Assaults, murders and walkers:

The impact of violent crime on physical activity[*]

Katharina Janke
University of Lancaster

Carol Propper
Imperial College and University of Bristol

Michael A. Shields
Monash University

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Abstract
We investigate an underexplored externality of crime: the impact of violent crime on individuals' participation in walking. For many adults walking is the only regular physical activity. We use a sample of nearly 1 million people in 323 small areas in England between 2005 and 2011 matched to quarterly crime data at the small area level. Within area variation identifies the causal effect of local violent crime on walking and a difference-in-difference analysis of two high-profile crimes corroborates our results. We find a significant deterrent effect of violent crime on walking that translates into a drop in overall physical activity.

Corresponding author: Carol Propper, Imperial College, London SW7 2AZ UK.
E-mail: C.Propper@imperial.ac.uk. Tel +44(0) 207 594 9291

1   Introduction

It has been long recognised that crime has important externalities. One concern is the impact of crime on individuals' ability to undertake their daily activities. For example, Kling et al. (2001) report that parents living in areas of high crime sought to keep their children indoors to avoid them becoming victims of violence and Hamermesh (1999) demonstrates that victimisation risk affects working time patterns in the USA. A related concern is the effect of crime on neighbourhood quality and community. Established negative neighbourhood externalities include flight to the suburbs (Cullen and Levitt 1999, Ellen and O'Reagan 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).

Such responses to crime are likely to impact on health, both mental and physical. Recent studies that have demonstrated a causal link from crime to poor mental health include Cornaglia et al. (2014) for Australia and Dustmann and Fasani (2015) for Britain. In addition, a number of papers have estimated 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 2015). There is also a large literature showing associations between crime in an area and various aspects of poor physical health.[1] However, many of these studies have difficulty showing causality and the relatively few causal studies have not, in the main, investigated the mechanisms by which crime affects health.

The aim of the present paper is to examine one route by which crime might impact upon health: through reducing individuals' participation in the most common form of physical activity, walking. We provide causal estimates of the impact of violent crime on walking. Walking and its potential link to crime is a substantive issue for several reasons. First, walking is an important form of exercise. It is free and available to everyone regardless of age, gender or income. For many adults walking is the only form of regular exercise. In our sample of individuals living in England, 30% of respondents report no exercise other than walking, while 20% of respondents report no exercise at all. Second, the importance of moderate physical activity as a determinant of good health is well established (US Department of Health and Human Services 1996, World Health Organization 2002) but

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[1] Examples include Bilger and Carrieri (2013), Sooman and Macintyre (1995), Sundquist et al. (2006) and Messer et al. (2006).

despite this, walking has been decreasing in many industrialised countries.[2] This fall has been linked to the rise in obesity and obesity related diseases (Bassett et al. 2008, Lindström 2008), which impose substantial costs on individuals and health care systems. Third, and related to the concern over the effect of crime on neighbourhoods, walking has important externalities. Individuals who walk in their local neighbourhood contribute to a sense of community (du Toit et al. 2007). A shift from walking to driving as a mode of transport increases carbon emissions, noise levels, air pollution and congestion (Sinnett et al. 2011). Costly motorised transport as a substitute for free walking imposes an economic burden on the individual. Pedestrians are also an important factor in ensuring a vibrant local economy (Sinnett et al. 2011).[3] Finally, serious physical crime is not uncommon. While homicide rates are low in Western Europe, other serious violent offences are more prevalent. In England, violent crime with injury accounts for 10% of all recorded crime and individuals tend to overestimate their chances of being a victim of such crimes.[4]

Concerns about personal safety have been often cited in research as a barrier to local walking (Foster and Giles-Corti 2008).[5] But the literature to date has not found clear results for the relationship between crime and walking or physical engagement in the community, in part due to non-causal research designs and small data sets (Foster and Giles-Corti 2008). We address both of these problems. We use a large sample – nearly 1 million people in 323 small areas (local authorities) in England over six years – matched to quarterly police recorded crime data at this small area level. England is a good test bed. Crime statistics are available at small area level, with the six-year period covered by our data providing considerable variation in crime rates across time and space. In addition, the English government collects information on physical activity on a consistent basis for a very large sample of adults every year, giving many observations at small area level.

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[2] In the UK, the average distance walked, per person per year, has fallen from 255 miles in 1975/76 to 201 miles in 2006 (NICE 2012).

[3] A survey of customers on a local high street found that shoppers who had walked there visited more shops than those arriving by car (Sustrans 2006).

[4] In a survey 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 reported being actual victims of violent crime in the last 12 months (Home Office 2010). Individuals get information about crime from the media (Duffy et al. 2008) and media reporting has been shown to be highly selective, focusing on the most serious examples of crime (Greer 2007). In contrast, the lower level property offences that make up the majority of recorded crime are given sparse attention (Greer 2007). As an example, Cornaglia and Leigh (2011) analyse local print media in Australia in 2001 to 2006 and find 600 media mentions of violent crime each year, compared to 230 mentions of property crime.

[5] Piro et al. (2006) look at the association between neighbourhood level violence/fear of violence and physical activity among the elderly in Norway.

These repeated cross-section data provide an identification strategy in which we can control for area effects, area specific time trends, national time effects and a number of potential time-varying confounders such as unemployment at the area level and local weather.[6] To further strengthen our search for causal estimates we complement this analysis by using a difference-in-difference approach to examine the impact on walking of two high-profile crimes that caused a crime shock at the local level. In December 2010, Joanna Yeates went missing in Bristol. Her body was discovered eight days later on Christmas Day. The hunt for her killer received extensive media coverage, with police issuing warnings to women to avoid walking home alone after dark in the local area while her killer remained at large. On 22 January 2011 Vincent Tabak was charged with her murder. In March 2009, Claudia Lawrence went missing in York. Her body was never found but one line of inquiry was that she was abducted while walking to work early in the morning. Her disappearance also received extensive media coverage.

We begin our analysis by showing 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. These results support our modelling assumption that increases in recorded violent crime in a local area induce greater concerns about personal safety, which in turn may lead to individuals changing their physical activity behaviour.

Our main results show that increased violent crime in the local area leads to a statistically significant reduction in walking and this drop translates into a drop in overall physical activity. Most of the drop is in transport walking, which is more likely to take place in the locality in which an individual lives compared to leisure walking. Our analysis of the impact of the murder of Joanna Yeates and the disappearance of Claudia Lawrence supports our main findings, showing a fall in walking and overall physical activity following these local crime shocks. Thus crime hurts walking and, partly because walking is the only form of exercise many people take, also the total amount of exercise taken by individuals. Back-of-the-envelope calculations suggest that reducing violent crime to the 25th percentile of our sample distribution could generate substantive health benefits. Further, as the main form of walking that is affected is transport walking (walking to get from place to place rather than

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

for leisure), these estimates do not take into account possible positive externalities from reductions in traffic congestion, pollution and noise or the effect on community cohesion.

The paper is structured as follows. In Section 2 we describe our data and 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 discusses our main estimates and robustness tests. Section 5 describes our analysis of the impact of the murder of Joanna Yeates and the disappearance of Claudia Lawrence. 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. The survey contains detailed measures of physical activity 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. Importantly, interviews are spread evenly across the 12 months of each survey period, and run from mid-October one year to mid-October the next year. Further details are in Appendix A.

We use five waves of these data, covering the period October 2005 to October 2011.[7] The first four waves of the survey cover all 354 local authorities in England. Local authorities 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.[8] 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), giving us a total pooled sample of 1,104,155 individuals aged 16 and above residing in 326 areas.

We drop a number of cases to obtain our working sample. We omit three local authorities: the Isles of Scilly and the City of London because of their very 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 who indicated that they are unable to walk and respondents aged 75 or over as their walking ability might be low. After eliminating

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[7] The survey did not run October 2006 to October 2007.

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

respondents with missing values for our outcome variables, we are left with a sample of 964,318 adults residing in 323 local authorities over a period of 22 quarters.

Our main outcome variable is the time spent walking at a steady average pace or faster continuously for at least 30 minutes in the last four weeks. This measure is derived from a series of questions respondents are asked about the number of days they walked, whether this was for 30 minutes continuously or not, and the pace of their walking. For more detail about these questions see Appendix A. We only count walking at a steady average pace or above, since walking at a slower pace will not count towards the UK government's physical activity target, which is based on the health benefits derived from exercise. We also split the walking variable into leisure and transport walking. Respondents are asked on how many of their walking days were they walking for the purpose of health or recreation (and not just to get from place to place). We define the number of days given in response to this question as leisure walking days and construct a measure of transport walking days by subtracting leisure walking days from all walking days. As respondents might interpret "for the purpose of health or recreation" in a way that counts transport walking as leisure walking, potentially causing measurement error in both the leisure walking and the transport walking variable, our focus is on all walking.

We also construct a measure of the total time spent doing at least moderate intensity physical activity in the last four weeks to examine whether the impact of crime is to decrease all activity or to substitute indoor or group activities for riskier walking. This measure is derived from the record of the length of time respondents undertook any activity from a list of over 400 other types of sport and recreational physical activity over the last four weeks. The most common activities are 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 of activity as well as how long they usually do each activity. We exclude any activity that, according to a list provided by Sport England, is only light intensity (for example bowls, darts and snooker).[9] For each at least moderate intensity activity, we multiply the number of days by the usual duration and sum over all activities. We add this sum to our measures of time spent walking and cycling (which is recorded in the same way as the walking variable)

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[9] There are some activities that can potentially be undertaken at light, moderate or vigorous intensity, such as table tennis, pilates or trampolining. We include such an activity if the respondent says "yes" to the question "During the last four weeks, was the effort you put into ... usually enough to raise your breathing rate?", as it indicates at least moderate intensity.

to obtain a measure of the total time spent doing at least moderate intensity physical activity in the last four weeks.

The top section of Table 1 shows a sample mean of 622 minutes of at least moderate intensity physical activity, which is equivalent to the recommended 150 minutes of moderate intensity activity per week (150 minutes × 4 weeks = 600 minutes). However, the median of 360 minutes suggests that half of all individuals do at most 90 minutes of physical activity. 20% of the sample do nothing. At the mean, 247 minutes are spent walking in the last four weeks. This value is 40% of the sample mean for all physical activity and shows that walking is an important, and for many individuals the only, form of exercise.[10]

Figure 1 shows the time trend (quarterly means) of all physical activity and of walking during the sample period. It is clear that walking is an important component of all activity and that there is no obvious time trend but a strong seasonal pattern in all physical activity and walking. Activity in the UK is lowest in the winter months (the last and first quarters of the year) and highest in the summer (quarter 3). On the other hand, there is little seasonal pattern in transport walking; the seasonality is driven by leisure walking.

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 – essentially the rolling annual crime rate. As most people experience 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 Appendix B.1 we examine the robustness of our results to alternative definitions of the crime measurement period.

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[10] Almost half (45 percent) of respondents who walk do no other form of physical activity.

Offences in the category violence against the person are split into two subgroups: violent crime with injury and violent crime without injury. We focus on violent crime with injury offences. The most common offences in this category are "actual bodily harm (ABH) and other injury", which accounts for 89% of offences, and "inflicting grievous bodily harm (GBH)", which accounts for around 10% of offences. The remaining 1% of violent crime with injury offences include murder, attempted murder, causing death by dangerous driving and racially or religiously aggravated ABH or other injury (Home Office 2011). For most people the main information source on crime is the local and national media and as already noted, violent crime dominates media reporting on crime (Williams and Dickinson 1993, Chermak 1994, Cornaglia and Leigh 2011). Therefore, it seems likely that individuals focus on this type of crime when evaluating the security aspects of their walking decision. Descriptive statistics in Table 1 show a sample average of 7.3 violent crime with injury offences per 1,000 population.[11]

The most common violent crime *without* injury offences are "harassment, public fear, alarm or distress", punishable with a fine, and "assault without injury", punishable with a fine or imprisonment not exceeding 6 months, each of them accounting for around 40% of offences in this category (Home Office 2011). Descriptive statistics in Table 1 show that the sample distribution of violent crime *without* injury offences is similar to the distribution of violent crime with injury offences. The other two major types of personal crime – sexual offences and robbery – together account for only 3% of all police recorded offences while property crime (burglary, offences against vehicles, other theft offences, fraud and forgery, criminal damage) accounts for 70% of police recorded offences.

We use violent crime without injury and all other crime (total crime minus violence against the person) 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.[12]

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[11] A common criticism levelled 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 impact on 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).

[12] 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). In Section 4.2 we examine the robustness of our results to including controls for the number of Police Officers and the number of PCSOs.

Figure 2 maps the local authority means of the violent crime with injury rate in the preceding four quarters and the time spent walking in the last four weeks. 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 suggest that areas with higher crime rates have lower walking rates (visually mainly in the northern half of England).

2.3   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 as well as 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 16) 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. Descriptive statistics for these controls are in Appendix Table A-2.

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2.4   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. Descriptive statistics for these variables are at the bottom of Table 1.

2.5   The relationship between recorded violent crime and concerns about personal safety in the British Crime Survey

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. This relationship has been shown elsewhere (e.g. Elo et al. 2009), but as it is a key assumption in our design we test it in our context. We examine the relationship between police recorded crime and survey data on perception of, 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 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 in which of the 38 police force areas in England the respondent resides and 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. We estimate linear probability models of the relationship between our recorded violent crime with injury variable and perception of and worry about crime, conditioning on a set of individual-level demographic and socio-economic controls similar to those in the APS (discussed in Section 2.3; means of BCS controls are in Table A-3.

Table 2 presents the coefficients on the (log of the) violent crime rate. 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 25th to the 75th percentile increases the probability of reporting an increase in crime by 3 percentage points ($0.35 \times 0.092=0.032$). Both variables measuring worry about crime are also correlated cross-sectionally and within police force areas with recorded crime.[13] 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.

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:

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

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[13] We also estimated the same model for men and women separately. We found that the association is stronger for women than for men for all three measures of crime. The coefficient (standard error) on perceiving an increase in crime is 0.105 (0.32) for females and 0.078 (0.03) for males. The coefficients on the other two variables are positive and significantly different from zero for women but are not significantly different from zero for men. Results available from authors.

Our main measure of physical activity is the time (in minutes) individual i in local authority a interviewed in time period t has spent walking at a steady average pace or faster continuously for at least 30 minutes in the last four weeks. We also analyse walking separated into leisure and transport walking and the total time spent doing at least moderate intensity physical activity in the last four weeks (walking + cycling + other activities). 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 nonparametric 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. Local authority-specific time trends $\delta_a t$ parametrically control for deviations from national time effects, capturing changes to the local infrastructure or policing that might confound the association between local crime rates and walking. X'_{at} and Z'_{iat} are vectors of local authority and individual-specific controls, respectively, as discussed in Sections 2.3 and 2.4. We estimate robust standard errors that allow for clustering at the local authority level.

3.2   Test of our empirical 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 assumption here. Essentially, Equation 1 is a generalised model for grouped individual and aggregate level data that incorporates standard difference-in-difference (d-i-d) models (see Hansen 2007). Formally, Equation 1 would be the same as a simple difference-in-difference estimator if there were only two periods (first difference) and two areas (second difference). In a d-i-d setting we would need to test the common trends assumption that treated and control areas evolve in the same way pre-policy. 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 common trends assumption is satisfied, we examine the relationship between the observed baseline conditions and subsequent changes in the violent crime rate. Any 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 unobserved factors, which would violate the assumptions underlying our causal design.

Table 3, Columns 1 to 3, presents 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 time spent walking. We see that neither are statistically significantly associated with subsequent crime growth, indicating that reverse causality is not an issue either.[14] 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   Main results

We begin by estimating the simple correlation between the local authority rate of violent crime with injury and the time spent walking at a steady average pace or faster 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. It shows a statistically significant negative association.

Columns 2 to 6 present results from regressions that sequentially add individual-level controls, local authority effects, time effects, local authority controls and local authority-specific trends. Adding individual-level controls reduces the coefficient on the crime rate by 20%. Additionally controlling for local authority effects increases the coefficient by 40%. Adding time effects halves the coefficient and subsequently adding local authority controls increases the coefficient by 20%. Adding local authority-specific trends in Column 6 – the specification in Equation 1 – increases the coefficient on the crime rate by 30% to 14.7.

The effect of the controls is as follows. The violent crime without injury rate is statistically insignificant, supporting our assumption that individuals mostly consider violent

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[14] We also added leads in crime rates to our main regressions in Table 4 and found no impact of a lead in crime on current walking.

crime *with* injury when evaluating the security of their local environment, probably as a result of the media's focus on the most serious violent crimes. Neither the local authority unemployment rate nor 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. 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 enjoyable.

To address possible concerns over possible measurement error near administrative boundaries and spatial correlation of the error terms between small areas, we clustered the standard errors at the level of the 46 historic counties. The standard error of the estimated effect of violent crime with injury increased but the coefficient remained statistically significant at the 5 percent level with a standard error of 6.0.[15]

To gauge the economic significance of our results, we calculate the predicted change in the time spent walking as a result of a fall in the crime rate from the 75th to the 25th percentile of the sample distribution. This drop is equal to a fall of 0.66 points in the log crime rate, so a fall of this size leads to 10 minutes increase in walking ($0.66 \times 14.7 = 9.7$), which is equivalent to a 4% increase at the sample mean of 247 minutes. In comparison, an increase in the average minimum temperature from the 25th to the 75th percentile results in a predicted increase in walking of 11 minutes. For the average maximum temperature the predicted increase is 6 minutes. Therefore, the impact of violent crime with injury on the time spent walking is comparable to the impact of temperature in England.

Next, we investigate the effect of crime separately for transport walking and leisure walking and also examine the effect on the total time spent doing at least moderate intensity physical activity. Intuitively, transport walking could be more affected than leisure walking, because individuals have less discretion over where and when to walk if the aim is to get from place to place, making the local crime rate more relevant. Table 5 presents the results. The first column reproduces our baseline estimate from the final column of Table 4. The crime coefficient in the transport walking regression is statistically significant at the 1% level and 70% larger than the statistically insignificant crime coefficient in the leisure walking regression. The predicted increase in transport walking as a result of a drop in the violent

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[15] In separate analyses we also estimated models at the 38 police force area level, allowing for police force area trends. The findings support our main model. Full results available from the authors.

crime rate from the 75th to the 25th percentile is 6 minutes, a 7% increase at the mean of 87 minutes.

The last column of Table 5 shows that a reduction in walking due to a crime increase leads to a drop in total time spent doing at least moderate physical activity in the last four weeks. Using the 25th to 75th percentile contrast, the predicted effect of an increase in crime is a 15 minute drop in total physical activity, a 2.4% decrease at the mean of 622 minutes.[16] As discussed above, the predicted effect on all walking is a 10 minute drop. The predicted drop in total physical activity therefore exceeds the predicted drop in walking. The reason could be that other outdoor activities such as jogging are also considered risky. But importantly, the fall suggests that individuals do not substitute other types of physical activity for walking. This overall fall is supported by Audrey et al. (2014), who used accelerometers to obtain an objective measure of physical activity and found that over a week total physical activity was lower in employees who travelled to work by car than those who walked.

For all four outcome variables the coefficient estimate for the violent crime without injury rate is small and statistically insignificant. This finding supports our proposed information mechanism: local media are much more likely to report violent crimes that result in injury and therefore individuals are less aware of violent crimes that do not result in injury.

We also examine whether the effect of crime is heterogeneous across gender by adding interactions of the area-level controls and the individual-level controls with the male dummy variable. For walking, the coefficient on log(violent crime with injury) is -19.6 (s.e. 5.1) and the coefficient on the interaction with male is 11.1 (s.e. 3.0) which suggests that males respond less than females. For all physical activity, the crime coefficient is -34.6 (s.e. (13.3) and the interaction coefficient is 30.2 (10.5), indicating that women reduce total physical activity in response to an increase in crime. One reason for women's stronger response is that walking is a more important form of exercise for women. For women 63% percent of the proportion of time spent doing moderate intensity physical activity is due to walking; for men the comparable proportion is 51%. Thus, a drop in walking due to an increase in crime translates into a larger drop in overall physical activity for women. This result also fits in with our finding above that the association between actual crime and perceived crime is stronger for women and with more general research that show that women

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[16] The coefficient for all activity is less well defined than the crime coefficient in the walking regression. However, a robustness test extending the crime measurement period from the previous four quarters to the previous six quarters in Appendix B.1 estimates a crime coefficient statistically significant at the 5% level of -42.0 (s.e. = 16.5). This result suggests that in the longer term an increase in crime from the 25th to 75th percentile reduces all physical activity by 28 minutes, a 4.5% decrease at the mean.

perceive crime to be higher than do men (e.g. Hipp 2010). In a recent study, Braakmann (2012) finds that (in Mexico) women respond differently from men to victimisation from crime. Specifically, women were more likely to change their mode of transport and to adopt other avoidance strategies while men were more likely to carry a weapon and go out more.

4.2   Robustness tests

Here we assess the robustness of our results to controlling for police resources and provide evidence that our findings are not driven by residential sorting. In Appendix B we demonstrate the robustness of our results to changes in the crime measurement period and present results from a nonlinear model that accounts for the lumpiness in the distribution of our main outcome variables.

While our econometric strategy controls for unobserved time-invariant differences between local authorities and local authority specific time trends, it is possible that time-varying differences between local authorities drive the results. One potential source of time-varying differences are differential changes in police resources across local authorities. For example, an increase in high visibility policing might reduce crime and simultaneously reassure local residents, thereby encouraging them to walk more. Hence, the coefficient on the crime variable could incorrectly reflect the effect of increased police presence on walking. On the other hand, police resources could be endogenous with respect to crime.

To investigate these issues, we re-estimate our main model with additional controls for police resources. The Home Office publishes full-time equivalents of police officers and Police Community Support Officers (PCSOs) for the 38 Police Forces in England. The count on 31 March of each year also provides separate numbers for the Basic Command Units of a Police Force and the Police Force's central services. The 323 local authorities in our sample are covered by 159 Basic Command Units.[17] For most urban areas the Basic Command Unit boundaries coincide with the local authority boundaries. In rural areas, a Basic Command Unit tends to cover several local authorities. We match the officer counts for the Basic Command Units, which exclude officers working in central services and therefore less likely to be a local presence, to the local authorities in our sample.

The results in Table 6 show that our finding of a deterrent effect of violent crime on walking and total time spent doing physical activity is robust to controlling for police

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[17] Some of the Basic Command Units in our data are different from the real Basic Command Units, because we had to aggregate some units to achieve consistency across our six-year sample period over which restructuring of local policing took place.

resources. The negative coefficients on log(police officers) suggest that police officers are endogenous. Presumably, an increase in police officer numbers signals an increase in crime, so the coefficient on police officers captures part of the deterrent effect of crime.

Another concern might be that our results do not capture changes in behaviour but sorting effects. In particular, individuals who like walking might move out of local authorities with increasing crime levels into local authorities with lower crime rates, generating a negative association between violent crime and walking. However, in Appendix B.1 we find a negative effect of crime on walking even when limiting the crime measurement period to the previous quarter only, a time frame that seems too short for relocation decisions.

To examine the potential sorting bias directly, we analyse population flows from internal migration data published by the Office for National Statistics. The data are a local authority's outflows and inflows over a yearly period ending in June. We match these data to the local authority's crime rate in the previous yearly period ending in June. For example, migration data for the period July 2005 to June 2006 is matched to crime data for the period July 2004 to June 2005. We use migration data for the years ending in June 2006 to 2011 and control for all other crime as well as year effects.[18] Table 7 presents the coefficients on the violent crime rate. The results in the first row are with local authority effects. The negative coefficients suggest that local authorities with higher violent crime rates experience smaller population flows. Results in the second row include local authority effects, indicating that a within local authority increase in crime is associated with a statistically significant drop in outflows and a very small and statistically insignificant rise in inflows. Therefore, there is no evidence of movements from local authorities with increasing crime rates to local authorities with decreasing crime rates.

5   Evidence from two high-profile crimes

We exploit two high-profile crimes as a further examination of our results. These are the murder of Joanna Yeates in Bristol in December 2010 and the disappearance of Claudia Lawrence in York in March 2009. Both events received extensive coverage in the British media as both victims were white and well educated and were therefore "ideal victims" from the media's perspective (Greer 2007).

Yeates was 25-year-old landscape architect who went missing on 17 December 2010 in Bristol after an evening out with colleagues. Her body was discovered on 25 December

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[18] As in our main analyses, we exclude the City of London, Westminster and the Isles of Scilly.

2010 about 3 miles from her home. On 30 December 2010, Yeates' landlord, who lived in the same building, was arrested on suspicion of her murder but released on bail on 1 January 2011 (Morris 2011a). On 2 January 2011, Bristol police issued a fresh warning to women to avoid walking home alone after dark as Yeates' killer remained at large (Morris 2011b). On 20 January 2011, police arrested Vincent Tabak (who lived next door to Yeates) and on 22 January 2011, Tabak was charged with the murder of Yeates (Morris 2011a).

Lawrence was a 35-year-old chef at the University of York. She was last seen nearing her home in Heworth, York, on the afternoon of 18 March 2009 as she returned from work. That evening she spoke to her parents by telephone and sent a text message to a friend. She failed to arrive at work for her early morning shift the following day and has not been seen since. On 20 March 2009 her father reported her missing after entering her house and finding everything as if she had left it to go to work: "Her bike was in the kitchen because it was a nice day and she was walking into work". Her mother spoke publicly of her fear that Lawrence had been taken on her walk to work, after her parents' attempts to persuade her to use a car failed. On 25 March 2009 police announced that Lawrence had "probably come to some harm" (Barkham 2009) and subsequently her death was treated as a potential murder.

5.1   Estimation method

We begin with a simple difference-in-difference estimator:

$$\hat{\gamma}^{DID} = \left(\bar{Y}_{TREAT,POST} - \bar{Y}_{TREAT,PRE}\right) - \left(\bar{Y}_{C,POST} - \bar{Y}_{C,PRE}\right)$$

$\bar{Y}$ is the mean of the time spent walking in the last four weeks reported by individuals in the treated local authorities after the event $\bar{Y}_{TREAT,POST}$ and before the event $\bar{Y}_{TREAT,PRE}$ and in the remaining English local authorities after the event $\bar{Y}_{C,POST}$ and before the event $\bar{Y}_{C,PRE}$. To implement this estimator we run the following regression:

$$Y_{iat} = \alpha + \beta_1 POST_t + \beta_2 TREAT_a + \beta_3 POST_t \cdot TREAT_a + \varepsilon_{iat} \qquad (2)$$

The dependent variable, Y_{iat}, is the time spent 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 after the event. $TREAT_a$ is an indicator equal to 1 if the respondent lives in a local authority affected by the event. The coefficient of interest is β_3.

One weakness of the difference-in-difference estimator is the common trend assumption. It might be violated if seasonal changes in walking differ between the treated

areas and the control areas. Therefore, we additionally employ the differentially adjusted difference-in-difference estimator proposed by Bell et al. (1999), which is similar to a triple difference estimator. 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 in the same time period in the year prior to the event. Hence, the differentially adjusted difference-in-difference estimator takes the form

$$\hat{\gamma}^{DID} = \left[\left(\bar{Y}_{T,POST,YEAR} - \bar{Y}_{T,PRE,YEAR}\right) - \left(\bar{Y}_{C,POST,YEAR} - \bar{Y}_{C,PRE,YEAR}\right)\right]$$
$$- \left[\left(\bar{Y}_{T,POST,YEAR-1} - \bar{Y}_{T,PRE,YEAR-1}\right) - \left(\bar{Y}_{C,POST,YEAR-1} - \bar{Y}_{C,PRE,YEAR-1}\right)\right]$$

In practice, we run the following regression:

$$Y_{iat} = \alpha + \beta_1 POST_t + \beta_2 TREAT_a + \beta_3 YEAR_t + \beta_4 POST_t \cdot TREAT_a + \beta_5 TREAT_a$$
$$\cdot YEAR_t + \beta_6 POST_t \cdot YEAR_t + \beta_7 POST_t \cdot TREAT_a \cdot YEAR_t + \varepsilon_{iat} \qquad (3)$$

$YEAR_t$ is a dummy variable indicating observations in the year of the event. The coefficient of interest is β_7.[19]

To analyse the impact of the murder of Joanna Yeates we define as the treatment area the local authorities of the former Avon area, i. e. the City of Bristol, South Gloucestershire, Bath & North East Somerset and North Somerset. We define the treatment window as from 27 December 2010, i.e. the day after police confirmed the body found by two walkers on Christmas day was indeed Joanna Yeates' body, to 22 January, the day Vincent Tabak was charged with Yeates' murder. We omit individuals interviewed between 25 December 2010 and 9 January 2011, as for these respondents a maximum of only 13 days of the 28-day reporting period were affected by the crime shock. Similarly, we include individuals interviewed up to 6 February 2011, as for them at least 14 days of the 28-day reporting period were affected by this event. The before period is 14 November 2010 to 24 December 2010, because for individuals interviewed during that period at least 14 days of the 28-day reporting period are after the end of daylight saving time on 31 October 2010, making the before period

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[19] There may also be concerns that other high profile crimes happened in the period in non-treated areas. This is very unlikely as both the Yeates and the Lawrence crimes were extremely high profile. Yeates is listed on a common crime site as the *only* high profile murder of 2011 https://en.wikipedia.org/wiki/List_of_major_crimes_in_the_United_Kingdom and Lawrence as the only high profile unsolved disappearance in 2009 https://en.wikipedia.org/wiki/List_of_people_who_disappeared_mysteriously#2007. Both events had rewards offered on the Crimestopppers web site of £50K. The Yeates murder occurred in the Christmas vacation, a period in which there is relatively little news, and as a result completely dominated the news reporting.

comparable to the treatment period. Table 8 shows the number of individuals in each of the four groups for the difference-in-difference analysis.

For our analysis of the impact of the disappearance of Claudia Lawrence we define the treatment area as the city of York and the local authorities that share a border with York, i.e. Hambleton, Ryedale, East Riding of Yorkshire, Selby and Harrogate. The treatment period begins on 25 March 2009, the day police admitted Lawrence had probably come to harm. We omit individuals interviewed between 19 March 2009 and 7 April 2009 to ensure at least 14 days of the 28-day reporting period are after the crime shock. As neither a body nor a suspect have been found to date, the end of the treatment period is less clear. We include individuals interviewed up to 17 May 2009, giving us five full weeks of interviews. The control period is 9 February 2009 to 18 March 2009, providing five full weeks of interviews before the shock. The number of observations in each of the four groups for the difference-in-difference analysis are in Table 8.

5.2   Results

Table 9 presents the results for the crime shock caused by the murder of Joanna Yeates. The first column shows results using the difference-in-difference estimator (Equation 2) and the second column provides results for the differentially adjusted difference-in-difference estimator (Equation 3).

Both the difference-in-difference estimator (d-i-d) and the differentially adjusted difference-in-difference estimator suggest that the shock decreased walking by around 30 minutes, a 15% drop at the mean of 235 minutes. Both estimates are statistically significant. The effect seems to be driven by a drop in leisure walking. The two estimators give different results for all physical activity. While the d-i-d estimate suggests that the shock reduced physical activity by 108 minutes – a 20% drop at the mean of 544 minutes – the differentially adjusted difference-in-difference estimate is positive but small and statistically insignificant.

Figure 3 shows the trend in the walking variable in the treated local authorities and in the control local authorities. We see a similar pre-treatment trend, a clear drop in walking in the treated local authorities in the after period and a bouncing back of walking to pre-treatment levels after the murderer is arrested.

Results for the crime shock caused by the disappearance of Claudia Lawrence are in Table 10. Both estimators suggest that Lawrence's disappearance lead to a drop in walking. The d-i-d estimate of –34 minutes is equivalent to a drop of around 15% at the sample mean while the differentially adjusted difference-in-difference estimate of –59 minutes is

equivalent to a 25% drop. The results for transport walking and leisure walking suggest that the drop in walking caused by Lawrence's disappearance is driven by a drop in transport walking. The d-i-d estimate of –38 minutes, a 45% drop in transport walking at the mean of 82 minutes, is statistically significant at the 1% level and similar to the differentially adjusted difference-in-difference estimate of –55 minutes. This pattern of response fits with the belief that Lawrence came to harm on her way to work. The d-i-d estimate and the triple difference estimates for physical activity are similar and indicate that the crime shock resulted in a 12 to 15% fall in total physical activity. This fall takes the mean individual well below the public health target of 600 minutes of physical activity over the four-week period.

Figure 4 shows the trend in transport walking in the treated areas and the control areas. Again we see a drop in transport walking during the treatment period and a bouncing back to pre-treatment levels after it became clear that the disappearance was not connected to a serial killer and that Lawrence might not have been a random victim.[20] The vertical lines in Figure 4 indicate the 25 March – the beginning of the treatment period – in the previous and following year. This shows that transport walking normally rose around this time in the treated areas.

The broad similarity of the simple d-i-d and the triple difference estimates supports the validity of our identification strategy. We conclude that these two high-profile crimes led to a drop in walking of between 30 and 60 minutes and a drop in total physical activity of between 70 and 100 minutes. These estimates are 3 to 6 times larger than our estimates in Section 4 for a fall in the local crime rate from the 75th to the 25th percentile. This makes sense. Most individuals experience crime only indirectly and therefore "everyday" changes in local crime rates have a small impact on the perceived probability of becoming a victim of crime while walking. The extensive media coverage of the Joanna Yeates and Claudia Lawrence cases, however, ensured a large impact of these two violent crimes on the perceived probability of becoming a victim of crime in the local areas where the women had been murdered/disappeared.

6   Conclusions

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. Our main focus is on the impact of crime on walking, as this is the most common

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[20] The lead detective made a statement about Lawrence's relationships having "had an element of complexity and mystery to them" in early June 2009 (Glendinning 2009).

and often *only* form of physical activity that individuals undertake. 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 up this analysis with evidence from two very high media profile crime shocks caused by the murder/disappearance of two young women.

We find that an increase in local area violent crime with injury leads to a statistically significant reduction in physical activity. First, the time spent walking continuously for at least 30 minutes over a four-week period falls.[21] The effect works mainly through reducing transport walking, rather than walking undertaken for leisure or recreational purposes, which could be undertaken outside the local area.[22] Second, not only does walking of residents in the local area fall, so does their total time spent doing physical activity. In fact, the overall fall in physical activity following a crime shock is greater than the fall in walking. As the most common forms of activity after walking are going to the gym, swimming and cycling, it appears that crime deters access to activity taken using indoor facilities as well as limiting outdoor activities. In a UK context where individuals often walk or use public transport to access such facilities this is perhaps not surprising.

The welfare implications of violent crime through its effect on physical activity are potentially wide-ranging. Increases in physical activity improve population health through reductions in the risk of cardiovascular disease, some cancers and type 2 diabetes, control of body weight, improvements in musculoskeletal health and reductions in depressive symptoms (World Health Organisation 2002). If transport walking replaced motorised transport, there would be less traffic congestion, road danger, noise and air pollution (Sinnett et al. 2011) with a knock-on effect on population health (see, for example, Janke et al. 2009). Further, walking provides opportunities for social interactions, which supports the development of social capital (Sinnett et al. 2011).

A fall in crime could potentially affect all of these outcomes, though precise quantification of the gains in welfare is difficult. As a (very) lower bound we calculated the direct benefits to the health service (the NHS) of a reduction in the number of acute myocardial infarction events (heart attacks) and newly diagnosed cases of type 2 diabetes due to an increase in walking if crime were to fall to the 25th percentile of the sample distribution. We estimated this for only the 53% of the population who either do not take any exercise at all or for whom walking is the only form of exercise, as these individuals are most likely to

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[21] The effect of reducing crime from the 75th to the 25th percentile of the sample distribution is of roughly the same magnitude as increasing the average daily minimum temperature over the four-week period by 7°C or as reducing average daily rainfall over the four-week period by 8 mm.

[22] Subject to the caveat that the exact split into transport and leisure walking is potentially measured with error.

benefit from increased walking. We obtain potential savings of £4.1 million per annum for this small part of the potential welfare impact alone (see Appendix C).

On one level, the policy implications are clear: efforts to reduce violent crime will reduce disincentives to walk and undertake physical activity. However, the implications are possibly more subtle. Targeting all crime is not likely to be a useful strategy as our results show that there is no causal link between violent crime without injury and either walking or overall physical activity. It is the less common and high profile crimes that people appear to react to. This finding supports the greater use of targeting resources on particular types of crime and types of perpetrators, an approach already espoused by police services world-wide who are facing budgetary pressures.[23] Our research also suggests that cost-benefit analyses of such policing activities should include the impact on physical activity.

In sum, our 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 wellbeing of non-victims and suggests that targeted policies to reduce the amount of – and fear of – violent crime in society could have positive effects well beyond the direct effects of fewer victims of crime.

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[23] An example from the Metropolitan Police Force can be found at http://www.london.gov.uk/mayor-assembly/london-assembly/publications/smart-policing.

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Figure 1: Quarterly means of walking days in last 4 weeks
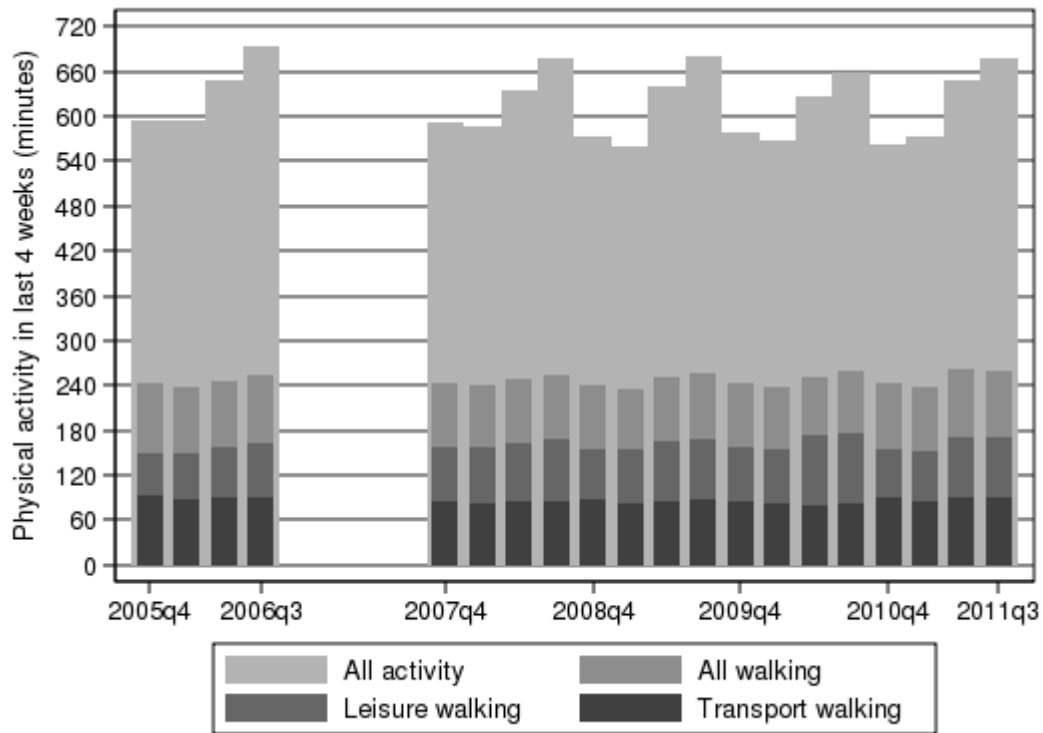
Figure 2: Local authority means of violent crime with injury rate and time spent walking in last 4 weeks
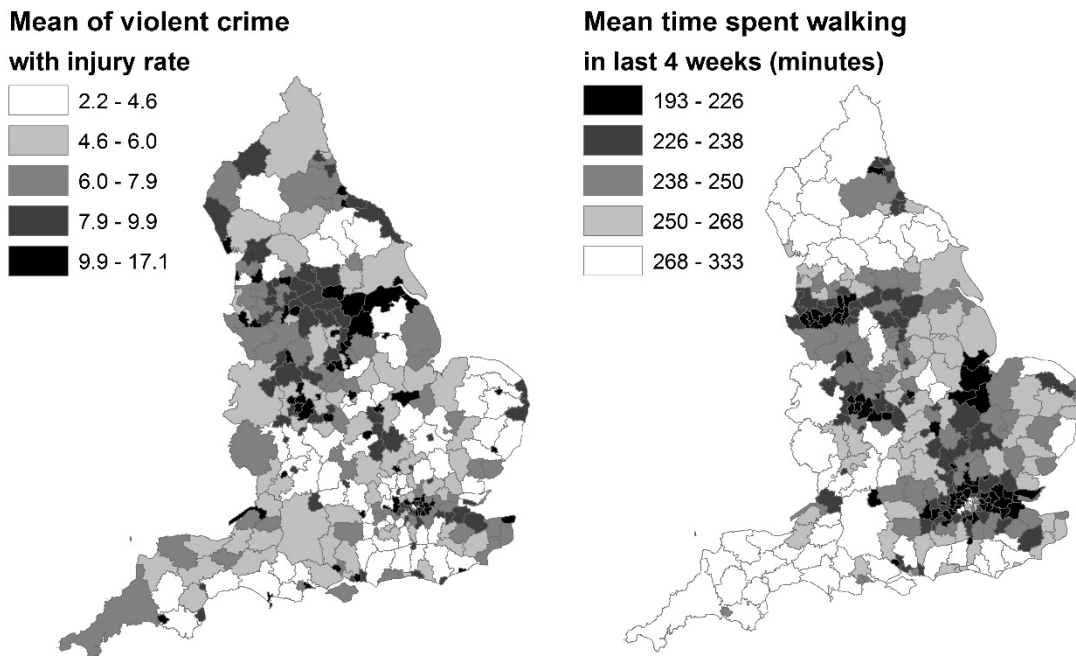
Figure 3: Trends in walking in local authorities affected by murder of Joanna Yeates and in control local authorities
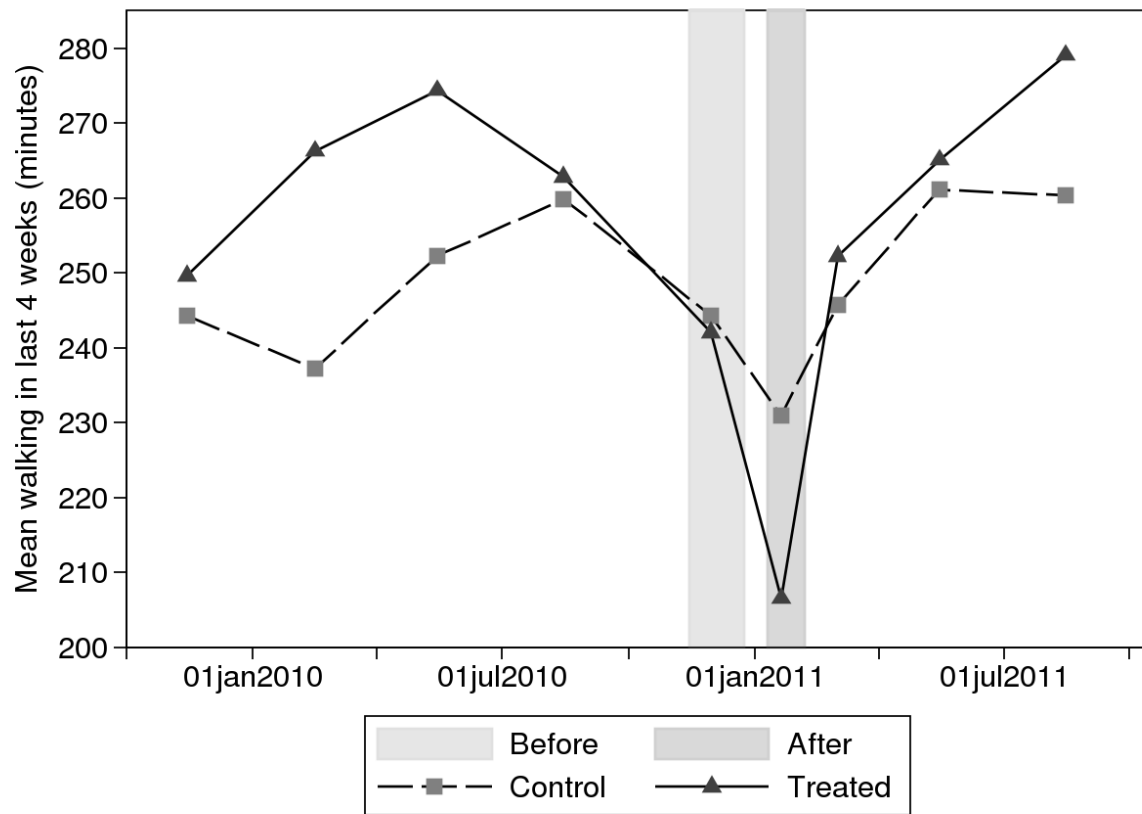
Figure 4: Trends in transport walking in local authorities affected by disappearance of Claudia Lawrence and in control local authorities. Vertical lines indicate 25 March (begin of treatment period) in previous and following year
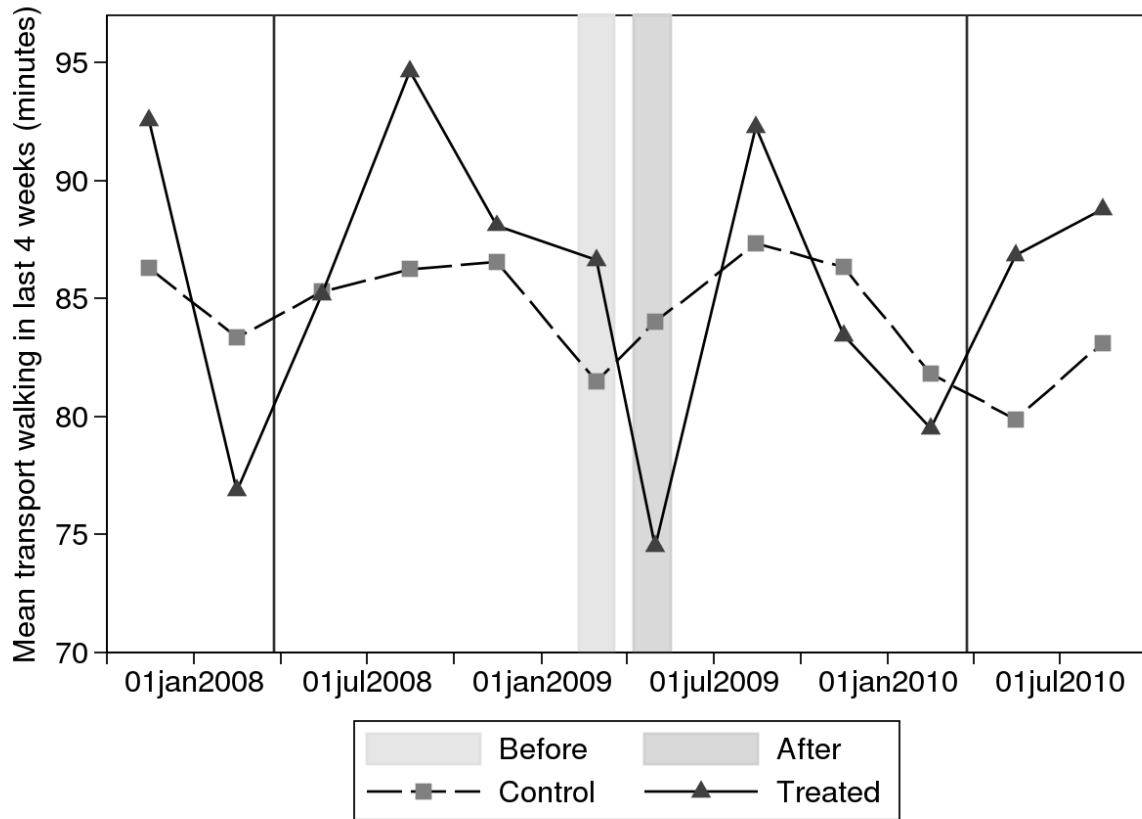
Table 1
Descriptive statistics

Variable	Mean	St. dev.	25th perc.	Median	75th perc.
Outcome variables (N = 964,318)					
Time spent walking in last 4 weeks (minutes)					
All	247.1	293.9	0	120	420
Transport	87.0	190.2	0	0	60
Leisure	160.1	250.7	0	30	210
All physical activity (minutes)	621.9	895.0	60	360	840
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			
Violent crime without injury	8.15	4.0	5.3	7.3	9.9
Between		3.7			
Within		1.3			
Remaining offences	63.7	24.4	45.6	58.4	77.4
Between		22.4			
Within		9.7			
Unemployment rate	5.8	2.3	4.1	5.4	7.1
Between		1.9			
Within		1.3			
Police officers per 100,000	165.9	59.5	129.3	149.0	181.0
Between		56.1			
Within		20.1			
PCSOs per 100,000 population	23.4	11.3	17.9	22.3	26.4
Between		9.0			
Within		6.9			
Weather variables					
(N = 389,105, n = 323, $\bar{t}$ = 1,204.7)					
Rainfall (mm)	2.0	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

Notes: PCSOs = Police Community Support Officers

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	0.016	0.140***	0.113***
	(0.030)	(0.037)	(0.032)
With area effects	0.092***	0.044***	0.047**
	(0.029)	(0.013)	(0.018)
Mean of dependent variables	0.40	0.35	0.35
Areas	38	38	38
Observations	91,290	113,753	113,750

Notes: 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%

Table 3: Association between growth rate of violent crime and lagged level of covariates, lagged walking and lagged violent crime rate. Dependent variables 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	Change in walking	Lagged violence with injury	Change in violence with injury
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
F-statistic	0.70	0.92	0.73				
p-value	0.94	0.45	0.92				
Coefficient				0.000	0.000	-0.273	0.006
				(0.000)	(0.000)	(0.008)	(0.013)
Obs.	6,447	6,447	6,447	6,447	6,124	6,447	6,124

Notes: 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 the lagged covariates $[X'_{a(t-1)}$ and $n^{-1}\sum_{i=1}^{n} Z'_{ia(t-1)}]$. 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.

Table 4: Estimates of the effect of local authority rate of violent crime with injury on time spent walking at steady average pace or faster in last four weeks

	1	2	3	4	5	6
Log(violent crime with injury)	-20.4***	-16.0***	-22.4***	-9.4***	-11.5***	-14.7***
	(2.6)	(2.4)	(1.8)	(3.2)	(3.7)	(5.0)
Log(violent crime without injury)					2.7	-0.8
					(2.4)	(3.5)
Log(other crime)					5.2	9.4
					(5.6)	(7.8)
Log(unemployment)					9.6***	2.1
					(3.2)	(4.0)
Rainfall					-1.2***	-1.2***
					(0.3)	(0.3)
Max. temperature					0.7**	0.6*
					(0.3)	(0.3)
Minimum temperature					1.3***	1.4***
					(0.4)	(0.4)
Individual controls	No	Yes	Yes	Yes	Yes	Yes
Local authority effects	No	No	Yes	Yes	Yes	Yes
Time effects	No	No	No	Yes	Yes	Yes
LA-specific trends	No	No	No	No	No	Yes
R-squared	0.001	0.027	0.032	0.033	0.033	0.033

Notes: 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. 964,318 observations in 323 local authorities in all regressions. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 5: Estimates of the effect of local authority rate of violent crime on time spent doing physical activity by type

	All walking	Transport walking	Leisure walking	All activity
Log(violent crime with injury)	-14.7***	-9.5***	-5.2	-22.3*
	(5.0)	(3.0)	(4.3)	(12.8)
Log(violent crime without injury)	-0.8	1.9	-2.6	1.5
	(3.5)	(2.1)	(3.1)	(9.4)
R-squared	0.033	0.046	0.045	0.077

Notes: 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. 964,318 observations in 323 local authorities in all regressions. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 6: Estimates of the effect of local authority rate of violent crime on time spent doing physical activity in last four weeks with additional controls for police resources

	Walking	All activity
Log(violent crime with injury)	-14.1***	-21.7*
	(5.0)	(12.8)
Log(violent crime without injury)	-1.4	0.4
	(3.5)	(9.4)
Log(other crime)	8.2	3.8
	(7.8)	(21.3)
Log(police officers)	-11.4*	-13.5
	(6.6)	(18.6)
Log(PCSOs)	5.6**	9.4
	(2.2)	(6.3)
R-squared	0.033	0.077

Notes: 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. 964,318 observations in 323 local authorities in all regressions. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 7: Association between local authority violent crime and population flows

	Outflow	Inflow
Without local authority effects	-214.4	-253.0
	(188.3)	(164.9)
With local authority effects	-45.9***	7.8
	(16.8)	(16.6)
Mean of dependent variable	7,914	7,883
Areas	323	323
Observations	1,938	1,938

Notes: Coefficient on violent crime with injury shown, with robust standard errors in brackets, clustered by local authority. All coefficients from separate regressions. All regressions control for all other crime and year effects. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 8: Number of individuals in each group
A. Murder of Joanna Yeates

	Before	After	Total
Untreated	17,941	10,721	28,662
Treated	229	95	324
Total	18,170	10,816	28,986

B. Disappearance of Claudia Lawrence

	Before	After	Total
Untreated	17,081	16,758	33,839
Treated	245	265	510
Total	17,326	17,023	34,349

Table 9: Difference-in-difference estimates of the impact of December 2010 murder of Joanna Yeates on time spent doing physical activity

	Difference-in-difference			Differentially adjusted diff-in-diff		
	Estimate	Mean	N	Estimate	Mean	N
All walking	-38.0***	234	28,986	-30.6*	235	64,937
	(14.6)			(16.4)		
Transport walking	8.9	88	28,986	-1.7	86	64,937
	(11.3)			(9.2)		
Leisure walking	-46.9*	146	28,986	-28.8**	149	64,937
	(24.4)			(14.2)		
All activity	-108.3***	544	28,986	11.1	548	64,937
	(35.2)			(30.1)		

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

Table 10: Difference-in-difference estimates of the impact of March 2009 disappearance of Claudia Lawrence on time spent doing physical activity

	Difference-in-difference			Differentially adjusted diff-in-diff		
	Estimate	Mean	N	Estimate	Mean	N
All walking	-34.1*	242	34,349	-58.8*	243	69,203
	(19.5)			(34.7)		
Transport walking	-38.3***	82	34,349	-55.3**	83	69,203
	(5.6)			(25.5)		
Leisure walking	4.1	161	34,349	-3.5	161	69,203
	(18.1)			(31.9)		
All activity	-72.7	597	34,349	-93.3	603	69,203
	(61.5)			(126.1)		

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

Appendix A   Data description

The Active People Survey (APS) 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 2\%. Various piloting stages ensure quality data.

We use the first five waves of the APS: 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 only 50% of the sample, including household income and car ownership.

At the beginning of the interview, respondents are asked "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?". The next question is "How would you describe your usual walking pace?" with the answer options being "a slow pace", "a steady average pace", "a fairly brisk pace" and "a fast pace". If the respondent selects at least "a steady average pace" we use the reported number of walking days to construct our walking measure. As the reported number of walking days refers to walks lasting at least 30 minutes, we approximate the time spent walking in the last four weeks by multiplying the number of walking days by 30 minutes.

The interview continues with "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 this question as leisure walking days and construct a measure of transport walking days by subtracting leisure walking days from all walking days. Again, we approximate the time spent walking for the purpose of leisure and the time spent walking for the purpose of transport by multiplying the number of walking days by 30 minutes.

After the questions about walking, the interview continues with a similar series of questions about cycling. We assume that all cycling is of at least moderate intensity and approximate the time spent cycling by multiplying the number of days on which the respondent cycled for at least 30 minutes by 30 minutes. The interviewer then asks about other types of sport and recreational physical activity the respondent may have done over the last four weeks.

Table A-1

Data Sources

Variables	Source of data	Time periods covered
Physical activity measures and individual-level controls	Active People Survey 1-5	Oct 2005-Oct 2006, Oct 2007-Oct 2011
Police recorded crime	Freedom of Information request to UK Home Office	II/2004-III/2001
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 2005-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

Variable	Mean		Variable	Mean
Male	0.41		Single adult	0.32
Age 16 to 24	0.09		Family status missing	0.03
Age 25 to 34	0.14		Child aged 0 to 4	0.11
Age 35 to 44	0.21		Child aged 5 to 10	0.16
Age 45 to 54	0.20		Child aged 11 to 15	0.14
Age 55 to 64	0.21		Child age missing	0.00
Age 65 to 74	0.16		< £10,400 per annum	0.09
White British	0.89		£10,400 to £ 20,700	0.17
Indian	0.02		£20,800 to £31,199	0.15
Pakistani	0.01		£31,200 to £41,599	0.11
Bangladeshi	0.00		£41,600 to £51,999	0.08
Caribbean	0.01		£52,000 or more	0.12
African	0.01		Household income missing	0.29
Chinese	0.00		Social rented housing	0.11
Other ethnic group	0.06		Housing missing	0.03
No qualifications	0.13		Car in household	0.78
Other	0.03		Car missing	0.08
O level	0.23		APS5 – missing questions	0.08
A level	0.16		Monday	0.16
Higher (less than degree)	0.10		Tuesday	0.17
Degree or higher	0.30		Wednesday	0.17
Qualification missing	0.05		Thursday	0.16
Working full-time	0.44		Friday	0.13
Working part-time	0.16		Saturday	0.12
Unemployed < 12 months	0.02		Sunday	0.09
Unemployed > 12 months	0.03		Observations	964,318
Retired	0.21			
Non-participant (home/child)	0.05			
Non-participant (disabled)	0.02			
Student	0.04			
Other	0.01			
Employment status missing	0.02			
Chronic limiting condition	0.15			
Limiting condition missing	0.02			

Table A-3
Descriptive statistics of British Crime Survey data

Variable	Mean	Variable	Mean
Male	0.46	Single adult	0.40
Age 16 to 24	0.09	Child aged 0 to 4	0.13
Age 25 to 34	0.16	Child aged 5 to 10	0.16
Age 35 to 44	0.22	Child aged 11 to 15	0.15
Age 45 to 54	0.18	< £5,000 per annum	0.06
Age 55 to 64	0.19	£5,000 to £9,999	0.09
Age 65 to 74	0.15	£10,000 to £14,999	0.09
White British	0.89	£15,000 to £24,999	0.16
Indian	0.02	£25,000 to £34,999	0.13
Pakistani	0.01	£35,000 to £49,999	0.14
Bangladeshi	0.00	£50,000 or more	0.13
Caribbean	0.01	Household income missing	0.20
African	0.01	Social rented housing	0.16
Chinese	0.00	Housing missing	0.00
Other ethnic group	0.06	Car in household	0.83
No qualifications	0.24	Observations	113,753
Other	0.10		
O level	0.22		
A level	0.12		
Higher (less than degree)	0.12		
Degree or higher	0.19		
Qualification missing	0.00		
Working full-time	0.47		
Working part-time	0.16		
Unemployed	0.06		
Retired	0.19		
Non-participant (home/child)	0.07		
Non-participant (disabled)	0.05		
Student	0.02		
Employment status missing	0.02		
Chronic limiting condition	0.16		

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

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Appendix B   Robustness checks

We examine the robustness of our results to changes in the crime measurement period. Next we show that results from a nonlinear model that accounts for the lumpiness in the distribution of our main outcome variables are in line with our main results and indicate that violent crime affects physical activity at the extensive as well as intensive margin.

B.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 B-1 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 annualise 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.

For both walking and all physical activity, the figure shows an increasing deterrent effect of crime as the period over which crime is measured is extended. The small effect of the more recent crime rate may be picking up the fact that respondents update their beliefs about local crime rates only slowly. 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 reasonably robust to the precise number of quarters used to define the crime rate.

B.2   The distribution of the outcome variable

The distribution of our dependent variables has peaks at various days, reflecting patterns in transport and leisure walking and other types of physical activity. For 32% of respondents our walking measure is zero minutes. There are spikes at 120, 240 and 360 minutes which correspond to walking once, twice or three times a week, respectively. A spike at 600 minutes corresponds to walking on 20 days and a smaller spike at 300 minutes to walking on 10 days, reflecting the 5 weekdays in each of the four weeks of the measurement period. For 13% of respondents our walking measure is 840 minutes, i.e. walking every day continuously for at least thirty minutes over the measurement period of 28 days. A similar pattern emerges for all physical activity: 21% of respondents report no physical activity at all while 30% of respondents report physical activity ranging from 840 minutes to 15,120 minutes.

To check the robustness of our linear specification, we estimate a multinomial logit model with four categories: 0 minutes, 1 to 120 minutes, 121 to 420 minutes and more than 420 minutes for walking and 0 minutes, 1 to 360 minutes, 361 to 840 minutes and more than 840 minutes for all physical activity. Each of these categories accounts for approximately one-quarter of the observations. We include the same controls as in our main specification. The results are in Table B-1.

For walking, the negative and statistically significant crime coefficient of -0.131 in the >420 minutes equation suggests that as crime increases the probability of walking for more than 420 minutes rather than 0 minutes decreases. The coefficient for the >420 minutes versus 1 to 120 minutes contrast is of similar size (-0.131 – 0.005 = -0.136) as is the coefficient for the >420 minutes versus 121 to 420 minutes contrast (-0.131 – -0.019 = -0.112), suggesting that an increase in crime also reduces the probability of walking for more

than 420 minutes rather than 1 to 120 minutes or 121 to 420 minutes. Thus, crime seems to affect walking at extensive as well as the intensive margin as these results suggest that an increase in crime induces individuals who walk regularly to stop walking altogether or to reduce the amount of walking.

The results for all physical activity are similar. The crime coefficient in the 361 to 840 minutes equations is negative and statistically significant, indicating that a crime increase reduces the probability of spending 361 to 840 minutes doing physical activity instead of doing no physical activity at all. The coefficient for the 361 to 840 minutes versus 1 to 360 minutes contrast is of similar size (-0.105 – -0.007 = -0.098). Again, crime seems to affect physical activity at the extensive as well as the intensive margin. Individuals who exercise regularly for 361 to 840 minutes stop exercising altogether or reduce the amount of exercise to below the target of 600 minutes. Overall, the results of the multinomial logit model are in line with the linear model's finding of a negative effect of crime on physical activity.

Figure B-1
Estimates for different measurement periods for crime variable. Coefficients on log(violent crime with injury) and 95% confidence intervals
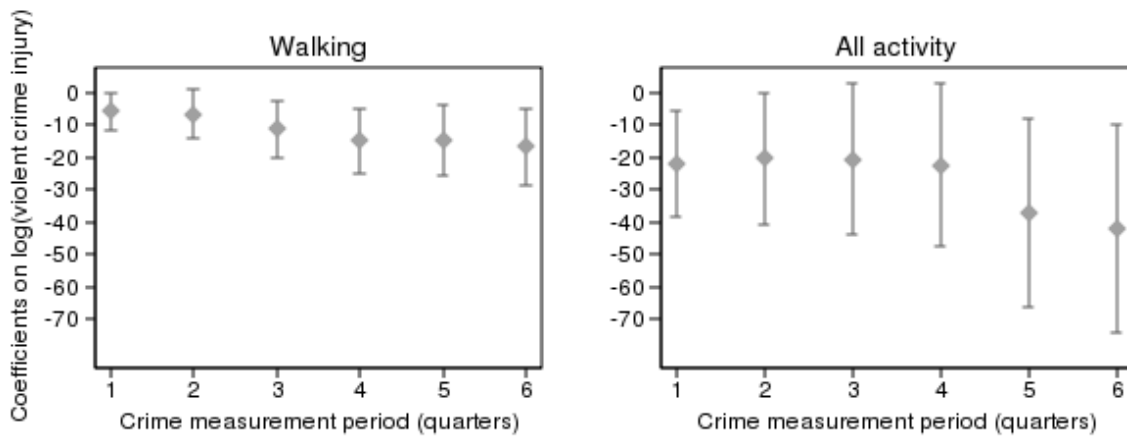
Table B-1

Multinomial logit models of time spent doing physical activity in last four weeks: Coefficients on log(violent crime with injury)

Categories	Walking	Categories	All activity
0 minutes	Base outcome	0 minutes	Base outcome
1 to 120 minutes	0.005	1 to 360 minutes	-0.007
	(0.044)		(0.046)
121 to 420 minutes	-0.019	361 to 840 minutes	-0.105**
	(0.051)		(0.048)
> 420 minutes	-0.131***	> 840 minutes	-0.057
	(0.048)		(0.049)

Notes: 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. 964,318 observations in 323 local authorities in all regressions. *Significant at 10%, **significant at 5%, ***significant at 1%.

Appendix C   Welfare implications

Example calculations for heart attacks and new cases of type 2 diabetes
To give some indication of the economic significance of our estimates, we examine the effect of the fall in walking on two health outcomes. The beneficial effects of walking are well established for both coronary heart disease and diabetes (World Health Organization 2002). We therefore calculate by how much an increase in walking following a drop in crime to the 25th percentile of the sample distribution could reduce the number of acute myocardial infarction events (heart attacks) and newly diagnosed cases of type 2 diabetes.

The bulk of the medical literature reports relative risks for quintiles of the sample distribution of energy usage. Researchers use a standardized classification of the energy expenditure associated with physical activities to calculate an energy expenditure score in metabolic equivalents (MET score) from responses to questions about frequency and duration of different types of physical activity in a typical week. They then calculate disease risks for each of the five quintiles of the distribution of these MET scores. Mirroring this study design, we use the regression model for walking (Column 6 of Table 4) to predict the time spent walking for respondents who report no cycling and no other types of sport and recreational physical activity and determine the quintiles of the predicted walking days distribution. This 53% of the sample who report walking as the only form of exercise or no exercise at all in the last four weeks are most likely to benefit from increased walking. We then replace the actual violent crime rate with the 25th percentile if it is above the 25th percentile, predict the number of walking days and calculate the number of respondents in each of the quintiles. The table below presents the results in the first panel.

We next calculate the number of acute myocardial infarction events we expect to happen in each of the quintiles for the original level of violent crime and for violent crime at the 25th percentile. We use a basic incidence rate of 80 per 100,000 population, which is the mean of the rates for men and women under 75 for the period 2005 to 2010 reported in British Heart Foundation (2012), and the multivariate relative risks according to quintiles of walking in Manson et al. (2002). These results are in the second panel of the table above. Results in the third panel are for new diagnoses of type 2 diabetes using a basic incidence rate of 431 per 100,000 population (Gonzalez et al. 2009) and the multivariate adjusted (including BMI) relative risks according to quintiles of walking from Hu et al. (1999).

The results show that a reduction in the violent crime rate to the 25th percentile could have reduced acute myocardial infarction events from 338 to 333 and new type 2 diabetes diagnoses from 1,884 to 1,860. Under the assumption that the proportion of the English population who do not do any exercise other than walking or do not do any exercise at all is given by our sample mean (53%), there are around 20.6 million people in the age range 15-74 years who could potentially benefit. This is 40 times the number in our sample (508,514 person-years) and therefore the total number of acute myocardial infarction events that could be prevented is 200 (= 40 × 5) and the total number of new type 2 diabetes diagnoses that could be prevented is 960 (= 40 × 24).

To put a monetary value on these numbers we take a lower bound and calculate only the direct costs to the NHS. The cost per hospital admission for acute myocardial infarction without complications is £2,037 and £3,029 with complications according to the Payment by Results tariff 2005/2006 (Department of Health 2004). From NHS discharge data (Hospital Episode Statistics) the proportion of cases with complications has a mean of 25% over our sample period. Thus the potential savings from reducing acute myocardial infarction events by 200 are £0.46 million (150 × £2,037 + 50 × £3,029). For type 2 diabetes, Kanavos et al. (2012) estimate the annual direct cost (drugs, inpatient and outpatient care) per patient in 2010 as £ 3,717. Therefore, 960 fewer cases could save £3.6 million annually. Assuming

patients are diagnosed at age 50 and live until age 70, the total savings could be £72 million (20 years ×£3.6 million).

Estimated number of acute myocardial infarction (AMI) events and new diagnoses of Type 2 diabetes according to quintile of distribution of predicted time spent walking for original violent crime rate and violent crime rate at 25th percentile

Quintile	1	2	3	4	5	Total
Observations in quintile						
Original crime rate	101,702	101,704	101,703	101,703	101,702	508,514
25th percentile	90906	86,715	96,298	108,503	126,092	508,514
Incidence of AMI (per 100,000 pop.)	80×1	80×0.91	80×0.82	80×0.75	80×0.68	
Original crime rate	81	74	67	61	55	338
25th percentile	73	63	63	65	69	333
Difference						5
Incidence of Type 2 diabetes (per 100,000 pop.)	431×1	431×0.95	431×0.80	431×0.81	431×0.74	
Original crime rate	438	416	351	355	324	1,884
25th percentile	392	355	332	379	402	1,860
Difference						24