outside London.[14]

With the possible exception of the male-female differences, these differences are expected. Even though older people perceive less crime, they have been shown to be more fearful of crime (Box et al. 1988). Individuals with children perceive more crime and are also more fearful (Ross and Jang 2000), possibly because of altruistic fear.[15] Individuals in public housing are in more deprived neighbourhoods in which crime and its effects may be more apparent. Individuals with access to cars can get away from local conditions more easily, so react less to local crime. Individuals in urban areas (and particularly in London because of higher road congestion and better public transport) are more likely to walk for transport reasons and therefore are more likely to react to changes in crime.[16] Finally, despite the fact that women are more fearful of crime, it is actually men who are more affected by violent crime and this may explain the male-female difference.[17]

[14]The differences between types are not statistically significant because the standard errors are relatively large. The t-statistics for differences are: men vs women (–1.14); respondents aged 65 to 74 compared to those aged 25 to 44 (–1.23); respondents with teenage children compared to those without children (1.59); social housing vs not in social housing (–0.77); no car vs car (1.42); urban vs rural (–0.67); London vs outside London (–1.44).

[15]Warr and Ellison (2000) show that parents' worry about their children's safety is highest for the age group 1 to 5 years. However, for sons worry is higher for the age range 11 to 15 years than 6 to 10 years. For daughters, worry tends to be higher at all ages, apart from the age range 11 to 15 years, when the proportion of survey respondents who are 'very concerned' is nearly identical for sons and daughters.

[16]The sample mean of transport walking days is 3.2 for respondents in urban areas and 2.6 for rural areas. For the London/outside London sample split the difference is more pronounced: 4.0 mean transport walking days in London and 2.7 outside London.

[17]Men are up to three times as likely as women to be a victim of violent crime (Home Office 2010a).

Table 6: Estimates of the effect of local authority rate of violent crime with injury on number of days walking in last four weeks by subgroup

	Estimate	Mean	N
Male	−0.713***	8.02	362,780
	(0.269)		
Female	−0.327	8.99	530,295
	(0.204)		
Age 25 to 44	−0.386	8.72	342,682
	(0.238)		
Age 45 to 64	−0.419*	8.70	395,856
	(0.235)		
Age 65 to 74	−0.946**	8.04	154,537
	(0.390)		
No children	−0.524**	8.53	632,692
	(0.203)		
Youngest child under 4 years	−0.340	8.46	100,596
	(0.464)		
Youngest child 5 to 10 years	0.217	8.80	91,934
	(0.501)		
Youngest child 11 to 15 years	−1.546**	9.17	65,780
	(0.610)		
Not in social housing	−0.395**	8.69	771,650
	(0.173)		
Social rented	−0.862	7.92	102,065
	(0.583)		
Car in household	−0.412**	8.48	695,565
	(0.195)		
No car in household	−1.181**	9.23	122,186
	(0.503)		
Urban area	−0.585**	8.10	325,688
	(0.248)		
Rural area	−0.367*	8.88	567,387
	(0.209)		
London	−1.502**	8.24	82,329
	(0.733)		
Outside London	−0.420**	8.63	810,746
	(0.172)		

Coefficient on log violent crime with injury shown, with robust standard errors in brackets, clustered by local authority. All regressions include local authority effects, year-quarter effects and local authority-specific trends as well as controls for all other crime, unemployment, rainfall, daily maximimum and minimum temperature and individual-level controls for gender, age, ethnicity, highest educational attainment, employment status, an indicator for a limiting long-standing illness or disability, family structure, household income, an indicator for living in social rented housing and an indicator for car in household. *Significant at 10%, **significant at 5%, ***significant at 1%

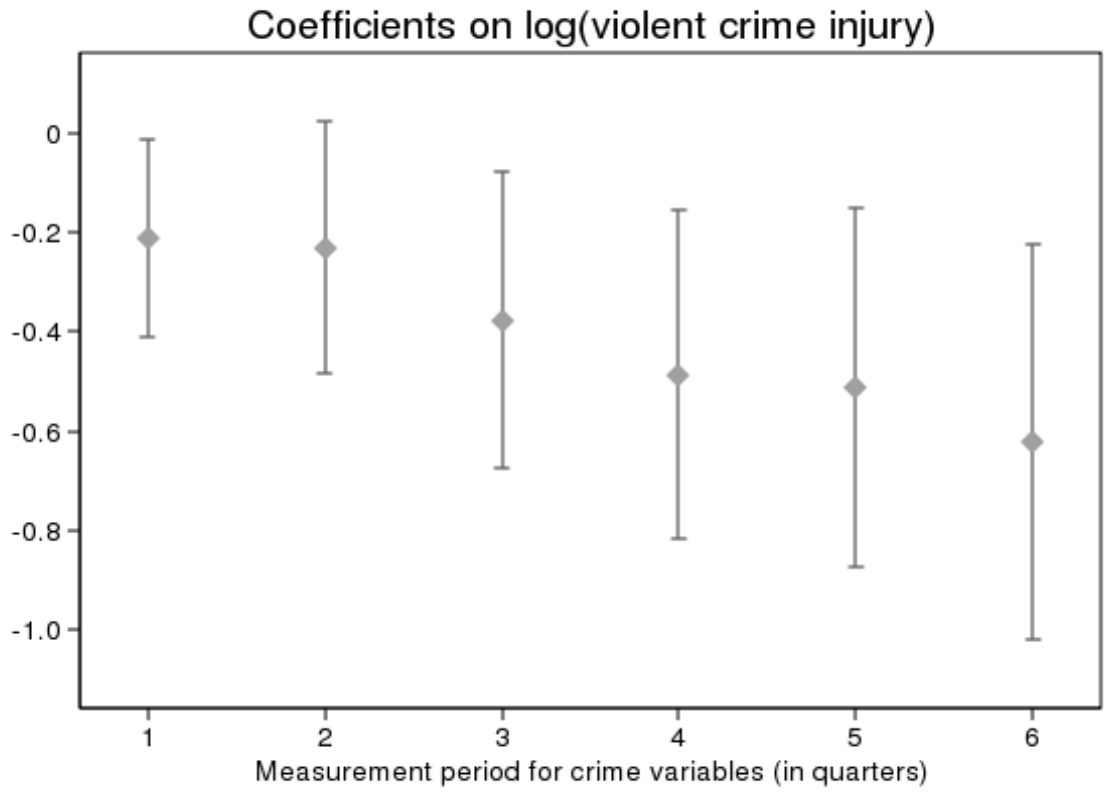

Figure 3: Estimates for different measurement periods for crime variable: Coefficients on log(violent crime injury) and 95% confidence intervals

4.4 Robustness tests

In this section, we examine the robustness of our results to changes in exactly how the crime and walking variables are measured.

4.4.1 Crime measurement period

Our measure of crime is the sum of the quarterly rates in the four quarters preceding the interview quarter. To explore the sensitivity of our results to different definitions of the crime measurement period, Figure 3 reports the crime coefficients and 95% confidences intervals from six different regressions. The first regression uses only the crime rate in the quarter preceding the interview, the second regression the sum of the crime rates in the two quarters preceding the interview and so on, with the sixth regression using the sum of the crime rates in the six quarters preceding the interview. To make coefficients comparable, we annulise the crime measures, i.e. we multiply the one-quarter measure by 4, the two-quarter measure by 2, the three-quarter measure by 4/3 and so on.

The figure shows an increasing and monotonic effect of crime as the period over which crime is measured is extended. The smallest effect of crime is for that measured over only

the quarter immediately before the interview, whilst the largest effect is for crime measured over the 6 quarters preceding the interview. The small effect of the most recent crime rate may be picking up the fact that respondents update their beliefs about local crime rates only slowly and so a lack of information is conveyed from crime changes which are only from the most recent time period. But it may also reflect measurement error from using a short time window. While the effect of crime is largest at 6 quarters (perhaps supporting the measurement error interpretation), the confidence intervals indicate there is little difference between crime measured over 4 quarters and crime measured over 6. We therefore conclude our results are robust to the precise number of quarters used to define the crime rate.

4.4.2 Spatial definition of crime

Our crime variable is measured at local authority level. This choice is motivated by the fact that walking is an activity undertaken in a small area and thus is likely to be affected by crime at that local area level. However, there may also be spillovers from crime in other areas and individuals may live in one small area but walk in another contiguous area, for example, if their places of residence and work are in different local authorities. London, in particular, contains many local authorities which individuals cross between on a daily basis. Therefore, we examine the robustness of our results to changing the area over which the crime variable is measured.

We construct the crime rate as the mean of the crime rate in the local authority of residence of the respondent and the crime rates in the local authorities whose centroid is within a certain radius of the centroid of the local authority of residence. Figure 4 reports the crime estimates from regressions using our baseline specification in Equation 1 altering the radii over which the crime rates are defined (for both violent crime with injury and all other crime) from 0 to 40 km in 5 km bands. The 0 km radius is our baseline crime variable as it is defined for the local authority of residence only. The figure shows that the coefficient on log(violent crime with injury) fluctuates around our main estimate of –0.49, ranging from –0.39 to –0.56, but the line is basically flat. This indicates that there are no spillover effects between local authorities. However, the widening confidence intervals show that as the area over which crime is measured grows larger, the coefficient estimate becomes less precise. By a radius of 15 km the estimate is no longer statistically significantly different from zero. This supports our use of crime in the individual's local area as determining their walking in their local area.[18]

[18]We also examine crime rates at police force area level. Police force areas cover large areas: there are only 38 in total compared to 326 local authorities and they are arguably too large an area to be relevant for daily activities such as walking. However, recent research on the UK has found that crime at this spatial level matters for mental distress (Dustmann and Fasani 2012). Using our main specification, the coefficient on log(violent crime with injury) measured as the mean of the violent crime rates in all the local authorities that make up the police force area of residence of the respondent is –0.331 (s.e. = 0.266). The coefficient is slightly larger when focussing on urban areas as Dustmann and Fasani (2012) do: –0.369 (s.e. = 0.338) versus –0.093 (s.e. = 0.315) for rural areas. Standard errors are clustered by police force area. This again suggests

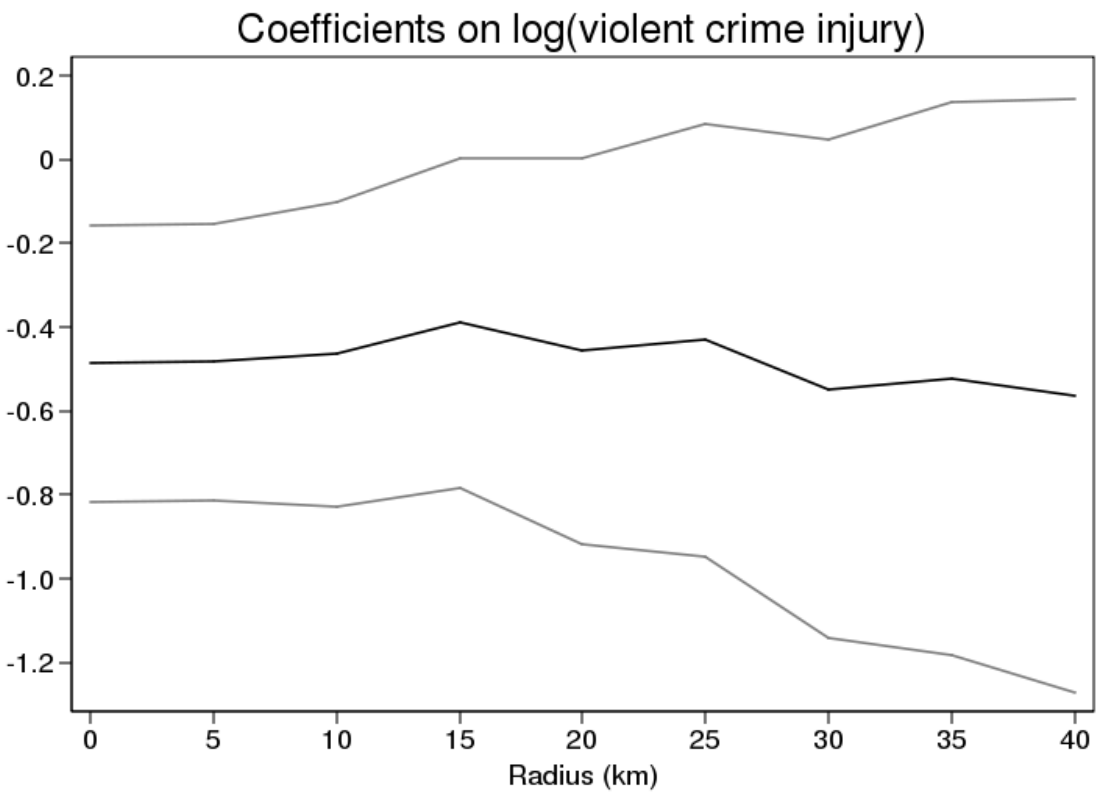

Figure 4: Estimates for different radii for crime variable: Coefficients on log(violent crime with injury) and 95% confidence intervals.

4.4.3 Crime type

We have focused on violence against the person with injury as these crimes seem most relevant for individuals' security while walking and receive extensive media attention, so that people are likely to hear or read about such incidents. However, there are other types of crime against the person and these may also have an effect, though our prior is that it is smaller. Table 7 examines this by presenting estimates for each type of personal crime. The covariates are the same as those in the baseline specification (Table 4, column 4) except that the control variable "all other crime" is crime type specific (i.e. defined with respect to the independent variable).

The results show that only violent crime with injury has a statistically significant effect on walking. Violent crime without injury has a (smaller) negative association but a large standard error. Sexual offences and robbery have essentially no association, though this result may reflect measurement error – both robbery and sexual offences are small in number.

Table 7: Estimates of the effects of different types of personal crime on number of days walking in last four weeks

	Log(violent crime with injury)	Log(violent crime without injury)	Log(sexual offences)	Log(robbery)
Coefficient	-0.556^{***}	-0.141	0.013	-0.012
	(0.169)	(0.125)	(0.086)	(0.056)

Robust standard errors in brackets, clustered by local authority. Regression includes local authority effects, year-quarter effects and local authority-specific trends as well as controls for all other crime types, unemployment, rainfall, daily maximimum and minimum temperature and individual-level controls for gender, age, ethnicity, highest educational attainment, employment status, an indicator for a limiting long-standing illness or disability, family structure, household income, an indicator for living in social rented housing and an indicator for car in household. 893,075 observations in 323 local authorities. *Significant at 10%, **significant at 5%, ***significant at 1%

In Table B-1 in the Appendix we also examine all types of crime. This shows that most crimes other than violent crime with injury are not associated with walking or are also negatively associated (for example, drug offences). However, criminal damage is associated with walking and the coefficient is positive, suggesting that an increase in this crime increases walking. We come back to this below.

4.4.4 The distribution of the walking variable

The distribution of our main dependent variable (the number of days walking continuously for at least 30 minutes in the last four weeks) has peaks at various days, reflecting patterns in transport and leisure walking. 28% of respondents report zero walking days and there are spikes at 10 days and 20 days, reflecting the 5 weekdays in each of the four weeks of the

that it is crime in the most local area which matters for walking.

measurement period and spikes at 4 days, 8 days and 12 days correspond to walking once, twice or three times a week respectively. 14% of respondents report 28 walking days, i.e. walking every day over the measurement period.

Table 8: Multinomial logit models of walking days in last four weeks: Coefficients on log(violent crime with injury)

Categories	All walking	Transport walking	Leisure walking
0 days	Base outcome	Base outcome	Base outcome
1 to 4 days	0.027	−0.063	0.098**
	(0.042)	(0.045)	(0.044)
5 to 14 days	−0.011	−0.095*	0.029
	(0.052)	(0.053)	(0.049)
> 14 days	−0.120**	−0.214***	−0.058
	(0.047)	(0.064)	(0.053)

Robust standard errors in brackets, clustered by local authority. All models include local authority effects, year-quarter effects and local authority-specific trends as well as controls for all other crime, unemployment, rainfall, daily maximum and minimum temperature and individual-level controls for gender, age, ethnicity, highest educational attainment, employment status, an indicator for a limiting long-standing illness or disability, family structure, household income, an indicator for living in social rented housing and an indicator for car in household. 893,075 observations in 323 local authorities in all models. *Significant at 10%, **significant at 5%, ***significant at 1%

To check the robustness of our linear specification, we re-estimated our main results using a multinomial logit model with four categories: 0 days, 1 to 4 days, 5 to 14 days and more than 14 days. Each of these categories accounts for approximately one-quarter of the observations. We also include the same controls as in our main estimates. The results are in Table 8, for all walking and for transport walking and leisure walking separately. For all walking, the deterrent effect of crime is largest for the $>$ 14 days versus 0 days contrast and decreases with the size of the contrast, becoming positive for the 1 to 4 days versus 0 days contrast. For transport walking, we see a similar picture and all coefficients are negative. In contrast, the coefficients on crime for leisure walking are small and the results show that the positive coefficient for the 1 to 4 days versus 0 days contrast in the estimates for all walking days is driven by leisure walking. These results confirm our findings above: violent crime primarily deters walking at the intensive margin rather than the extensive margin and the main effect is on transport rather than leisure walking.

Overall we conclude that our results are robust to an extensive set of checks. We now turn to the additional evidence provided by the English riots of 2011.

5 Exploiting the English riots

In August 2011 rioting erupted unexpectedly in selected urban areas of England. This was accompanied by national media coverage, including repeated television pictures of individuals jumping from burning buildings, looting of commercial property and police unable to control crowds of angry people in the commercial areas of towns. The riots were very localised and of short duration. They started in a deprived area of North London (Tottenham) on Saturday, 6 August 2011. Unrest spread to other parts of London, again in a very localised way, on 7 and 8 August. On 8 August incidents of disorder occurred in parts of the cities of Bristol, Birmingham and Liverpool and continued on 9 August. On that day, rioting began in Reading, Milton Keynes, Leeds, Leicester, Salford and Manchester. Widespread disorder had largely died out by the 10 August 2011 (Home Office 2011).

We exploit this sudden increase in crime to corroborate our finding on the impact of shocks in local crime on walking. We examine both walking and other physical activity.[19] The riots caused a sudden upsurge of crime, particularly in city centres, and are therefore likely to affect any physical activity that involves leaving the home. In addition, the riots were in in the holiday month of August when individuals are less likely to walk to work and the rural and suburban areas where individuals might undertake leisure walking were unaffected. We thus might expect a smaller effect on walking than on other types of physical activity.

5.1 Estimation method

We use a triple difference methodology to analyse the effects of the riots. We define treated areas as those for which the total number of recorded crimes were greater than 100 (more details below). We define the treatment window as from the date of the riots to 14 October 2011) and define a comparable time window before the riots (1 June to August) as a treatment period. We could compare changes pre- and post-riots in treated and non-treated areas, but one weakness of the standard difference-in-difference estimator is the common trend assumption. In our context, this might be violated if seasonal changes in physical activity differ between the relatively deprived and more urban riot areas and the control areas. We therefore employ the differentially adjusted difference-in-difference estimator proposed by Bell et al. (1999). Essentially, we take another time interval over which a similar seasonal trend has occurred to purge the difference-in-difference estimates from differential trends. The same seasonal changes are likely to have occurred between 1 June and 14 October in the year prior to the riots, 2010.

In this case, the differentially adjusted difference-in-difference estimator takes the form

[19] For these activities individuals have to leave the home, as the main types of physical activity undertaken in England are outside the home.

$$\begin{aligned}\widehat{\gamma}^{DADID} &= \left[\left(\overline{Y}_{RIOT,POST,2011} - \overline{Y}_{RIOT,PRE,2011}\right) - \left(\overline{Y}_{C,POST,2011} - \overline{Y}_{C,PRE,2011}\right)\right] \\ &\quad - \left[\left(\overline{Y}_{RIOT,POST,2010} - \overline{Y}_{RIOT,PRE,2010}\right) - \left(\overline{Y}_{C,POST,2010} - \overline{Y}_{C,PRE,2010}\right)\right]\end{aligned}$$

To implement this we run the following regression:

$$\begin{aligned}Y_{iat} &= \alpha + \beta_1 POST_t + \beta_2 RIOT_a + \beta_3 2011_t + \beta_4 POST_t \cdot RIOT_a + \beta_5 RIOT_a \cdot 2011_t \\ &\quad + \beta_6 POST_t \cdot 2011_t + \beta_7 POST_t \cdot RIOT_a \cdot 2011_t + \varepsilon_{iat} \qquad (2)\end{aligned}$$

The dependent variable, Y_{iat}, is either the number of walking days or the number of physical activity episodes other than walking in the last four weeks reported by individual i in local authority a on day t. $POST_t$ is an indicator equal to 1 if individual i is interviewed on or after 20 August. We omit individuals interviewed between 6 August and 19 August, as for these a maximum of only 13 days of the 28-day reporting period could have been affected by the riots. $RIOT_a$ is an indicator equal to 1 if the respondent lives in a local authority affected by the riots. We define as treated the 17 local authorities for which the total number of recorded crimes related to the disorder exceeds 100 (Home Office 2011). We omit observations for the 29 local authorities that were less heavily affected but for which more than "isolated incidents" were reported (Home Office 2011). 2011_t is a dummy variable indicating observations from 2011. The control group is all other local authorities in England. The coefficient of interest is β_7.

5.2 Results

Table 9 presents results for the number of days walking in the last four weeks in the first block and for the number of physical activity episodes other than walking in the second. The first panel presents estimates for the whole sample, the second and third split the sample into women and men respectively. Within each panel we present results for the overall effect and then the extensive and intensive margins separately. The estimates for the extensive margin are the change in the probability of participation.

Looking at the first block, Row 1 shows the riots reduced the number of walking days by -0.21, which is a 2.3% drop at the mean. The falls at both the extensive and intensive margins are also small. None of the estimates are statistically different from zero. The second and third panels of the first block of Table 9 investigate gender differences in walking. Women appear to react more negatively than men. For women the estimated effect overall is similar to the effect of local crime shocks in Section 4: 0.56 fewer walking days, equivalent to a 6% drop at the mean. There is also a fall at both the extensive and intensive margin. For men, in contrast, the total amount of walking rises and increases at the extensive margin. However,

for both genders these changes are not statistically significant.

Table 9: Differentially adjusted difference-in-difference estimates of the impact of 2011 England riots on physical activity in last four weeks

	Walking days			Other physical activity episodes		
	Estimate	Mean	N	Estimate	Mean	N
All						
No. of days/episodes	−0.210	9.05	80,768	−0.676	5.86	80,768
	(0.540)			(0.519)		
Extensive (0,1)	−0.015	0.74	80,768	−0.008	0.50	80,768
	(0.020)			(0.024)		
Intensive (1-28/200)	−0.059	12.30	59,413	−1.182	11.78	40,175
	(0.622)			(0.842)		
Female						
No. of days/episodes	−0.555	9.48	49,008	−1.545***	5.26	49,008
	(0.674)			(0.519)		
Extensive (0,1)	−0.041	0.75	49,008	−0.062***	0.46	49,008
	(0.025)			(0.021)		
Intensive (1-28/200)	−0.121	12.70	36,572	−1.868	11.36	22,686
	(0.733)			(1.136)		
Male						
No. of days/episodes	0.228	8.39	31,760	0.924	6.79	31,760
	(0.829)			(0.973)		
Extensive (0,1)	0.022	0.72	31,760	0.089**	0.55	31,760
	(0.039)			(0.040)		
Intensive (1-28/200)	−0.023	11.67	22,841	−0.593	12.32	17,489
	(0.870)			(1.247)		

Robust standard errors in brackets, clustered by local authority. *Significant at 10%, **significant at 5%, ***significant at 1%

In contrast, the second block of Table 9 shows a significant impact on all other physical activity for both women and men. The first row shows an overall large decrease in activity in general and a large fall at the intensive margin, though the overall estimates are not statistically significantly different from zero. However, when we separate the sample by women and men, we see that this overall estimate masks a strong decrease by women. The riots reduced the number of physical activity episodes by 1.5 (a 30% drop at the mean), the probability of participating in physical activity fell by 6.2 percentage points and the intensive margin fell by -1.9 episodes (a 17% drop at the mean). In contrast, the final panel shows that men increased their physical activity, driven by a significant increase at the extensive margin. There is a fall at the intensive margin but it is approximately a third of the size of that of women.[20]

[20]The estimates in Table 9 do not include weather controls. Estimates with weather controls are very close to those presented here (available from authors) and we preferred to keep the specification as simple as possible given the size of the data set.

Thus women and men appear to react differently to this sudden increase in crime. Women are less likely to walk or engage in other physical activity, whilst men are more likely to do so. This finding of a gender difference echoes responses from Mexico to local crime, where women respond by undertaking activities to avoid crime whilst men appear to 'man up' by going out more and arming themselves more (Braakmann 2012).

Our main analysis showed no association between physical activity and violent crime (Table 5, final column). The riot analysis has shown an impact on physical activity. To explore this further, we note that the riots were a mixture of violent crime and criminal damage (primarily looting from shops). We therefore use data covering the full period of October 2005 to October 2011 to examine the relationship between two measures of crime – violent crime with injury and criminal damage – and physical activity excluding walking. We split the sample into men and women as the riot analysis indicates a different response by gender.

Table 10: Estimates of the effect of local authority rate of violent crime with injury and criminal damage on episodes of physical activity other than walking in last four weeks

	All	Males	Females
Log(violent crime with injury)	−0.066	0.130	−0.163
	(0.138)	(0.230)	(0.195)
Log(criminal damage)	0.048	0.206	−0.083
	(0.184)	(0.304)	(0.213)
Observations	893,075	362,780	530,295
Clusters	323	323	323

Robust standard errors in brackets, clustered by local authority. All regressions include local authority effects, year-quarter effects and local authority-specific trends as well as controls for all other crime, unemployment, rainfall, daily maximum and minimum temperature and individual-level controls for gender, age, ethnicity, highest educational attainment, employment status, an indicator for a limiting long-standing illness or disability, family structure, household income, an indicator for living in social rented housing and an indicator for car in household. *Significant at 10%, **significant at 5%, ***significant at 1%

The results are in Table 10. The first row shows that the average effect of violent crime with injury on physical activity other than walking is zero (as in Table 5). But the male response is positive and the female response negative. The same pattern is seen for criminal damage: men increase their physical activity whilst women do less. None of the estimates are significant, but the pattern in physical activity is the same as that seen for the riots - a positive effect for men and a negative effect for women. As the riots were a much bigger shock than the normal quarterly variation in crime rates at local area level, their effect is, not surprisingly, larger and statistically better estimated. In conclusion, these analyses indicate that violent crime causes less walking in both genders, whilst criminal damage induces a differential response in men and women.

6 Conclusion

We contribute to the literature on the wider consequences of crime in society by providing evidence on the causal effect of local area violent crime on adults' participation in physical activity. We focus on walking as it is the most common form of physical activity, contributes to individual health and through individuals' interactions with people in their neighbourhood may contribute to neighbourhood quality. To provide causal evidence we use a sample of nearly one million people residing in over 320 local authority areas across England over 22 quarters and back this up with additional evidence which uses the 2011 riots as a quasi-experiment.

We find that an increase in local area violent crime leads to a statistically significant reduction in the number of days individuals walked for at least 30 minutes over a four-week period. The effect of reducing crime from the 75^{th} to the 25^{th} percentile is of roughly the same magnitude as increasing the average daily minimum temperature over the four-week period by 6 °C or as reducing average daily rainfall over the four week period by 7 mm. The effect works mainly through reducing transport walking, rather than walking undertaken for leisure or recreational purposes. This is consistent with the fact that much transport walking is likely to take place close to home, whereas some recreational walking is likely to take place outside of the local area. We find suggestions of heterogeneity in the response to violent crime with respect to gender and age, with males reducing walking days more than females and individuals post retirement age responding more than younger individuals. In response to the 2011 England riots we find that females reduced other physical activity rather than walking. This effect is quantitatively large: our estimates suggest that the riots reduced the number of physical activity episodes in females by around 30%. In contrast, men appear to either not change activity or increase physical activity.

Overall, the evidence points to a negative effect of violent crime on the wider community through the mechanism of increased concern about personal security. Our research adds to recent studies that identify causal effects of violent crime on daily activity and mental well-being of non-victims and suggests that policies that reduce the amount of violent crime in society have positive effects well beyond the direct effects of fewer victims of crime.

Acknowledgements

We thank seminar participants at the Universities of Bristol, Melbourne and Monash for their helpful comments. This research was funded by the Economic and Social Research Council through the Centre for Market and Public Organisation at Bristol University.

Appendix A Data description

Table A-1: Data sources

Variables	Source of data	Period
Physical activity measures and individual-level controls	Active People Survey 1-5	IV/2005-IV/2006, IV/2007-IV/2011
Police recorded crime	Freedom of Information request to UK Home Office	II/2004-III/2011
Local authority population	Mid-year population estimates from Office for National Statistics	2004-2010
Unemployment rate	Model-based estimates of local authority unemployment for one year periods from Nomis (www.nomisweb.co.uk)	Oct 2004/Sep 2005-Oct 2010/Sep 2011
Weather	Met Office – MIDAS Land Surface Stations data	Sep 2004-Oct 2011
Perception of crime	British Crime Survey 2005-06, 2006-07, 2007-08	II/2005-I/2008

Table A-2: Descriptive statistics of individual-level controls from Active People Survey data

Variable	Mean
Male	0.41
Age 25 to 34	0.15
Age 35 to 44	0.23
Age 45 to 54	0.21
Age 55 to 64	0.23
Age 65 to 74	0.17
White British	0.90
Indian	0.01
Pakistani	0.01
Bangladeshi	0.00
Caribbean	0.01
African	0.01
Chinese	0.00
Other ethnic group	0.06
No qualifications	0.14
Other	0.03
O level	0.22
A level	0.14
Higher (less than degree)	0.10
Degree or higher	0.31
Qualification missing	0.05
Working full-time	0.45
Working part-time	0.16
Unemployed $<$ 12 months	0.02
Unemployed $>$ 12 months	0.03
Retired	0.23
Non-participant (home/child)	0.05
Non-participant (disabled)	0.03
Student	0.01
Other	0.01
Employment status missing	0.02
Chronic limiting condition	0.17
Limiting condition missing	0.02

Variable	Mean
Single adult	0.34
Family status missing	0.03
Child aged 0 to 4	0.11
Child aged 5 to 10	0.16
Child aged 11 to 15	0.13
Child age missing	0.00
$<$ £10,400 per annum	0.10
£10,400 to £20,700	0.17
£20,800 to £31,199	0.15
£31,200 to £41,599	0.11
£41,600 to £51,999	0.08
£52,000 or more	0.12
Household income missing	0.28
Social rented housing	0.11
Housing missing	0.02
Car in household	0.78
Car missing	0.08
APS5 - missing questions	0.08
Monday	0.16
Tuesday	0.17
Wednesday	0.17
Thursday	0.16
Friday	0.13
Saturday	0.12
Sunday	0.09
Observations	893,075

Table A-3: Descriptive statistics of British Crime Survey data

Variable	Mean
Male	0.46
Age 25 to 34	0.18
Age 35 to 44	0.24
Age 45 to 54	0.20
Age 55 to 64	0.21
Age 65 to 74	0.17
White British	0.89
Indian	0.02
Pakistani	0.01
Bangladeshi	0.00
Caribbean	0.01
African	0.01
Chinese	0.00
Other ethnic group	0.06
No qualifications	0.26
Other	0.10
O level	0.20
A level	0.11
Higher (less than degree)	0.13
Degree or higher	0.20
Qualification missing	0.00
Working full-time	0.48
Working part-time	0.16
Unemployed	0.03
Retired	0.21
Non-participant (home/child)	0.07
Non-participant (disabled)	0.05
Student	0.01
Employment status missing	0.00
Chronic limiting condition	0.17

Variable	Mean
Single adult	0.36
Child aged 0 to 4	0.12
Child aged 5 to 10	0.16
Child aged 11 to 15	0.14
$<$ £5,000 per annum	0.05
£5,000 to £9,999	0.10
£10,000 to £14,999	0.09
£15,000 to £24,999	0.16
£25,000 to £34,999	0.14
£35,000 to £49,999	0.14
£50,000 or more	0.13
Household income missing	0.18
Social rented housing	0.16
Housing missing	0.00
Car in household	0.84
Observations	103,000

Variable	Mean	St. dev.	25^{th} perc.	Median	75^{th} perc.
Violent crime with injury	9.13	2.3	7.5	8.7	10.6
Between		2.1			
Within		0.9			
Observations	456				

Appendix B

Table B-1: Estimates of the effects of different crime types on number of days walking in last four weeks

	Coefficient	Mean of crime variable	St. dev.
Log(violent crime injury)	−0.556***	7.32	3.28
	(0.169)		
Log(violent crime no injury)	−0.141	8.15	3.97
	(0.125)		
Log(sexual offences)	0.013	0.94	0.41
	(0.086)		
Log(robbery)	−0.012	1.11	1.60
	(0.056)		
Log(criminal damage)	0.574**	16.50	6.48
	(0.227)		
Log(burglary)	−0.191	9.62	3.88
	(0.146)		
Log(vehicles)	−0.162	9.86	5.29
	(0.142)		
Log(other theft)	0.337	18.22	8.50
	(0.221)		
Log(drug offences)	−0.116*	3.33	2.58
	(0.067)		
Log(fraud)	0.022	2.95	1.71
	(0.077)		
Log(other offences)	0.115	1.16	0.62
	(0.085)		
R-squared	0.034		

Robust standard errors in brackets, clustered by local authority. Regression includes local authority effects, year-quarter effects and local authority-specific trends as well as controls for unemployment, rainfall, daily maximimum and minimum temperature and individual-level controls for gender, age, ethnicity, highest educational attainment, employment status, an indicator for a limiting long-standing illness or disability, family structure, household income, an indicator for living in social rented housing and an indicator for car in household. 893075 observations in 323 local authorities. *Significant at 10%, **significant at 5%, ***significant at 1%

References

Ayres, I. and Levitt, S. D.: 1998, Measuring positive externalities from unobservable victim precaution: An empirical analysis of lojack, *Quarterly Journal of Economics* **113**(1), 43–77.

Bassett, D. R., Pucher, J., Buehler, R., Thompson, D. L. and Crouter, S. E.: 2008, Walking, cycling, and obesity rates in europe, north america, and australia, *Journal of Physical Activity and Health* **5**(6), 795–814.

Bell, B., Blundell, R. and Reenen, J. V.: 1999, Getting the unemployed back to work: The role of targeted wage subsidies, *International Tax and Public Finance* **6**, 339–360.

Box, S., Hale, C. and Andrews, G.: 1988, Explaining fear of crime, *British Journal of Criminology* **28**(3), 340–356.

Braakmann, N.: 2012, How do individuals deal with victimization and victimization risk? longitudinal evidence from mexico, *Journal of Economic Behaviour & Organization* **84**(1), 335–344.

Chermak, S. M.: 1994, Body count news: How crime is presented in the news media, *Justice Quarterly* **11**(4), 561–582.

Cohn, E. G.: 1990, Weather and crime, *British Journal of Criminology* **30**(1), 51–64.

Coleman, C. and Moynihan, J.: 1996, *Understanding crime data - Haunted by the dark figure*, Crime and Justice, Open University Press.

Cornaglia, F. and Leigh, A.: 2011, Crime and mental wellbeing, *CEP Discussion Paper 1049*, Centre for Economic Performance.

Cullen, J. B. and Levitt, S. D.: 1999, Crime, urban flight, and the consequences for cities, *The Review of Economics and Statistics* **81**, 159–169.

Department for Transport: 2012, *National Travel Survey 2011 - Statistical Release*, Department for Transport.

du Toit, L., Cerin, E., Leslie, E. and Owen, N.: 2007, Does walking in the neighbourhood enhance local sociability?, *Urban Studies* **44**(9), 1677–1695.

Duffy, B., Wake, R., Burrows, T. and Bremner, P.: 2008, Closing the gaps - crime and public perception, *International Review of Law Computers & Technology* **22**(1-2), 17–44.

Dustmann, C. and Fasani, F.: 2012, The effect of local area crime on the mental health of residents. Unpublished Manuscript.

Ellen, I. G. and O'Regan, K. M.: 2010, Crime and urban flight revisited: The effect of the 1990s drop in crime on cities, *Journal of Urban Economics* **68**(3), 247–259.

Foster, S. and Giles-Corti, B.: 2008, The built environment, neighborhood crime and constrained physical activity: An exploration of inconsistent findings, *Preventive Medicine* **47**, 241–251.

Gibbons, S.: 2004, The costs of urban property crime, *The Economic Journal* **114**(499), F441–F463.

Greenbaum, R. T. and Tita, G. E.: 2004, The impact of violence surges on neighbourhood business activity, *Urban Studies* **41**(13), 2495–2514.

Greer, C.: 2007, News media, victims and crime, *in* P. Davies, P. Francis and C. Greer (eds), *Victims, Crime and Society*, Sage Publications Ltd., London, chapter 2, pp. 20–49.

Grossman, M.: 2006, Education and nonmarket outcomes, *in* E. A. Hanushek and F. Welch (eds), *Handbook of the Economics of Education, Volume I*, North-Holland, pp. 577–633.

Hamermesh, D. S.: 1999, Crime and the timing of work, *Journal of Urban Economics* **45**, 311–330.

Hipp, J. R.: 2010, Resident perceptions of crime and disorder: How much is "bias" and how much is social environment differences?, *Criminology* **48**(2), 475–508.

Home Office: 2010a, *Crime in England and Wales 2009/10 - Findings from the British Crime Survey and police recorded crime*, Home Office.

Home Office: 2010b, *Public perceptions of policing, engagement with the police and victimisation: Findings from the 2009/10 British Crime Survey*, Home Office.

Home Office: 2011, *An overview of recorded crimes and arrests resulting from disorder events in August 2011*, Home Office.

Jacob, B., Lefgren, L. and Moretti, E.: 2007, The dynamics of criminal behavior: Evidence from weather shocks, *The Journal of Human Resources* **42**(3), 489–527.

Johnston, L.: 2006, Diversifying police recruitment? the deployment of police community support officers in london, *The Howard Journal of Criminal Justice* **45**(4), 388–402.

Kling, J. R., Liebman, J. B. and Katz, L. F.: 2001, Bullets don't got no name: Consequences of fear in the ghetto, *JCPR Working Paper 225*, Northwestern University/University of Chicago Joint Center for Poverty Research.

Lindström, M.: 2008, Means of transportation to work and overweight and obesity: A population-based study in southern sweden, *Preventive Medicine* **46**(1), 22–28.

Messer, L. C., Kaufman, J. S., Dole, N., Herring, A. and Laraia, B. A.: 2006, Violent crime exposure classification and adverse birth outcomes: a geographically-defined cohort study, *Internationa Journal of Health Geographics* **5**.

Metcalfe, R., Powdthavee, N. and Dolan, P.: 2011, Destruction and distress: Using a quasi-experiment to show the effects of the september 11 attacks on mental well-being in the united kingdom, *The Economic Journal* **121**(550), F81–F103.

NHS Information Centre: 2011, Statistics on obesity, physical activity and diet: England. **URL:** *http://www.ic.nhs.uk/cmsincludes/_process_document.asp?sPublicationID=1298456207227&sDocID=6897*

Rosenthal, S. S. and Ross, A.: 2010, Violent crime, entrepeneurship, and cities, *Journal of Urban Economics* **67**(1), 135–149.

Ross, C. E. and Jang, S. J.: 2000, Neighborhood disorder, fear, and mistrust: The buffering role of social ties with neighbors, *American Journal of Community Psychology* **28**(4), 401–420.

Rubin, G. J., Brewin, C. R., Greenberg, N., Simpson, J. and Wessely, S.: 2005, Psychological and behavioural reactions to the bombings in london on 7 july 2005: cross sectional survey of a representative sample of londoners, *British Medical Journal* **331**(606).

Sampson, R. J., Raudenbusch, S. W. and Earls, F.: 1997, Neighborhoods and violent crime: A multilevel study of collective efficacy, *Science* **277**(918), 918–924.

Sundquist, K., Theobald, H., Yang, M., Li, X., Johansonn, S.-E. and Sundquist, J.: 2006, Neighborhood violent crime and unemployment increase the risk of coronary heart disease: A multilevel study in an urban setting, *Social Science & Medicine* **62**, 2061–2071.

U.S. Department of Health and Human Services: 1996, *Physical activity and health: a report of the Surgeon General*, U.S. Department of Health and Human Services, Atlanta (GA).

Warr, M. and Ellison, C. G.: 2000, Rethinking social reactions to crime: Personal and altruistic fear in family households, *American Journal of Sociology* **106**(3), 551–578.

Williams, P. and Dickinson, J.: 1993, Fear of crime: Read all about it? - the relationship between newspaper crime reporting and fear of crime, *British Journal of Criminology* **33**(1), 33–56.

World Health Organization: 2002, *The World Health Report 2002 - Reducing Risks, Promoting Healthy Life*, World Health Organization, Geneva.