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THE EFFECT OF LOCAL AREA CRIME ON MENTAL HEALTH*

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This study analyses the effect of local crime rates on residents' mental health. Using longitudinal information on individuals' mental well-being, we address the problem of sorting and endogenous moving behaviour. We find that crime causes considerable mental distress for residents, primarily driven by property crime. Effects are stronger for females, and mainly related to depression and anxiety. The distress caused by one SD increase in local crime is 2–4 times larger than that caused by a 1 SD decrease in local employment, and about one-seventh of the short-term impact of the 7 July 2005 London Bombings.

According to the Eurobarometer, crime has been among the top five concerns of European citizens in recent years and the fight against crime is among the main priorities respondents believe their governments should have.[1] These concerns seem hardly justified by actual crime rates, where European countries rank very low in comparison to other parts of the world,[2] which suggests that crime leads to distress for a large part of the population through channels other than direct victimisation. These indirect costs of crime, through inflicting fear and anxiety, and leading to changes in daily routines and behaviour (Hamermesh, 1999; Braakman, 2013; Janke *et al.*, 2013), may be far larger than the direct costs. Indeed, in a recent paper, Becker and Rubinstein (2011) argue that major criminal acts such as terrorist attacks inflict most harm by creating fear and by inducing changes in behaviour and individual choices. Measuring the magnitude of these indirect costs of crime is crucial for assessing the optimal investment into crime prevention. While the direct costs (response costs of police and the Criminal Justice System, and costs through

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[1] Summary reports on Eurobarometer waves since 1974 can be downloaded at: http://ec.europa.eu/public_opinion/archives/eb_arch_en.htm.

[2] For instance, over the last decade, EU27 countries experienced a homicide rate below 2 per 100 thousand population, which contrasts with a world estimate of almost 8 (estimated in 2004) and with average rates in Southern Africa and Central America between 20 and 30 (Harrendorf *et al.*, 2010).

the impact on victims) are routinely assessed,[3] evaluations of indirect costs, including those of non-victims, are scarce, and far more difficult.

In this study, we analyse costs of crime that are indirect and intangible. While indirect but tangible costs – such as changes in behaviour (not going out at night, not wearing jewellery, carrying a self-defence weapon etc.) and investment in security (burglar alarms, armoured doors and windows, weapons etc.) – can in principle be inferred from surveys, intangible costs (fear, anxiety, mental distress etc.) are particularly difficult to measure. Our main contribution is to estimate the effect local crime has on the mental health of individuals who live in the area where this crime takes place, by combining official crime statistics with detailed information on individuals' mental well-being, which we obtain from the British Household Panel Survey (BHPS) and the English Longitudinal Study of Ageing (ELSA). Both these surveys are panel surveys, which allows us to use a design that eliminates possible correlation between area crime and mental distress due to sorting of more distressed individuals into areas with higher (or lower) crime incidences. By matching each individual to detailed local-area crime statistics for various types of crimes, we are able to distinguish further between the effects that particular types of crime have on mental health, thus identifying the most distressing criminal offences. We also analyse the impact of crime on different dimensions of mental health and we study heterogeneity in responses across different groups of residents.

Our findings show a significant, and negative, impact of overall local crime rates on the mental distress of residents in urban areas. The impact is sizeable: a 1 SD increase in the overall local crime rate causes an increase in mental distress that accounts for between 8% and 15% of the (within-individual) standard deviation in self-reported mental well-being. This is about twice to four times as large as the effect of a 1 SD decrease in the areas' employment rate on mental distress. Burglary, car theft and vandalism are the crime types which seem to cause major anguish. In addition, we find heterogeneity in responses. While individuals react only to property crime when crime rates are measured in the immediate residential location, violent crime causes mental distress when including the surrounding areas, suggesting that this crime type impacts through affecting individuals' daily routines, like travel to work etc. When distinguishing between men and women, we find that women are more responsive to changes in crime rates than men. Our results based on the ELSA, a data set which contains alternative measures of mental health and focuses on a particularly vulnerable group, those above the age of 50, produces very similar results.

To assess the magnitude of our findings further, we estimate the effect of the London bombings on the 7 July 2005 on mental distress. Using a difference-in-differences approach, we show that in the months following the attack, citizens of London and the other major cities in the UK experienced a significant drop in their

[3] See Soares (2010) for a recent survey of the different approaches to estimating costs of crime. In its most recent estimation, the UK Home Office puts the cost of crime against individuals and households in the UK at about £36.2 bn in 2003/04, which amounts to about 3% of GDP (Dubourg *et al.*, 2005). Following the methodology suggested in Dolan *et al.* (2005), these estimates carefully appraise 'physical and emotional impact on direct victims' – which accounts for about 50% of total cost of crime. However, they do not consider the additional cost imposed by the fear of crime on the overall British society, which is one objective of this study.

self-reported mental health. We find that the reduction in mental wellbeing following a 1 SD increase in local crime is about one-seventh of the fall in mental well-being caused by the London Bombings.

Our article contributes to the literature on estimating intangible costs of crime by focusing on a new and specific aspect. While most of the previous literature has implemented either contingent valuation methods based on stated preferences (Cohen *et al.*, 2004; Atkinson *et al.*, 2005),[4] or hedonic price models based on revealed preferences (Gibbons, 2004; Linden and Rockoff, 2008),[5] our study focuses on the detrimental impact of exposure to changes in local crime on mental well-being of residents. Our work is also related to a recent paper by Cornaglia *et al.* (2014) on the relationship between mental well-being and crime for Australia.[6] While Cornaglia *et al.* (2014) focus most of their discussion on the difference between being victimised and being exposed to crime (but not victimised), our article develops an in-depth analysis of the consequences for mental health of exposure to local crime.[7]

Our article is also related to the literature on neighbourhood effects and mental well-being. Several non-experimental studies – almost entirely based on cross-sectional analysis – find significant associations between the mental health of residents and aspects of the neighbourhood environment.[8] Based on the Moving to Opportunity (MTO) experiment, a randomised experiment on residential mobility conducted in five US cities in the 1990s, a number of studies have shown that moving away from deprived (high crime) neighbourhoods leads to significant improvements in adult physical and mental health and subjective well-being in the short (Katz *et al.*, 2001), medium (Kling *et al.*, 2007) and long term (Ludwig *et al.*, 2012).[9] We add to this literature by focusing on the direct link between area crime rates and mental distress of residents who are living in the area, and by providing a precise assessment of the magnitude of these effects. We use longitudinal data and exploit repeated information on both mental well-being and area crime to eliminate potential sorting biases. Moreover, we analyse which specific dimensions of mental well-being are affected by crime, we distinguish the effects of different types of crime on mental distress and we assess the heterogeneity in responses across different population groups.

[4] See Hausman (2012) for a criticism of the reliability of contingent valuation methods in assessing social costs of changes in environmental quality, and a more positive assessment by Carson (2012).

[5] Gibbons (2004) and Linden and Rockoff (2008) show that house prices fall in response to, respectively, increases in local property crime and the presence of convicted sexual offenders in the area. Similarly, Besley and Mueller (2012) look at the impact of conflict in Northern Ireland (rather than crime) and establish a negative correlation between killings and house prices.

[6] The two papers were part of the project 'Crime and mental wellbeing' supported by an ESRC grant (grant number: RES-000-22-1979).

[7] With respect to Cornaglia *et al.* (2014), we use two alternative data sets, three different measures of mental health and measures of crime rates at two levels of geographical disaggregation. Further, we analyse both timing and heterogeneity of the effects, consider single mental health items and single criminal offences and benchmark the magnitude of the effects we find against the mental health consequences of a major terrorist attack.

[8] See Mair *et al.* (2008) and Diez-Roux and Mair (2010) for recent reviews of this literature. In the UK, Propper *et al.* (2005) find a limited association between neighbourhood characteristics and levels (and changes) in mental health of residents.

[9] Oreopoulos (2003) exploits quasi-experimental variation in assignment to different public housing projects in Toronto to estimate the impact of neighbourhood characteristics on long-term labour market outcomes of residents but does not investigate health and mental well-being as possible outcomes.

The research we provide in this article adds to the policy debate on the cost of mental distress to the overall society and on the role played by crime in reducing people's well-being. Layard (2005) argues that mental issues represent one of the biggest problems in British society, with serious consequences for the welfare system. He estimates the cost of mental illness at about 2% of GDP.[10] Crime is an important aggravating factor: According to the National Institute for Mental Health in England (2005), reducing fear of crime would improve mental health and well-being of Britain's populations. Following an influential independent report on health inequalities produced in the late 1990s (Acheson, 1998), the British Department of Health identified decreasing exposure to crime in the neighbourhood as a crucial policy to restrict disparities in health hazard among the British population (Department of Health, 1999) and this is still a key focus of their intervention (Department of Health, 2009). Clearly, the problem is not limited to Britain. The WHO Commission on Social Determinants of Health recognised the level of crime and violence in the area of residence as an important social cause of poor health (CSDH, 2008). Our study contributes to this debate, by providing a precise assessment of the relationship between crime and mental distress.

The article is structured as follows. Section 1 provides a brief discussion of the underlying mechanisms which link exposure to crime to mental distress, describes the data used for the empirical analysis and reports some descriptive evidence on crime and mental distress in the UK. Our main estimating equation, identification issues and empirical strategy are discussed in Section 2. Section 3 reports estimation results and robustness checks. In this Section, we also describe how we estimate the impact of the 2005 London bombings, present the estimates and benchmark our previous estimation results on the impact of local crime rates. Finally, the last Section contains a brief discussion of our findings and some concluding remarks.

1. Background, Data and Descriptive Evidence

1.1. *Local Crime and Mental Distress*

There are at least three channels through which exposure to higher crime in the area of residence may lead to mental distress: an increased level of anxiety and fear of being victimised, a reduced sense of freedom implied by limitations to behaviour (not going out at night, buying a cheaper vehicle than desired, not wearing jewellery etc.) and the need to plan – and invest in – pre-emptive and deterrent strategies to avoid victimisation (e.g. checking carefully windows and back doors when leaving home; hiding valuables; taking longer, but safer, routes to return back home; parking the car only in some areas; etc.).[11]

[10] According to the Mental Health Minimum Dataset (MHMDS) in 2008–9, about 1.2 million people (about 2.3% of total population) were in contact with National Health Service (NHS) mental health services in England for serious mental illnesses. Individuals treated for serious mental illness are only a fraction of those suffering from mental distress.

[11] A more indirect effect of area crime on residents' mental distress could go through the negative effect crime produces on house prices (Gibbons, 2004). For such a mechanism to be at work, crime shocks should have a persistent effect on expectations of future area crime. We discuss this potential channel in Section B.2 in the online Appendix.

The extent to which actual crime rates trigger any of these channels depends on how actual crime translates into fears and perceptions about crime. A large literature in the social sciences focuses on the fear of crime (rather than crime itself; see Hale, 1996) and how perceptions of crime affect mental health (Ross and Mirowsky, 2001; Green *et al.*, 2002; Whitley and Prince, 2005; Stafford *et al.*, 2007; Jackson and Stafford, 2009). Some authors (Ferraro, 1995; Smith and Torstensson, 1997; Chadee *et al.*, 2007) point out that far more people believe they are likely to be a victim of crime than actually end up being victimised. Further, groups who face low objective risks of victimisation are often more concerned about such risks; the elderly are one such example (Mawby, 1992). How actual crime rates translate into individual perceptions and fears, possibly along the channels we outline above, and are then converted into mental distress, is not what we address (and can address) in this article. Instead, we focus here on estimating the causal effect of local area crime on mental distress of residents. It is this effect – namely, the impact a reduction in crime has on the mental distress of residents, possibly induced by a combination of the different channels discussed above, and probably amplified by individual perceptions – which is an important and relevant policy parameter.

In order to get a sense of the complexity of crime perceptions and of the role played by actual crime in shaping them, consider data for the UK. During the period, we analyse in this article (2002–8), total recorded crime has decreased by 24%: this reduction has been mainly driven by property crime (Figure 1). In spite of this significant fall in crime, the majority of households interviewed in the British Crime Survey believe that crime rates have increased at the national level in

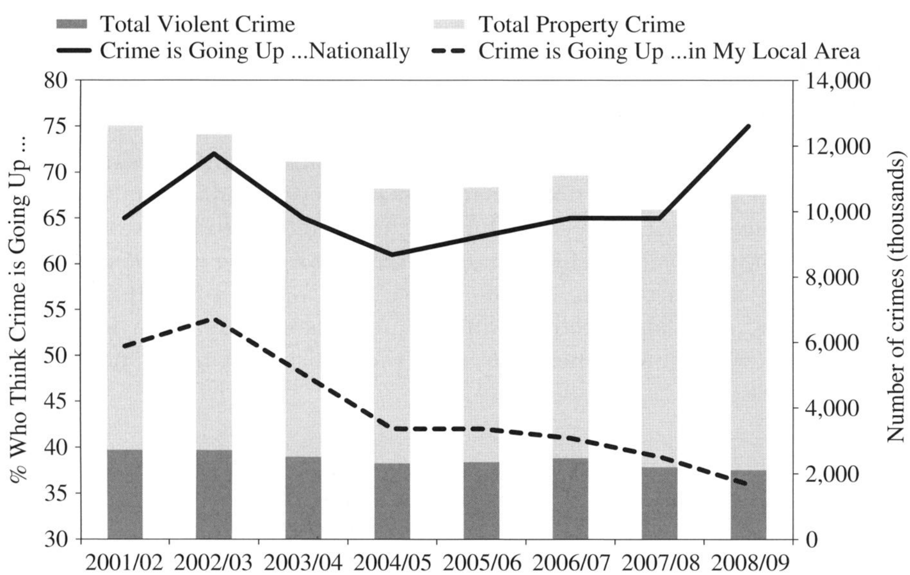

Fig. 1. *Trends in Crime and in Perceptions About Crime: 2001–9*
Note. Authors' calculations from British Crime Survey (BCS); waves 2001/2 – 2008/9.

recent years.[12] Indeed, as Figure 1 shows, the fraction of households who believe that crime rates have increased at the national level changed from 65% in 2001/2 to about 75% in 2008/9. However, respondents seem to have a more accurate assessment about crime rates in their more proximate environment. The share of households that believes crime went up in the neighbourhood is always smaller and shows a decreasing trend, dropping from 50% in 2001/2 to about 35% in 2008/9.

Further evidence on the fact that residents are informed about crime rates in the area of residence is reported in Figure A1 (see Appendix A) where we have plotted the share of respondents particularly worried about a certain criminal offence (burglary, car crime and violent crime) or a risky behaviour (drug use and dealing, anti-social behaviour) against the actual crime rate of that particular offence in the Police Force Areas (PFA) of residence (period 2002–8). The positive slope of the fitted lines suggests that concern is higher in regions where crime rates are actually higher. The negative relationship in the last graph, instead, shows that respondents are more satisfied with the police intervention in areas where total crime is lower.

1.2. *Data*

Our empirical analysis is based on two large longitudinal surveys, the British Household Survey Panel (BHPS) which contains repeated observations on subjective measures of individual mental health for a representative sample of the British population, and the English Longitudinal Study of Ageing (ELSA), which collects similar information for a sample of individuals above the age of 50. For both data sets, we match individual records to the crime rate recorded in the months before the interview in their area of residence. Local crime data are provided by the UK Home Office.

1.2.1. *British Household Survey Panel*

The BHPS is an annual survey, which consists of a nationally representative sample of about 5,500 households, containing a total of approximately 10,000 individuals interviewed in the launch year 1991.[13] A key advantage of this data set for our purpose is that it contains rare information about mental health and general well-being of interviewees, which is recorded in multiple waves. Under a special permission agreement it is possible to obtain the information about the local authority of residence of the interviewees at the time of the interview, which allows us to match each respondent to the local crime rates and other area controls in the

[12] The BCS is a systematic victimisation survey of a representative sample of people resident in England and Wales. It interviews about 50,000 adults who are asked about their experiences and perceptions of crime. Victimisation surveys usually produce estimates of total crime which are significantly larger than the levels of crime recorded by the police because they manage to capture all the criminal offences (in general, the minor ones) which are not reported to the police. Nevertheless, BCS does not allow us to work with geographically detailed and quarterly crime data that we need for the analysis carried out in this article.

[13] See https://www.iser.essex.ac.uk/bhps for more information, documentation and data access.

neighbourhood in the period before the interview.[14] Given that quarterly crime data are available since 2002, we use the BHPS waves from 2002 to 2008. Our main estimating sample comprises about 35,000 individual-year observations of residents in urban areas: this corresponds to about 9,400 individuals, whom we observe on average 3.7 times. Almost 40% of the respondents are interviewed in all six waves.

The main measure of subjective well-being of our empirical analysis is a 12-item version of the General Health Questionnaire (GHQ-12) which is collected in all BHPS waves. The GHQ was developed as a screening instrument for psychiatric illness but is widely used as an indicator of psychological well-being (Goldberg, 1978). It can detect disorders of a temporary nature such as depression and anxiety but also permanent conditions such as schizophrenia and psychotic depression. GHQ has been used in recent studies by several economists (Clark, 2003; Gardner and Oswald, 2007; Metcalfe *et al.*, 2011). The BHPS version of the GHQ has twelve questions, which are combined into a single index by assigning each response between 0 and 3 points and by then summing up across all questions (Likert scoring method).[15] The highest level of distress, therefore, scores 36 and the lowest scores 0.[16] In our empirical analysis, we normalise this index to range between 0 (least distressed) and 1 (most distressed).

Apart from the overall GHQ index, Graetz (1991) identifies three separate and clinically meaningful factors: anxiety and depression, social dysfunction and loss of confidence. In our empirical analysis, we adopt this disaggregation of the GHQ index and we construct three sub-measures of mental wellbeing (GHQ – Anxiety and Depression; GHQ – Social Dysfunction; GHQ – Confidence Loss). This disaggregation allows identifying which particular dimensions of respondents' psychology are affected. As for the main GHQ index, we normalise all these indices to range between 0 (least distressed) and 1 (most distressed). Further details on the GHQ questions and on the disaggregation in sub-indices are provided in Appendix A.1.1.

In Table 1, we report detailed descriptive statistics on individual characteristics and GHQ measures, all normalised between zero (least distressed) and one (most

[14] We match individual information from the BHPS to crime data which is provided quarterly by the Home office starting from the first of January of each year. As interviews in the BHPS are collected throughout (almost) the entire year, it is not meaningful to match individuals interviewed in the first weeks of each quarter with crime rates recorded in the current quarter because most of those criminal events have not taken place at the time of the interview. We thus match interviews collected in the first two months of each quarter with crime rates in the previous quarter, while those collected in the last month of the quarter are matched with crime rates recorded in the current quarter. This implies that people interviewed between the 1 March and the 31 May are matched with crime recorded between the 1 January and the 31 March, those interviewed between the 1 June and the 31 August with crime recorded between the 1 April and the 30 June, and so on. Our results are not sensitive to changes by plus or minus 30 days in this matching rule.

[15] Respondents are asked how often (on a four-point category scale) they have recently: lost sleep over worry; felt constantly under strain; felt they could not overcome difficulties; been feeling unhappy and depressed; been losing confidence; been feeling like a worthless person; were playing a useful part in things; felt capable of making decisions; been able to enjoy day-to-day activities; been able to concentrate; been able to face up to problems; and been feeling reasonably happy. See Table A1 for more details.

[16] An alternative scoring method is the 'Caseness' bi-modal scoring (0-0-1-1) which gives a total scoring ranging from 0 (least distressed) to 12 (most distressed). Piccinelli *et al.* (1993) shows that the two methods are basically equivalent. All our empirical results are robust to using the 'Caseness' scoring method (as in Metcalfe *et al.*, 2011) rather than the Likert one.

Table 1

Mental Health: Descriptive Statistics (BHPS and ELSA)

	Mean	Median	SD	Within SD	Observations (individual-year)	% of total observations
		BHPS				
GHQ index						
GHQ – overall	0.31	0.28	0.15	0.10	35,605	–
GHQ – anxiety and depression	0.32	0.33	0.21	0.13	35,605	–
GHQ – social dysfunction	0.35	0.33	0.14	0.10	35,605	–
GHQ – confidence loss	0.19	0.17	0.23	0.13	35,605	–
Demographic characteristics						
Gender						
Female	0.33	0.31	0.16	0.10	19,447	54.62
Male	0.29	0.25	0.14	0.09	16,158	45.38
Age group						
15–30	0.30	0.28	0.16	0.10	9,061	25.45
31–45	0.32	0.31	0.16	0.10	9,984	28.04
46–60	0.32	0.31	0.16	0.09	8,392	23.57
61–75	0.30	0.28	0.14	0.07	5,525	15.52
Over 75	0.33	0.31	0.15	0.08	2,643	7.42
Education						
No qualification	0.34	0.31	0.16	0.09	6,766	19.00
O level – vocational	0.31	0.28	0.15	0.10	19,376	54.42
A level – degree	0.31	0.28	0.15	0.10	9,463	26.58
Marital status						
Married – civil partnership	0.31	0.28	0.15	0.09	18,382	51.63
Separated	0.37	0.33	0.20	0.11	540	1.52
Divorced	0.33	0.31	0.17	0.10	3,168	8.90
Widowed	0.34	0.31	0.16	0.09	2,625	7.37
Single – never married	0.30	0.28	0.16	0.10	10,890	30.59
Employment status						
Self-employed	0.29	0.28	0.13	0.08	2,209	6.20
Employed	0.30	0.28	0.14	0.09	18,643	52.36
Unemployed	0.36	0.33	0.19	0.07	1,111	3.12
Retired	0.31	0.28	0.15	0.08	7,453	20.93
Other (maternity leave, students, etc.)	0.35	0.31	0.19	0.09	6,189	17.38
		ELSA: PSH and CASP-19				
PSH	0.20	0.13	0.25	0.14	16,656	–
CASP-19	0.27	0.25	0.16	0.06	13,702	–

Notes. Authors' calculations from BHPS and ELSA data. All mental well-being indices (GHQ, GHQ subcategories, PSH and CASP-19) vary between zero (least distressed) and one (most distressed). Urban LAs.

distressed). The average level of this index is 0.31, with a median value of 0.28, an overall standard deviation of 0.15 and a within-individual standard deviation of 0.1. However, there is clear heterogeneity with respect to individual characteristics: mental distress is slightly higher for females, increases (but not monotonically) with age, is lower for the better educated, higher for separated, divorced or widowed individuals and higher for the unemployed or for people out of the labour force (students, maternity leave etc.). When GHQ is disaggregated into its three components, the measure of anxiety and depression has a mean of 0.32 with standard deviation of 0.21 (within-individual standard deviation is 0.13), while the measure of 'social dysfunction' is slightly higher (0.35), with standard deviation of 0.14 (within-individual standard deviation is 0.1). The measure of confidence loss, instead, is substantially lower, with an average of 0.19 and standard deviation equal to 0.23 (within-individual standard deviation is 0.13).

1.2.2. *English Longitudinal Study of Ageing*

The ELSA is an interdisciplinary biennial survey on health, economic position and quality of life, and representative for people aged 50 and above, living in private households in England. It comprises about 12,000 respondents. ELSA has now run four waves (2002, 2004, 2006 and 2008). Similarly to the BHPS, information on the local authority of residence allows us linking the survey to the crime data.

A rare feature of ELSA is the Psychosocial Health Module (PSH), surveyed in each wave, asking respondents 12 questions about symptoms of depression. This module is one of the most common screening tests to determine individuals' depression quotient. Besides this depression index, the ELSA contains also a theory-based measure of the quality of life of older adults which consists of 19 questions (CASP-19). Although this latter measure is not exactly conceived as an index of mental well-being, it measures perceived general well-being of respondents which should reflect also their level of mental distress. Indeed, the type of questions asked to measure GHQ, PSH and CASP-19 are similar in nature (compare Table A1, Table A3 and Table A4). More details on these indices are provided in Appendix A.1.2. The number of respondents answering all questions of the PSH index is higher than those for the CASP index. Therefore, the sample used to study the latter is slightly larger. After matching respondents with local crime rates, our sample contains about 16,600 (PSH sample) and 13,700 (CASP-19 sample) individual-year observations. Similarly to the GHQ measures, we normalise both the PSH index and the CASP-19 index between 0 (least distressed) and 1 (most distressed).

For the population aged 50 or more, descriptive statistics from the ELSA survey for PSH and CASP-19 indexes are reported in the last rows of Table 1. As for the GHQ indexes, both PSH and CASP-19 have been normalised to vary between zero (highest well-being) and one (lower well-being). The PSH depression index has a mean value equal to 0.20, with a standard deviation equal to 0.25 and a within-individual standard deviation equal to 0.14. The mean value of the CASP-19 index, instead, is 0.27, with a standard deviation (within-individual standard deviation) equal to 0.16 (0.06).

1.2.3. *Crime Data for England and Wales*

The UK Home Office provides quarterly data by Local Authority for various types of criminal offences recorded in England and Wales.[17] Over the period, we analyse (2002–8) we consistently identify 375 local authorities (LAs), 188 of which are urban LAs.[18] The London area is split in 33 LAs. The average population in one Local Authority is about 145,000 individuals – 110,000 in rural and 180,000 in urban LAs.

[17] National police forces separately record criminal offences in Scotland and Northern Ireland. Definitions and recording practices are not currently standardised at the UK level. This generates issues of comparability across countries not only for single types of crime but also for total crime rates. We, therefore, focus our analysis on England and Wales where data are fully comparable.

[18] According to the British Office for National Statistics definition, urban LAs are defined as LAs where at least 74% of the population lives in urban census output areas. A census output area is urban if it has a population of over 10,000.

Table 2

Quarterly Crime Rates (Per 10,000 Population) – Period 2002–8

	England and Wales (375 LAs)								Urban areas (188 LAs)							
Crime type	Mean	Median	SD	Within-LA SD	Max	Min	% of total crime	% of crime in the broader category	Mean	Median	SD	Within-LA SD	Max	Min	% of total crime	% of crime in the broader category
Total crime	225.7	206.1	94.9	30.6	1074.3	16.6	–	–	279.8	264.9	97.1	36.9	1074.3	74.9	–	–
Robbery	2.9	1.3	4.5	1.2	39.3	0.0	1.3	6.4	5.0	2.9	5.5	1.6	39.3	0.0	1.8	8.6
Sexual offence	2.5	2.2	1.3	0.8	45.5	0.0	1.1	5.3	3.0	2.7	1.5	1.0	45.5	0.0	1.1	5.1
Violence	40.6	37.2	18.3	7.6	129.8	2.9	18.0	88.3	50.2	47.3	18.8	8.7	129.8	10.7	17.9	86.3
Total violent crime	46.0	41.2	22.3	8.0	157.6	3.2	20.4	100.0	58.2	54.2	23.3	9.2	157.6	13.3	20.8	100.0
Burglary	28.3	25.4	14.1	7.5	140.5	0.0	12.5	16.7	34.2	31.4	15.1	8.7	140.5	7.3	12.2	16.4
Criminal damage	49.3	46.1	18.5	7.9	148.7	3.8	21.8	29.0	57.4	54.9	18.9	9.1	148.7	17.2	20.5	27.5
Fraud and forgery	9.9	8.1	7.1	4.7	149.8	0.0	4.4	5.8	12.7	10.7	8.0	5.6	69.2	0.0	4.5	6.0
Vehicle crime	32.7	28.4	18.9	9.4	174.0	0.0	14.5	19.2	42.4	38.9	19.8	11.6	174.0	2.2	15.2	20.3
Other theft	49.7	43.1	32.4	9.2	595.3	0.0	22.0	29.2	62.5	53.0	40.1	11.2	595.3	14.4	22.3	29.9
Total property crime	169.9	155.0	72.6	28.6	866.4	12.1	75.3	100.0	209.2	197.7	75.4	35.0	866.4	56.9	74.8	100.0
Drug offence	7.0	5.5	6.0	3.4	68.8	0.0	3.1	71.2	9.0	7.0	7.2	4.1	68.8	0.9	3.2	72.3
Other crime	2.8	2.5	1.7	0.9	19.4	0.0	1.3	28.8	3.4	3.2	1.7	0.9	16.7	0.0	1.2	27.7
Total other crime	9.8	8.1	6.9	3.6	79.0	0.0	4.3	100.0	12.4	10.5	8.1	4.3	79.0	1.0	4.4	100.0

Note. Authors' calculations from UK Home Office recorded crime statistics.

Data can also be aggregated to 43 PFA, which reflect the territorial organisation of British police forces.[19]

Crime data are available from April 2002 and distinguish between ten categories of crime (burglary, criminal damage, drug offences, fraud and forgery, offences against vehicles, other theft offences, robbery, sexual offences, violence against person and other offences).[20] The sum of all these items accounts for the 'total crime' recorded in England and Wales (see Table A5 in the Appendix for crime definitions). We can further group these types of offences into two broader categories: 'violent crime' (robbery, sexual offences, violence against person) and 'property crime' (burglary, criminal damage, fraud and forgery, offences against vehicles, other theft offences).[21] To compute crime rates, we divide the total number of offences in each local authority (or PFA) by the resident population in the area (crime rates are expressed in number of offences per 10,000 population).

Table 2 reports descriptive statistics on quarterly crime rates in England and Wales over the period 2002–8. The average quarterly total crime rate was about 226 crimes per 10,000 population. This rate rises to 280 in urban LAs, with a standard deviation of 97, a within-LA standard deviation of 37 and substantial regional variation (the maximum and the minimum realisations of crime rates being, respectively, 1,075 in the London Borough of City of Westminster and 75 in Rochford). Property crime accounts for almost 75% of total offences recorded, violent crime for about 21% and the remaining 4% corresponds to the residual category of 'total other crime'. In urban areas, the highest crime rates are recorded for 'other theft' (62.5), criminal damage (57.4), violence (50.2), vehicle crime (42.4) and burglary (34.2). When considered together, these five types of criminal offence account for about 88% of total recorded crime.

2. Empirical Strategy

We estimate the following regression equation:

$$MD_{irt} = a_0 + a_1 CR_{rt} + \boldsymbol{a}_2\mathbf{Z}_{rt} + \boldsymbol{a}_3\mathbf{X}_{it} + T_t + LA_r + \eta_i + u_{irt}, \tag{1}$$

where the dependent variable MD_{irt} is a measure of self-reported mental distress of individual i who lives in region r at time t. Our main variable of interest is CR_{rt}, which is the (log) crime rate in area r at time t. In our estimation, we distinguish between different types of crime. Regional time-varying characteristics are given by $\mathbf{Z}_{rt}$, while $\mathbf{X}_{it}$ are time-varying individual characteristics. Time and regional (local authority, LA) fixed effects are captured respectively by T_t and LA_r. Finally, η_i is an individual fixed effect and u_{irt} is an idiosyncratic error term.

[19] PFA are structured such that a number of local authorities lie uniquely within a single PFA.

[20] Police recording practice is governed by the National Crime Recording Standard (NCRS) which was introduced in all police forces in April 2002 in order to make crime recording more consistent. Before that date, data from different years and geographical locations are not directly comparable.

[21] 'Drug offences' and 'other offences' can be considered neither violent nor property crime. They will enter in our empirical analysis only when we look at 'total crime' and when we separately analyse each criminal offence.

The parameter of interest is a_1, the effect of local crime rates on mental distress. Two problems arise in the estimation of this parameter.[22] First, sorting of individuals into residential areas may lead to a correlation between area crime rates and mental health that is not causal. Second, even if the sorting problem can be addressed, the parameter a_2 measures the effect of crime and all associated time-varying unobserved neighbourhood characteristics on mental health. While this is a causal parameter (if the sorting problem is solved), it does not measure the pure effect of crime on mental health outcomes.

Our estimation strategy deals with both these problems. Suppose first that individuals do not move across LAs over our sample period. In this case, conditioning on individual fixed effects η_i corresponds to exploiting only within-area and within-individual variation in crime and eliminates composition effects that are induced through sorting. In addition, this strategy eliminates also area effects that are correlated with both crime rates and mental health status, and that are likely to be constant over the period we consider, such as care institutions, segregation, neighbourhood composition, etc. Moreover, to capture relevant time-varying neighbourhood characteristics, we condition on a large set of area characteristics. These include the LA employment rate which controls for the local economic cycle that could affect both crime rates (Raphael and Winter-Ebmer, 2001; Gould *et al.*, 2002) and the mental health of residents (Clark and Oswald, 1994).[23] Further, local controls include the share of residents receiving welfare benefits, the share of young adults, the share of immigrants, the number of policemen *per capita* and the log population. In addition, we condition on a large set of time-varying individual controls (age, age squared, presence of children in the household, marital status, employment status, education level and log household income). Finally, we include a full set of year-quarter dummies to capture any common time effect and potential seasonality in respondents' mental well-being.

Some of the respondents in our sample do change area of residence during our observation window. Although movements across LAs are rare (e.g. in the BHPS sample, only about 3.4% of respondents change local authority of residence every year), we address this problem by considering an individual as a different individual in each area of residence, with a different individual fixed effect and we only use observations when the respondent has spent two consecutive periods in the same area. This strategy raises two issues. First, it may create across-individuals correlation in the error terms. While this may be a concern in a cross-sectional estimation, differencing out all fixed effects should remove this potential source of across-individuals correlation. Second, and more importantly, it may introduce some selection bias in our estimation. This bias will materialise only if the decision to move to a new area in period t is affected by the crime rate in the previous residence area in period $t-1$. The sign of the bias depends on the sign of the correlation of the shocks to mental health and to the level of area dislike (which drives moving decisions) and we derive formally it in Appendix A.2.

[22] Local crime realisations are clearly exogenous to individual shocks to mental health. We assume strict exogeneity of the local crime rates, which is plausible, as a shock to individual mental health in any period is unlikely to affect area crime in the same, or in any other, period.

[23] In unreported regressions, we have checked that our results are robust to the inclusion of local unemployment – rather than employment – rates and of labour market controls at the PFA rather than LA level. Results can be provided upon request.

The likelihood that individuals' moves are induced by realisations of crime in the area of residence in the period before the move can be assessed. In all waves, interviewees who live in a different location than in the previous wave are asked to report the main reason of their move. Of these, only 2% respond that the main reason was that the previous area was unsafe or unfriendly.[24] Crime-related moving decisions do thus not seem particularly relevant in our data.

To deal with any remaining concerns, we internalise moves by using larger spatial areas for analysis. We do that by aggregating from local authority level to police force areas (PFAs), thus collapsing the 165 urban LAs into the corresponding 41 PFAs. This reduces the share of annual movers in our BHPS sample considerably, from about 3.4% to 1.4%.[25] Choosing larger spatial areas as the unit of analysis has an added advantage: as individuals may be exposed in their daily routine to different LAs (e.g. when going to work or school, shopping, visiting relative and friends, going out etc.), crime rates in the immediate residence area alone may be too a narrow spatial definition of crime that causes mental distress. Furthermore, crime perceptions may respond to media coverage that relates to larger areas, better captured by PFA spatial units. We present our main results using both LA and PFA crime rates.[26]

3. Results

We first report estimation results based on BHPS data. Our dependent variables are the overall GHQ and its three sub-components (GHQ-Anxiety, GHQ-Social Dysfunction and GHQ-Confidence). Our main regressor of interest is the log crime rate recorded in the area of residence of the interviewee during the last quarter before the interview.[27] We also present results from the ELSA sample that covers individuals aged 50 and above. In all regressions, we remove individual fixed effects by using a First Difference estimator.[28]

3.1. *The Effects of Area Crime on Mental Distress*

Table 3 reports our main estimates for the impact of local crime on the overall GHQ measure, which has been normalised between zero (least distressed) and one (most distressed). We have normalised log crime rates by their standard deviation to ease the interpretation of our results. A positive coefficient estimate implies that an increase in

[24] Accommodation-related reasons (buying a property, being evicted, moving to smaller/larger house, etc.) account for about 45% of the responses, followed by roughly 22% for family-related reasons.

[25] Moreover, our results from the ELSA survey are exempt from this potential bias, given that mobility among individuals aged 50 and over is basically zero.

[26] In the online Appendix B.1, we follow an alternative approach to deal with movers across spatial units. We estimate (1) using all available observations (rather than only using observations when the respondent has spent two consecutive periods in the same area) and without treating individuals who move as different individuals in each location. We then use an IV type strategy, where we instrument the crime rate to which movers are exposed to with the contemporaneous crime rate in the area where they resided in the first wave of our observation window. All our empirical findings are robust to this alternative estimation strategy.

[27] Estimates with crime rates rather than log crime rates provide very similar results.

[28] We have also estimated the same models using the Within Group estimator, obtaining very similar estimates. Results can be provided upon request.

Table 3
Mental Health (GHQ) and Crime

GHQ	1	2	3	4	5	6
		LA crime				
log (total crime rate)	0.008**	0.008**				
	(0.004)	(0.004)				
log (violent crime rate)			0.001	0.001		
			(0.002)	(0.003)		
log (property crime rate)					0.008**	0.008**
					(0.004)	(0.004)
Employment rate (LA)	−0.070*	−0.080*	−0.066	−0.075*	−0.067	−0.078*
	(0.040)	(0.042)	(0.040)	(0.042)	(0.040)	(0.042)
		PFA crime				
log (total crime rate)	0.014***	0.014***				
	(0.004)	(0.004)				
log (violent crime rate)			0.005*	0.006**		
			(0.003)	(0.003)		
log (property crime rate)					0.015***	0.015***
					(0.005)	(0.005)
Employment rate (LA)	−0.069**	−0.078**	−0.067**	−0.076**	−0.067*	−0.075**
	(0.033)	(0.035)	(0.033)	(0.035)	(0.034)	(0.036)
Individual controls	X	X	X	X	X	X
Year-quarter dummies	X	X	X	X	X	X
Other LA controls		X		X		X
Observations	25,647	25,647	25,647	25,647	25,647	25,647

Notes. This Table reports FD estimates of GHQ index on log crime rates recorded during the quarter before the interview in, respectively, the LA (upper part of the Table) or PFA (lower part of the Table) of residence. The GHQ index has been normalised to vary between 0 (least distressed) and 1 (most distressed). Other controls are: individual controls (age, age squared, a dummy for children in the household, dummies for marital status, for employment status and for education level and log household income); a full set of year-quarter dummies; employment rate in the LA of residence (yearly average); other LA controls (share of residents receiving welfare benefits, share of individuals aged 15–24 over total adult population, immigrants share, number of policemen *per capita* and log population size). Sample: BHPS data. Urban LAs. Standard errors: robust and clustered by LA (upper part of the Table; 165 clusters) or by PFA (lower part of the Table; 41 clusters); *significant at 10%; **significant at 5%; ***significant at 1%.

crime rates in the area of residence increases the level of mental distress of respondents. Standard errors are robust and clustered at the same geographical level as the crime rate variable. In all regressions, we control for individual characteristics (age, age squared, a dummy for children in the household, dummies for marital status, for employment status and for education level and log household income) and we include a full set of year-quarter dummies to capture any common time effect and potential seasonality in respondents' mental wellbeing. We always condition on the LA employment rate but in columns 2, 4 and 6 we add further local controls in order to capture additional time-varying local characteristics.[29] We focus in the Table (and in

[29] These include: share of residents receiving benefits, share of young adults (individuals aged 15–24 over total adult population), immigrant share, number of policemen *per capita* and log population size. In unreported regressions, we have also included controls for weather conditions from the UK Met Office (maximum temperature, minimum temperature, days of air frost, total rainfall and total hours of sunshine) in the PFA of residence in the quarter before the interview. This does not affect our estimates.

the reminder of the article) on estimates obtained for urban areas only, where the upper part and lower part of the Table report coefficient estimates of the (log) crime rate in the LA and PFA of residence respectively (both measured in the quarter before the interview).[30]

The point estimates reported in the first two columns in the upper part of Table 3 suggest a positive impact in LA log total crime on individual mental distress. The coefficient is significant at the 5% level; inclusion of additional LA controls (column 2) does not affect the estimate. When we separate violent (columns 3 and 4) and property crime (columns 5 and 6), the estimated coefficients on both types of crime are positive but the coefficient on violent crime is substantially smaller and not significantly different from zero. The coefficient on property crime is identical to the one estimated for total crime and statistically significant. Thus, these results suggest that local crime affects mental well-being of residents in urban areas and that the effect is driven mainly by property crime.

How large are these effects? The average value of the GHQ index is 0.31 with an overall standard deviation of 0.15 and a within-individual standard deviation of 0.1 (see Table 1). Thus, and assuming linearity, an estimated coefficient of 0.008 means that a 1 SD increase in log total crime rate (or property crime rate) causes a 2.6% increase in the GHQ index. It explains about 5.3% of its overall standard deviation and 8% of its within-individual standard deviation. This is a sizeable impact.

In the lower part of Table 3, we report estimates where crime rates are measured at the PFA level. The estimated coefficients are now larger in magnitude and more significant. We find that 1 SD increase in PFA log total crime causes a 0.014 increase in individual mental distress of residents (or 4.5%). The coefficient is significant at the 1% level even when all the additional LA controls are included in the regression. The coefficient on property crime is of similar magnitude and strongly significant. These regressions also show that violent crime in the area reduces mental well-being of residents: the coefficient estimate is about 0.005–0.006 and significant. One reason for the larger estimates when using PFAs is that the mental distress of people is related to changes in crime in an area larger than the local authority of residence. Indeed, as we discuss above, individuals may respond to property and violent crime outside their immediate residence area because they commute to work or they socialise outside their residence LA. Moreover, for relatively rare criminal offences such as violent crime, changes in local crime rates may be hardly observables for local residents who may instead look at larger areas in forming their expectations about victimisation risk. In both cases, measuring crime on LA level may simply be too a small measure of neighbourhood crime to pick up harmful effects through mental distress. In fact, it is easy to see that including crime rates on LA level, if what matters for mental distress are crime rates on PFA level, will lead to an underestimate of the effect of crime, while including

[30] We do not find a significant relationship between the GHQ index and area crime rates in rural areas, which may be related to the far lower crime rates in these areas (see Table 1), the lower population density and the therefore lower variation in crime over time.

crime rates at PFA level, if what matters are crime rates at LA level, will not lead to a bias.[31] Thus, throughout the article, we mainly focus on PFA crime rates.

To gain further insight on the magnitude of these effects, we compare the estimated effects with those of the local employment rate on residents' mental well-being. The coefficient estimates in the last row show that changes in the local employment rate are significantly, and negatively, associated with changes in mental distress of residents. The estimated coefficients suggest that a 10 percentage points increase in local employment rate improves residents' mental health by about 8% of its within-individual standard deviation. Thus, a 1 SD reduction in the LA (PFA) log total crime rate improves residents' mental distress by roughly the same amount as a 10 (20) percentage points increase in the local employment rate. Given that the standard deviation of the local employment rate is just 5 percentage points, the impact of a 1 SD decrease in the crime rate on mental health is about twice to four times as large as a 1 SD increase in the local employment rate.

Further comparisons can be made by looking at the estimated coefficients on individual controls (reported in Table A6 in the Appendix). Consistently with the literature on the impact of major individual life events (getting married, divorcing, having a baby, being laid off etc.) on individual happiness (see, among others: Clark *et al.*, 2008; Frijters *et al.*, 2011; Clark and Georgellis, 2013), we find strong and negative short-run effects on mental well-being of losing a partner, becoming unemployed or suffering a disabling injury. According to our estimates, the effect of a 1 SD increase in the local crime rate on mental distress is about one-seventh to one-fifth of the short-run effect of becoming unemployed. This is quite substantial, in particular when considering that the estimates for local crime rates are the average effects for all residents, while the effects of changes in personal circumstances relate only to those who are affected.

We report some robustness checks in Table A7, where we include, alternatively, a linear trend at the PFA level (columns 2) and at the LA level (columns 3). In addition, we test whether initial conditions in mental health, crime rates and other controls matter for the empirical relation we uncover. For each LA in our sample, we have computed initial average crime rates (total, property and violent) in year 2002. Moreover, for the period 1999–2001, we compute the average GHQ score, averages of all BHPS individual controls and averages of all LA controls used in the main specification. In column 4 to 7 of Table A7, we progressively include these baseline LA controls interacted with year dummies in our estimating equation. In columns 8 and 9, we alternatively add to these controls a PFA and a LA linear trend. The estimates are remarkably similar across all these specifications.

[31] To see that, consider the equation $CR_{LA} = CR_{PFA} + d_{LA\text{-}PFA}$, where CR_{LA}, CR_{PFA} are crime rates on LA and PFA level, and $d_{LA\text{-}PFA}$ captures within-PFA variation in crime rates. Thus, $d_{LA\text{-}PFA}$ can be thought of as a residual when regressing CR_{LA} on a set of PFA dummies, which makes it immediately clear that it is not correlated with CR_{PFA}. In this special case, erroneously using CR_{PFA} as regressor while CR_{LA} should be used will lead to unbiased estimates, as the measurement error $d_{LA\text{-}PFA}$ is not correlated with the included regressor CR_{PFA}; however, using CR_{LA} as a regressor when CR_{PFA} is the correct measure of area crime will lead to a downward bias in estimates. See also Wooldridge (2002, p. 74).

3.2. *Decomposing Mental Distress Measures*

We now address the question whether the overall impact of local crime on mental distress established above is related to increased levels of anxiety and depression, or loss of self-confidence or social functionality. To do that, we use the disaggregated indicators GHQ-Anxiety and Depression, GHQ-Social Dysfunction and GHQ-Confidence Loss (see Appendix A.1.1). In Table 4, we report estimates for the specification that include all controls.

If anything, one would expect exposure to crime to induce stress and anxiety, and to reduce the capability of enjoying daily activities. This direct effect could then reduce self-confidence and social interaction. Indeed, Stafford *et al.* (2007) find that individuals with pronounced fear of crime are twice as likely to suffer from depression as individuals who are less concerned about crime. In line with this, our estimates show a strong adverse effect of local crime on the level of anxiety and depression of residents. The other two dimensions – social dysfunction and confidence loss – are also affected but to a lesser extent. As before, the effects seem to be mainly driven by property crime and estimates are larger when aggregating data up on PFA level. At that aggregation level, violent crime has also an effect on anxiety and depression as well as on confidence loss, although smaller in magnitude.[32]

3.3. *Different Crime Types*

Our data distinguish between ten different categories of crime.[33] This allows us to investigate more specifically which type of crime causes mental distress to residents. For the overall GHQ and its three sub-components, using the PFA aggregation, we report estimation results in Table A9. We find strong effects on mental health of almost all property crime types, such as burglary, criminal damage, vehicle crime and 'other theft', which all significantly increase the level of mental distress of residents in the area. These types of crime account together for about 70% of total recorded crime in the UK (see Table 2).[34] Moreover, we find a clear detrimental effect of violence on the mental health of people. Violence is by far the most frequent crime type in the category 'violent crime', accounting for more than 86% of the total (Table 2). The non-significant effects of robbery and sexual crime need to be interpreted bearing in mind that these are extremely rare events. Indeed, these two criminal offences together account for less than 3% of total recorded crime: on average, only 3 (5) individuals per 10 thousand population are victims of sexual offences (robberies) in each quarter.

[32] We have also broken down the GHQ index into its 12 components. Eight out of 12 of them are significantly affected by local crime rates at the PFA level, with a detrimental impact of crime on the ability to concentrate, the perception of playing a useful role in life, the feeling of being constantly under strain, the ability to overcome difficulties, the enjoyment of daily activities, the feeling of being depressed, the sense of worthiness and the level of happiness (see Table A8).

[33] These are: burglary, criminal damage, drug offences, fraud and forgery, offences against vehicles, other theft offences, robbery, sexual offences, violence against the person and other offences (see Table A5 for crime definitions).

[34] 'Fraud and forgery', although having a positive coefficient, is non-significant. One reason could be that this type of crime is recorded where the victims reside but has no clear connection with the local environment (like e.g. credit card forgery).

Table 4

Mental Health and Crime: Disaggregating GHQ into Anxiety, Social Dysfunction and Confidence

	1	2	3	4	5	6	7	8	9	10	11	12
	GHQ – overall			GHQ – anxiety and depression			GHQ – social dysfunction			GHQ – confidence loss		
					LA crime							
log (total crime rate)	0.008** (0.004)			0.015*** (0.005)			0.002 (0.004)			0.011** (0.005)		
log (violent crime rate)		0.001 (0.003)			0.004 (0.003)			−0.001 (0.003)			0.003 (0.003)	
log (property crime rate)			0.008** (0.004)			0.015*** (0.005)			0.003 (0.004)			0.011** (0.006)
					PFA crime							
log (total crime rate)	0.014*** (0.004)			0.019*** (0.007)			0.012** (0.005)			0.011* (0.006)		
log (violent crime rate)		0.006** (0.003)			0.009** (0.004)			0.004 (0.003)			0.006* (0.003)	
log (property crime rate)			0.015*** (0.005)			0.020** (0.008)			0.014*** (0.005)			0.010 (0.007)
Individual controls	X	X	X	X	X	X	X	X	X	X	X	X
Year-quarter dummies	X	X	X	X	X	X	X	X	X	X	X	X
All LA controls	X	X	X	X	X	X	X	X	X	X	X	X
Observations	25,647	25,647	25,647	25,647	25,647	25,647	25,647	25,647	25,647	25,647	25,647	25,647

Notes. This Table reports FD estimates of the four GHQ indices (Overall, Anxiety and Depression, Social Dysfunction; Confidence Loss) on log crime rates recorded during the quarter before the interview in, respectively, the LA (upper part of the Table) or PFA (lower part of the Table) of residence. All four GHQ indices have been normalised to vary between 0 (least distressed) and 1 (most distressed). Other controls are: individual controls (age, age squared, a dummy for children in the household, dummies for marital status, for employment status and for education level and log household income); a full set of year-quarter dummies; employment rate in the LA of residence (yearly average); all LA controls (employment rate, share of residents receiving welfare benefits, share of individuals aged 15–24 over total adult population, immigrants share, number of policemen *per capita* and log population size). Each row reports results from a separate regression, with total crime, violent crime and property crime included alternatively in the regression. Sample: BHPS data. Urban LAs. Standard errors: robust and clustered by LA (upper part of the Table; 165 clusters) or by PFA (lower part of the Table; 41 clusters); *significant at 10%; **significant at 5%; ***significant at 1%.

When the GHQ index is decomposed into its three sub-factors, we find – as before – the largest effects on the anxiety and depression index.

3.4. *Heterogeneous Effects of Crime*

Different individuals may respond to crime in different ways. Indeed, both actual crime risk and fear of crime are socially stratified, with some social groups being more affected than others. Some research suggests that women and the elderly are more concerned about crime (Lagrange and Ferraro, 1989), possibly because they feel particularly vulnerable (Smith and Torstensson, 1997). The more educated may also be more aware of changes in local crime rates and, therefore, react more. On the other hand, insofar as their higher level of education reflects their income group, they may be less exposed to criminal hazard. The presence of children in the household may be an additional reason of added mental distress through area crime for parents and older relatives. To investigate whether responses are heterogeneous along these dimensions, we interact area crime rates with observed individuals characteristics and report results in Table 5.

We find a clear gender dimension in the impact of exposure to crime on mental health.[35] While a 1 SD increase in log total crime causes an increase of 0.008 points in the overall GHQ index for men, the effect on women is more than twice as large. Breaking crime down into violent crime and property crime shows that the effects of property crime are similar to those of total crime, with an effect on female residents which is exactly twice as large as those on males. Moreover, the effects of violent crime discussed earlier are driven only by females, with a 1 SD increase in the violent crime rate increasing women's overall GHQ index by about 0.008 points.

We have also investigated whether the effect of crime is more/less pronounced for those under 30, over 65, with a higher education, or living in household with children. As the estimates in Table 5 show, these interaction terms are mostly non-significant, while the gender heterogeneity is robust to their inclusion.

3.5. *The Timing of the Effect of Crime on Mental Distress*

Our indices of mental health are subjective and self-reported measures that refer to interviewees' assessment as to how they felt around the time of the interview along different dimension of mental well-being.[36] So far, we have shown that exposure to crime shocks in the quarter before the interview leads to lower mental well-being of residents. One important question is whether the effect of crime on mental distress fades away quickly, or whether it causes more persistent mental distress.

We now investigate whether previous lags of local crime rates produce a significant effect on current mental well-being. In addition, we test the robustness

[35] This finding is consistent, for instance, with Frijters *et al.* (2011) who demonstrate that life satisfaction of Australian women is more strongly affected by (property) crime than that of men.

[36] All 12 GHQ questions use the following wording: 'Have you recently ... felt/been/etc.?' (see Table A1).

Table 5

Mental Health (GHQ) and Crime: Heterogeneous Effects

	1	2
	GHQ – overall	
log (total crime rate)	0.008*	0.005
	(0.004)	(0.004)
log (total crime rate) × female	0.011**	0.011**
	(0.005)	(0.005)
log (total crime rate) × under 30		0.000
		(0.000)
log (total crime rate) × over 65		0.000
		(0.000)
log (total crime rate) × (a level – degree)		0.000
		(0.006)
log (total crime rate) × children		0.010
		(0.007)
log (violent crime rate)	0.001	−0.003
	(0.003)	(0.003)
log (violent crime rate) × female	0.008**	0.008**
	(0.004)	(0.004)
log (violent crime rate) × under 30		0.000
		(0.001)
log (violent crime rate) × over 65		0.001
		(0.001)
log (violent crime rate) × (a level – degree)		0.006
		(0.005)
log (violent crime rate) × children		0.006
		(0.005)
log (property crime rate)	0.010*	0.008*
	(0.005)	(0.005)
log (property crime rate) × female	0.010**	0.010**
	(0.005)	(0.005)
log (property crime rate) × under 30		0.000
		(0.000)
log (property crime rate) × over 65		0.000
		(0.000)
log (property crime rate) × (a level – degree)		−0.004
		(0.005)
log (property crime rate) × children		0.009
		(0.007)
Individual controls	X	X
Year-quarter dummies	X	X
All LA controls	X	X
Observations	25,647	25,647

Notes. This Table reports FD estimates of GHQ indexes on log crime rates recorded during the quarter before the interview in the PFA of residence. Other controls are: individual controls: age, age squared, a dummy for children in the household, dummies for marital status, for employment status and for education level and log household income; a full set of year-quarter dummies; employment rate in the LA of residence (yearly average); all LA controls (employment rate, share of residents receiving welfare benefits, share of young adults (individuals aged 15–24 over total adult population), immigrants share, number of policemen *per capita* and log population size. Total crime, violent crime and property crime (and their respective interactions) are included alternatively in the regression. Sample: BHPS data. Urban LAs. Standard errors: robust and clustered by PFA (41 clusters); *significant at 10%; **significant at 5%; ***significant at 1%.

of our results to a straightforward – but powerful – falsification exercise, by regressing current mental health status on future crime.

Table 6 reports estimation results for total crime at the PFA level. Given that crime data start in April 2002 (see subsection 1.2), when working with crime lags we gradually lose observations of individuals interviewed in 2002–3. Thus, to allow meaningful comparison of coefficients across different regressions, we restrict the sample to all those who have non-missing values for the third lag of the quarterly crime rate. This implies a 20% reduction with respect to our main estimation sample. In the Table, we define as 'quarter Q' the last quarter before the interview (i.e. our main measure of crime throughout the article), while lags (leads) are defined as respectively $Q-1$, $Q-2, \ldots$ ($Q+1$, $Q+2, \ldots$).

The first column reports an estimate of the effect of local crime recorded in the last quarter before the interview on mental well-being of residents. The coefficient is almost identical to our baseline estimate reported in Table 3. We then include lags and leads of crime, each one at a time (columns 2–6) and all of them together (column 7). There seems to be some persistence of the effect: the first and second lags of crime (columns 2–3) have a sizeable and significant effect on current mental well-being, but the effect disappears with the third lag (column 4). Instead, future realisations of crime do not explain current mental health (columns 5–6). In column 7, we include current crime, as well as all leads and lags. The estimated coefficients for quarter Q is identical in magnitude (although the standard error is slightly larger), remaining unaffected by the inclusion of the other crime controls. All the other coefficients, instead, are smaller, and far from significant.

In our data, adjacent changes in quarterly crime rates are strongly correlated (correlation is about 0.7), suggesting the existence of local crime cycles that last more than one quarter, which may suggest that it is meaningful to consider more than one quarter as a time window to crime exposure. We have done this in the last three columns of the Table, where we have repeated the same analysis using six-month intervals (average crime rate over two quarters) rather than single quarters (columns 8–10).[37] The pattern we observe does not change: crime rate in the six months before the interview (column 8) produces a sizeable and significant detrimental effect on mental health, while crime rate 6–12 months before the interview does not seem to have any effect (column 9). Taken together, these findings suggest that fluctuations in local crime produce a temporary effect on subjective mental well-being of residents.

We find further evidence of the temporariness of this effect by investigating the impact of local crime on more permanent measures of mental health and on the overall health of the interviewees. The BHPS questionnaire includes questions on whether respondents suffer from depression or anxiety among their main health problems, whether they are addicted to alcohol or drugs and whether they visited a psychotherapist during the last year. The BHPS also records both a subjective assessment of health status and more objective measures such as whether the respondent went to see her GP or she was in-patient/out-patient at the hospital in the last year. We have run regressions using our main specification but replacing GHQ

[37] When six-month periods are considered rather than quarters, the correlation between contiguous changes in crime rate drops from 0.7 to 0.3.

Table 6

Mental Health (GHQ) and Crime: Timing of The Effect

	1	2	3	4	5	6	7	8	9	10
	PFA crime									
log (total crime rate) – quarter Q	0.013**						0.013			
	(0.005)						(0.009)			
log (total crime rate) – quarter $Q - 1$		0.012*					0.000			
		(0.006)					(0.009)			
log (total crime rate) – quarter $Q - 2$			0.012**				0.009			
			(0.005)				(0.009)			
log (total crime rate) – quarter $Q - 3$				0.001			–0.005			
				(0.006)			(0.008)			
log (total crime rate) – quarter $Q + 1$					0.009		–0.006			
					(0.006)		(0.012)			
log (total crime rate) – quarter $Q + 2$						0.001	–0.000			
						(0.006)	(0.008)			
log (total crime rate) – avg (Q, $Q - 1$)								0.015**	0.015**	0.017**
								(0.006)	(0.007)	(0.008)
log (total crime rate) – avg ($Q - 2$, $Q - 3$)									–0.000	–0.001
									(0.006)	(0.007)
log (total crime rate) – avg ($Q + 1$, $Q + 2$)										–0.003
										(0.007)
Individual controls	X	X	X	X	X	X	X	X	X	X
Year-quarter dummies	X	X	X	X	X	X	X	X	X	X
All LA controls	X	X	X	X	X	X	X	X	X	X
Observations	20,307	20,307	20,307	20,307	20,307	20,307	20,307	20,307	20,307	20,307

Notes. This Table reports FD estimates of GHQ index on log total crime rates recorded during the months before the interview in the PFA of residence. The GHQ index has been normalised to vary between 0 (least distressed) and 1 (most distressed). In the Table, we define as 'quarter Q' the last quarter before the interview (i.e. our main measure of crime throughout the article), while lags (leads) of crime rate are defined as, $Q - 1$, $Q - 2$, ... ($Q + 1$, $Q + 2$, ...). Other controls are: individual controls (age, age squared, a dummy for children in the household, dummies for marital status, for employment status and for education level and log household income); a full set of year-quarter dummies; all LA controls (employment rate, share of residents receiving welfare benefits, share of individuals aged 15–24 over total adult population, immigrants share, number of policemen *per capita* and log population size). Sample: BHPS data. Urban LAs. Standard errors: robust and clustered by PFA (41 clusters); *significant at 10%; **significant at 5%; ***significant at 1%.

indices with each of these outcomes as dependent variable. We find no significant relationship between any of these outcomes and crime rates recorded in the last three, six or twelve months before the interview. Estimation results can be provided upon request.

All this evidence points at exposure to crime being a stressful but temporary event, which creates mental distress in the short run but has no immediate repercussions on more permanent mental conditions, subjective health or attendance of health services. The temporariness of the effect we identify is fully consistent with the existing literature on well-being which shows that individuals tend to adapt fairly quickly to major individual life events such as getting married, divorcing, having a baby, being laid off, etc., see for instance work by Clark *et al.* (2008), Frijters *et al.* (2011) and Clark and Georgellis (2013). However, temporariness of the effects does not imply that exposure to crime in the area of residence can be disregarded. Rather, although area crime may not have persistent effects on mental distress, it is a repeated shock: different from other personal lifetime events that occur rarely, residents are permanently exposed to temporary crime shocks. Even if individuals fully recover after each shock, this implies that in any given period there will be a sizeable fraction of the population – those living in areas hit by negative crime shocks – who is more mentally distressed than in the absence of such shocks. This may have important consequences for their behaviour, relationships and productivity.[38]

3.6. *Results Using the English Longitudinal Study of Ageing*

We now turn to the data from the ELSA, focusing on people aged 50 and above. ELSA contains two alternative measures of mental well-being: a depression index (PSH), and a measure of quality of life of older adults (CASP-19). To check the robustness of our results, we replicate our previous analysis using this alternative data set and measures of mental well-being.[39]

Table 7 reports FD estimates of regressing the PSH and the CASP-19 indices on local crime in the LA (upper part of the Table) or PFA (lower part of the Table) of residence. In spite of the differences in data, sample and measure of mental distress, our empirical findings are fully consistent with our previous results. Local crime increases mental distress of residents, with property crime seemingly playing a larger role. In particular, the depression index PSH is significantly higher for individuals exposed to higher crime: a 1 SD increase in total crime in the LA of residence increases the PSH index by 0.024 points. This implies a 12% increase with respect to its mean value (0.2) and would explain up to 17% of its within-individual standard deviation (0.14). Similarly, a 1 SD increase in crime raises the CASP index by 0.008 points, which corresponds to a 3% increase with respect to its mean value (0.27) and to 13% of its

[38] Although our setting does not allow us to identify the cumulative impact of having being exposed to repeated temporary crime shocks, the evidence from the MTO experiment, shows that moving away from deprived areas – that is, areas where individuals are more exposed to crime shocks – leads to significant improvements in both subjective and objective well-being (Katz *et al.*, 2001; Kling *et al.*, 2007; Ludwig *et al.*, 2012).

[39] Given the age profile of the respondents, residential mobility is almost non-existent in the ELSA data set: in each period, between 0% and 0.3% of interviewees have changed LA of residence with respect to the previous wave.

Table 7

Mental Health and Crime: Evidence from ELSA

	1	2	3	4	5	6
		PSH			CASP-19	
		LA crime				
log (total crime rate)	0.024**			0.008**		
	(0.010)			(0.004)		
log (violent crime rate)		0.013*			0.001	
		(0.007)			(0.003)	
log (property crime rate)			0.018*			0.008**
			(0.009)			(0.003)
		PFA crime				
log (total crime rate)	0.024**			0.006		
	(0.010)			(0.006)		
log (violent crime rate)		0.016**			0.002	
		(0.007)			(0.004)	
log (property crime rate)			0.019*			0.003
			(0.010)			(0.006)
Individual controls	X	X	X	X	X	X
Year-quarter dummies	X	X	X	X	X	X
All LA controls	X	X	X	X	X	X
Observations	10,816	10,816	10,816	7,825	7,825	7,825

Notes. This Table reports FD estimates of PSH and CASP-19 indexes on log crime rates recorded during the quarter before the interview in the LA (upper part of the Table) or PFA (lower part of the Table) of residence. Both indices have been normalised to vary between 0 (least distressed) and 1 (most distressed). Other controls are: individual controls (age, age squared, a dummy for children in the household, dummies for marital status, for employment status and for education level and log household income); a full set of year-quarter dummies; employment rate in the LA of residence (yearly average); all LA controls (employment rate, share of residents receiving welfare benefits, share of individuals aged 15–24 over total adult population, immigrants share, number of policemen *per capita* and log population size). Each row reports estimation results from separate regressions, with each type of crime included alternatively in the regression. Sample: ELSA data. Urban LAs. Standard errors: robust and clustered by LA (upper part of the Table; 165 clusters) or by PFA (lower part of the Table; 41 clusters); *significant at 10%; **significant at 5%; ***significant at 1%.

within-individual standard deviation (0.06). Very similar coefficients are found for PFA crime rates.

In unreported regressions, we have looked at which specific crime types produce the strongest negative impact on resident mental well-being. Consistently with the evidence from the BHPS data discussed above (subsection 3.3), we find the largest and more significant coefficients for burglary, vehicle crime and violence.[40]

3.7. *Assessing the Magnitude of Crime Effects*

How large is the effect of being exposed to exogenous changes in local crime rates on individuals' mental health? We gave a first answer to this question by comparing our estimates with the impact of the local employment rate (see subsection 3.1), and the impact of changes in personal circumstances, such as becoming unemployed. In this subsection, we investigate this aspect further, by contrasting the effects of changes in

[40] Results can be provided upon request.

local crime rates to the effect to a major violent terrorist attack which had a dramatic impact on the UK: the 7 July 2005 London bombings. This was a series of coordinated suicide attacks on London's public transport system during the morning rush hours. The different explosions killed 52 people and injured about 700. The attacks were completely unexpected and represented the first terrorist act of Muslim extremists in the UK. The impact of this event on British residents was quite dramatic.[41]

The BHPS data allow us to investigate the impact the 7/7 attack had on UK residents' self-reported mental health, as interviews are carried out throughout the entire year, so that, in 2005, some individuals have been interviewed before, and some after, that event. Unfortunately, the immediate period before and after the terrorist attack is not covered by the data, as interviews routinely stop in May and start again in September (see Table A10). We make use of a difference-in-differences (DID) approach to identify the effect of interest. A similar identification strategy has been implemented with BHPS data by Metcalfe *et al.* (2011) to estimate the effect of the September 11 attacks on the subjective well-being of the British population.

We identify the causal impact of the London bombings on British citizens' mental health by comparing those interviewed in the months preceding the bombing with those interviewed in the months following the event. Our identification strategy assumes that the timing of the interview – with respect to the date of the London bombings – is random. A first concern arises from the possibility that interviewers could manipulate the date of their interview in response to the London bombings. This seems unlikely as the terrorist attack – by definition – was unexpected and there is no reason to expect it to have affected the scheduled timings of BHPS interviews.[42] In any case, if individuals more negatively affected by the 7/7 attack refused to answer the BHPS questionnaire in the months after the event, we would estimate a lower bound of the overall effect. A second, more relevant, problem with this identification strategy is seasonality in responses: mental distress may differ in different months during the year. If autumn and winter months have a detrimental effect on mental well-being, then at least part of the increase in mental distress after the 7/7 bombings could be driven by this seasonal effect. We remove these effects by combining the before-after analysis with a DID approach, comparing the difference in 2005 (before and after July) with that measured in the year before (2004).[43] We thus estimate the following regression:

$$MD_{it} = \beta_0 + \beta_1 AfterJuly_i + \beta_2 year2005_t + \beta_3 (AfterJuly \times year2005)_{it} + v_{it}. \qquad (2)$$

Here, MD_{it} is the level of mental distress of individual i at time t. We identify the treated group with a dummy variable *Year2005* which is equal to one if the interview was carried out in 2005 (rather than in 2004). The 'treatment' dummy *AfterJuly*, instead, is equal to one if the interview took place after July. The coefficient of interest is β_3, which is equal to one for those individuals interviewed between September and December in 2005

[41] Rubin *et al.* (2005, 2007) illustrate the impact on stress and perceived threat as well as travel behaviour among Londoners in the aftermath of the event. Similar negative effects on mental well-being have been observed among the American population after the 9/11 attacks (Stein *et al.*, 2004).

[42] In addition, BHPS does not carry out interviews during the summer (Table A10). Thus, the possible disruptions in the interview schedule by the terrorist attack in its immediate aftermath are not a concern here.

[43] Including year 2003 does not substantially alter our findings. We do not use years after 2005, because permanent changes – such as the permanently higher levels of alert described in the previous Section – may confound the effects.

(that is, in the aftermath of the bombing). As before, we use as dependent variable the mental well-being measured by GHQ (or by its sub-components: anxiety, social dysfunction and confidence). Alternatively, we use the residuals from regressing GHQ measures on individual characteristics, local authority fixed effects and year and month dummies.[44] Our design should randomise individuals across all these characteristics. Indeed, using either measure leads to basically the same results, which is what one would expect if respondents' characteristics are orthogonal with respect to the date of the interview. In all regressions, we cluster the standard errors by local authority of residence to allow for any possible correlation in the mental distress shocks of individuals living in the same area.

We report results of our DID estimates in Table 8. We start by looking at all LAs. We then progressively restrict the sample to the main 20 cities (in terms of population), the main five cities and, finally, Greater London (which contains 33 local authorities).[45] In each case, our dependent variable is first the GHQ index and then the residual GHQ. In the third column of each sample, we restrict the observations of those interviewed 'after July' only to the interviews collected in September (rather than using the period September-December).[46] In the last three columns, instead, we look at the three (residual) GHQ subcategories (still using only individuals interviewed in September in the 'after July' group).

In all regressions, we find a positive coefficient on β_3, suggesting that, in the aftermath of the London bombings, individuals reported a higher level of mental distress. The coefficient increases in size and becomes strongly significant when we restrict the sample to the main 20 cities, the main five cities or just London. Thus, the impact of the London bombings is larger on urban residents who are more exposed to the risk of a terrorist attack. Results for GHQ or residual GHQ are almost identical, as are results we obtain when we drop individuals interviewed between October and December. Finally, columns 3–6 show that most of the impact seems to be on anxiety and depression. This is similar to the results we find for overall crime. There are also sizeable effects on Social Dysfunction but no significant effect on Confidence Loss – again, similar to what we find for local area crime.

When we focus on the main five cities and on Greater London, in the months immediately following the bombing, the self-reported mental distress increased by roughly 0.1 points, implying that the GHQ index increased by more than 30% with respect to its mean value (which is about 0.3); this accounts for about 65% of its standard deviation (and for 100% of its within standard deviation).

How large are the effects of crime changes in the area of residence in comparison to those we find for the London bombings? We report above that a 1 SD increase in log

[44] As in our previous analysis, individual controls are: gender, age, age squared, a dummy for children in the household, dummies for marital status, employment status, categorical variables for education level and log household income.

[45] The main 20 cities are: Birmingham, Bradford, Bristol, Cardiff, Coventry, Derby, Kingston-upon-Hull, Leeds, Leicester, Liverpool, London, Manchester, Newcastle upon Tyne, Nottingham, Plymouth, Sheffield, Southampton, Stoke-on-Trent, Swansea and Wolverhampton. The main five cities are: Birmingham, Bradford, Leeds, London and Sheffield.

[46] The limited simple size of those interviewed in the first six month of the year, does not allow us to restrict the control group only to individuals interviewed in May (see Table A10).

Table 8

The Impact of 2005 London Bombings on Mental Health: DID Estimates

	1	2	3	4	5	6
	GHQ	GHQ (residual)	GHQ (residual)	GHQ – anxiety and depression (residual)	GHQ – social dysfunction (residual)	GHQ – confidence loss (residual)
	2004 *versus* 2005		2004 *versus* 2005 (only September)			
All LAs						
After July × year 2005	0.012	0.013	0.012	0.015	0.009	0.012
	(0.016)	(0.016)	(0.016)	(0.024)	(0.013)	(0.024)
Observations	17,790	17,790	9,158	9,158	9,158	9,158
Main 20 cities						
After July × year 2005	0.069**	0.070**	0.073**	0.096**	0.058*	0.072
	(0.032)	(0.033)	(0.032)	(0.046)	(0.030)	(0.058)
Observations	3,421	3,421	1,766	1,766	1,766	1,766
Main 5 cities						
After July × year 2005	0.093**	0.098**	0.096**	0.142***	0.076**	0.059
	(0.038)	(0.037)	(0.035)	(0.052)	(0.037)	(0.055)
Observations	2,006	2,006	1,063	1,063	1,063	1,063
London (inner and outer)						
After July × year 2005	0.100**	0.106***	0.103***	0.141**	0.089**	0.069
	(0.038)	(0.039)	(0.037)	(0.054)	(0.042)	(0.059)
Observations	1,262	1,262	695	695	695	695

Notes. This Table reports DID estimates of the impact of the 2005 London bombings on GHQ index (and its subcategories) of respondents. The dummy variable '*Year 2005*' is equal to one if the interview was carried out in 2005 (rather than in 2004) and identifies the treatment group. The dummy '*After July*' is equal to one if the interview took place after July and identifies the 'treatment'. In columns 1–2, this includes individuals interviewed between September and December (included), while in columns 3–6 we restrict it only to interviews collected in September. The Table reports the coefficient estimated on the interaction between the '*Year 2005*' dummy and the '*After July*' dummy, which is equal to one for those individuals interviewed after July in 2005. The GHQ indices have been normalised to vary between 0 (least distressed) and 1 (most distressed). Residual GHQ measures are obtained computing the residuals after regressing GHQ measures on individual characteristics (gender, age, age squared, a dummy for children in the household, dummies for marital status, for employment status and for education level and log household income), local authority fixed effects and year and month dummies. Main 20 cities are: Birmingham, Bradford, Bristol, Cardiff, Coventry, Derby, Kingston-upon-Hull, Leeds, Leicester, Liverpool, London, Manchester, Newcastle upon Tyne, Nottingham, Plymouth, Sheffield, Southampton, Stoke-on-Trent, Swansea and Wolverhampton. Main 5 cities are: Birmingham, Bradford, Leeds, London and Sheffield. London (inner and outer) includes 33 LAs. Each cell reports estimation results from a separate regression. Sample: BHPS data. Years 2004–5. Standard errors: robust and clustered by LA; *significant at 10%; **significant at 5%; ***significant at 1%.

crime rates implies an increase in the GHQ index of 0.014 points. This implies that the effect of a 1 SD change in the local crime rate on residents' mental well-being is about 1/7 of that induced by the 2005 London bombing in the months immediately following the terrorist attack. This is sizeable, given the dramatic effect the London bombings had on the British population. Moreover, while the London bombings were a one-off incident, changes in local crime happen on a continuous scale.

4. Conclusions

In this article, we analyse the indirect and intangible costs of crime, through inflicting mental distress, depression and anxiety, on individuals who live or work in the vicinity where crime takes place. We exploit detailed panel data on mental well-being from two longitudinal surveys and we find that local crime rates have a significant, negative and substantial effect on mental well-being in urban areas. While most of this effect works through property crime, violent crime turns out to be important when we increase the area within which crime is recorded. This suggests that – while property crime concerns individuals mostly when committed in their immediate neighbourhood – violent crime is also relevant for the mental distress of citizens when it takes place in a larger spatial area around their habitation. We benchmark our results with the impact on mental health of British citizens of local unemployment rates, and the London bombings in July 2005. We show that the effect of a 1 SD increase in the crime rate on mental health is about twice to four times as large as a 1 SD increase in the local employment rate; and about one-seventh of the impact of the London bombings – which was a dramatic event. We conclude that the effects of local crime on mental distress of citizens are large, with possibly significant economic costs. Thus, crime reduction and crime prevention may have benefits far beyond those typically suggested.

Appendix A. Additional Information

A.1. *Measures of Mental Health*

A.1.1. *BHPS: The General Health Questionnaire* (*GHQ*-12)

The GHQ-12 questionnaire administered in the BHPS is as shown in Table A1.

Table A1

GHQ-12 Questionnaire

Have you recently....	(1) Been able to concentrate on whatever you are doing? (2) Lost much sleep over worry? (3) Felt that you were playing a useful part in things? (4) Felt capable of making decisions about things? (5) Felt constantly under strain? (6) Felt that you could not overcome your difficulties? (7) Been able to enjoy your normal day-to-day activities? (8) Been able to face up to your problems? (9) Been feeling unhappy and depressed? (10) Been losing self-confidence in yourself? (11) Been thinking of yourself as a worthless person? (12) Been feeling reasonably happy, all things considered?
Answer	Less than usual/no more than usual/rather more than usual/much more than usual

While the longer versions of the GHQ are normally considered multidimensional, the GHQ-12 is often regarded as measuring only a single dimension of psychological health. However, several authors suggested that the GHQ-12 contained two or three clinically meaningful factors. Following Graetz's (1991) disaggregation of GHQ-12 into three factors – (*a*) anxiety and depression; (*b*) social dysfunction; (c) loss of confidence) – GHQ-12 questions can be grouped in the following way (Table A2).

Table A2

GHQ-12 Disaggregation

Anxiety and depression	(2) Lost much sleep over worry? (5) Felt constantly under strain? (6) Felt that you could not overcome your difficulties? (9) Been feeling unhappy and depressed?
Social dysfunction	(1) Been able to concentrate on whatever you are doing? (3) Felt that you were playing a useful part in things? (4) Felt capable of making decisions about things? (7) Been able to enjoy your normal day-to-day activities? (8) Been able to face up to your problems? (12) Been feeling reasonably happy, all things considered?
Loss of confidence	(10) Been losing self-confidence in yourself? (11) Been thinking of yourself as a worthless person?

A.1.2. *Measures of Mental Health in ELSA*

A.1.2.1. *ELSA Psychosocial Health Module (PSH)*

The ELSA Psychosocial Health Module (PSH) assesses symptoms of depression, based on the Centre for Epidemiologic Studies Depression Scale (CES-D), which is one of the most common screening tests for helping an individual to determine his or her depression quotient (Radloff, 1977). Interviewees are asked whether they recently had symptoms of depression (feeling of unhappiness, loneliness, fatigue etc.). An index of depression can be constructed by assigning one point for each positive answer (and zero for negative ones). The measure ranges between 0 (least distressed) and 8 (most distressed). In our empirical analysis, we normalise the variable to range between 0 (least distressed) and 1 (most distressed).

The PSH questions in ELSA are shown in Table A3.

Table A3

Psychosocial Health Module (PSH)

Much of the time during the past week ...	(1)... have you felt depressed? (2)... you felt that everything you did was an effort? (3)... your sleep was restless? (4)... you were happy? (5)... you felt lonely? (6)... you enjoyed life? (7)... you felt sad? (8)... you could not get going?
Answer:	Yes/no

A.1.2.2. *CASP*-19

The ELSA contains also a theory-based measure of the quality of life of older adults which consists of 19 questions (CASP-19). Although this latter measure is not exactly conceived as an index of mental well-being, it measures perceived general well-being of respondents which should reflect also their level of mental distress. Indeed, the type of questions asked to measure GHQ, PSH and CASP-19 are very similar in nature.

CASP-19 is a theory-based measure of the quality of life of older adults (Hyde *et al.*, 2003), which consists of 19 questions (CASP-19). Although this latter measure is not exactly conceived as an index of mental well-being, it measures perceived general well-being of respondents which should reflect also their level of mental distress. Indeed, the type of questions asked to measure

GHQ, PSH and CASP-19 are very similar in nature (compare Tables A1, A3, and A4). The CASP-19 questions cover four theoretical domains:

(*i*) control: the ability to intervene actively in one's own environment;
(*ii*) autonomy: the feeling of an individual to be free from unwanted interference by others;
(*iii*) self-realisation: the active processes of human fulfilment; and
(*iv*) pleasure: the sense of fun derived from the more active aspects of life.

The CASP-19 measure takes account of whether or how often (often, sometimes, not often or never) statements on the four domains of quality of life apply to older people. A scale is created that ranges from 0, which represents total satisfaction on all domains, to 57, which represents a complete absence of quality of life. In our empirical analysis, we adopt the Likert scoring method and we normalise the variable to range between 0 (least distressed) and 1 (most distressed). The CASP-19 questionnaire is shown in Table A4.

Table A4
CASP-19

Control	(1) My age prevents me from doing the things I would like to
	(2) I feel that what happens to me is out of my control
	(3) I feel free to plan for the future
	(4) I feel left out of things
Autonomy	(5) I can do the things that I want to do
	(6) Family responsibilities prevent me from doing what I want to do
	(7) I feel that I can please myself what I do
	(8) My health stops me from doing things I want to do
	(9) Shortage of money stops me from doing the things I want to do
Pleasure	(10) I look forward to each day
	(11) I feel that my life has meaning
	(12) I enjoy the things that I do
	(13) I enjoy being in the company of others
	(14) On balance, I look back on my life with a sense of happiness
Self-realisation	(15) I feel full of energy these days
	(16) I choose to do things that I have never done before
	(17) I feel satisfied with the way my life has turned out
	(18) I feel that life is full of opportunities
	(19) I feel that the future looks good for me
Answer:	Often/sometimes/not often/never

A.2. *Identification and Empirical Issues*

We estimate the following regression, where, we have written the region index r as a function of the individual i and time t, and where the dependent variable $\widetilde{MD}_{ir(i,t)t}$ are the residuals after time changing region and individual characteristics, and time dummies have been netted out:

$$\widetilde{MD}_{ir(i,t)t} = a_0 + a_1 CR_{r(i,t)t} + LA_{r(i,t)} + \eta_i + u_{ir(i,t)t}, \tag{A.1}$$

Suppose we estimate this equation in first differences. For individuals who do not move across LAs, the FD transformation removes both the LA and individual fixed effects:

$$\Delta\widetilde{MD}_{ir(i,t)t} = a_1 \Delta CR_{r(i,t)t} + \Delta u_{ir(i,t)t}. \tag{A.2}$$

The parameter a_1 can be consistently estimated given that $\mathrm{cov}(\Delta CR_{r(i,t)t}, \Delta u_{ir(i,t)t}) = 0$.

For individuals who moved from region r to region r', instead, we have:

$$\widetilde{MD}_{ir'(i,t)t} - \widetilde{MD}_{ir(i,t-1)t-1} = a_1 \left(CR_{r'(i,t)t} - CR_{r(i,t-1)t-1}\right) + \left[\varepsilon_{ir'(i,t)t} - \varepsilon_{ir(i,t-1)t-1}\right], \tag{A.3}$$

where: $\varepsilon_{ir'(i,t)t} = LA_{r'(i,t)} + u_{ir'(i,t)t}$ and $\varepsilon_{ir(i,t-1)t-1} = LA_{r(i,t-1)} + u_{ir(i,t-1)t-1}$.

Therefore, first differencing will only eliminate the area fixed effects for non-movers, while for movers the error term contains the difference in the area fixed effects of the two locations, which may be correlated with the difference in crime rates across the two locations. This will introduce a bias in our estimates whose sign is ambiguous (it depends on the relative size of the correlations between crime realisations and LA fixed effects within and across areas).

The main strategy we employ to address this identification problem is to consider an individual as a different individual in each area of residence, with a different individual fixed effect. We thus only use observations when the respondent has spent two consecutive periods in the same area. However, this approach may introduce some selection bias in our estimation: if moving decisions are affected by past crime rates, individuals who did not move in response to a given realisation of crime must have received shocks to their moving decision different from those who moved somewhere else. If shocks to mental distress and to moving decisions are correlated, this will potentially bias our estimates.

To see this, we start by modelling the moving decision. An individual i living in area r in time period t will move away ($m_{irt=1}$) from that area if his or her level of unobserved dislike for the area (m^*_{irt}) is above a certain threshold $\overline{m}_i$. Suppose that the moving decision in one period depends on the level of crime recorded in the region in the previous period:

$$m_{irt} = 1 \text{ if } m^*{}_{irt} > \overline{m}_i, \tag{A.4}$$

$$m^*{}_{irt} = \beta_0 + \beta_1 CR_{rt-1} + \phi_i + v_{irt}. \tag{A.5}$$

Now, when estimating (A.1) using only 'stayers', we obtain consistent estimates if:

$$\begin{aligned} &\mathrm{E}[(CR_{irt} - CR_{irt})(u_{irt} - u_{irt-1})|m_{irt} = m_{irt-1} = 0] \\ &\quad = \mathrm{E}[(CR_{irt} - CR_{irt})(u_{irt} - u_{irt-1})|v_{irt} \le \bar{m}_i - \beta_0 - \beta_1 CR_{rt-1} - \phi_i, v_{irt-1} \le \bar{m}_i - \beta_0 - \beta_1 CR_{rt-2} - \phi_i] = 0. \end{aligned} \tag{A.6}$$

This is the case if shocks to dissatisfaction with the area and to mental distress are not correlated (i.e. $\mathrm{E}(u_{irt}, v_{irt}) = 0$). Note that this allows the unobserved individual-specific term η_i in (A.1) to be correlated with the term ϕ_i in (A.5), which should eliminate most sources of correlation due to individual-specific heterogeneity. However, if moving decisions are affected by past crime rates (i.e. $\beta_1 \neq 0$)), and if u_{irt} and v_{irt} are correlated, then estimates based on 'stayers' may be biased. The sign of the bias depends on the correlation between the shocks u_{irt} and v_{irt}. Assume that shocks affecting area dislike are positively correlated with shocks that determine mental distress. Now suppose that crime was very high in area r in the last period. People who decide not to move away from area r must have experienced a low shock v_{irt} to their level of dislike of the area in the current period. By focusing only on 'stayers', we may thus create a negative correlation between CR_{rt-1} and v_{irt}. If u_{irt} and v_{irt} are positively correlated, this implies a negative correlation between CR_{rt-1} and u_{irt} which can potentially create an upward bias in our estimates. Indeed, if we compute:

$$\begin{aligned} \mathrm{E}(\Delta CR_{rt}, \Delta u_{irt}|m_{irt} = m_{irt-1} = 0) = {} & \mathrm{E}(CR_{rt}, u_{irt}|m_{irt} = m_{irt-1} = 0) - \mathrm{E}(CR_{rt}, u_{irt-1}|m_{irt} = m_{irt-1} = 0) \\ & - \mathrm{E}(CR_{rt-1}, u_{irt}|m_{irt} = m_{irt-1} = 0) + \mathrm{E}(CR_{rt-1}, u_{irt-1}|m_{irt} = m_{irt-1} = 0) \end{aligned} \tag{A.7}$$

even if the first, second and last term in the summation are equal to zero, the third conditional covariance is negative $\mathrm{E}(CR_{rt-1}, u_{irt} \mid m_{irt} = m_{irt-1} = 0)$. This implies that:

$$\mathrm{E}(\Delta CR_{rt}, \Delta u_{irt}|m_{irt} = m_{irt-1} = 0) > 0. \tag{A.8}$$

Therefore, if moving decisions are actually affected by past crime rates (i.e. $\beta_1 \neq 0$), and if u_{irt} and v_{irt} are positively correlated, our estimates may be upward biased.

As we discuss in Section 2, we consider this a minor concern, given that crime-related moving decisions do not seem particularly relevant in our data. Nevertheless, in the online Appendix B.1, we use an IV strategy to deal with this potential concern, where we instrument the crime rate to which movers are exposed to with the contemporaneous crime rate in the area where they resided in the first wave. The estimation results of this alternative strategy fully confirm our main results.

A.3. *Appendix Figures*

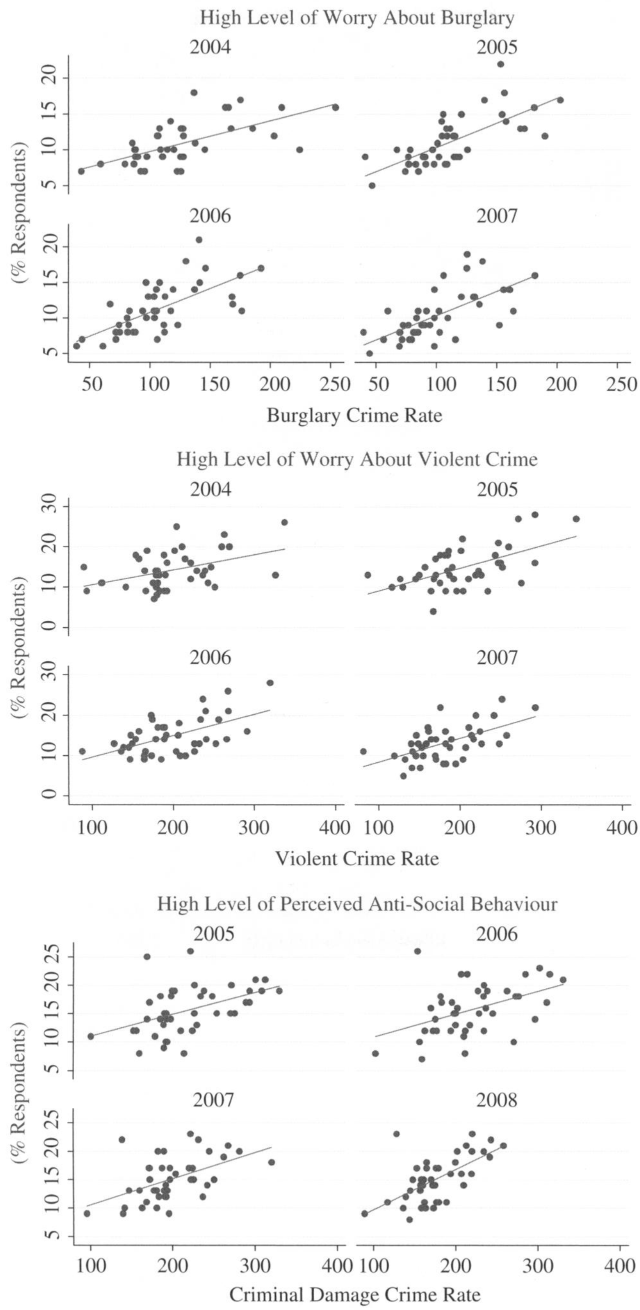

Fig. A1. *Concern about Crime and Risky Behaviour, Rating of Local Police and Local Crime, by PFA; BCS data (2005–8)*

Note. Authors' calculations from British Crime Survey (BCS) data and UK Home Office recorded crime statistics.

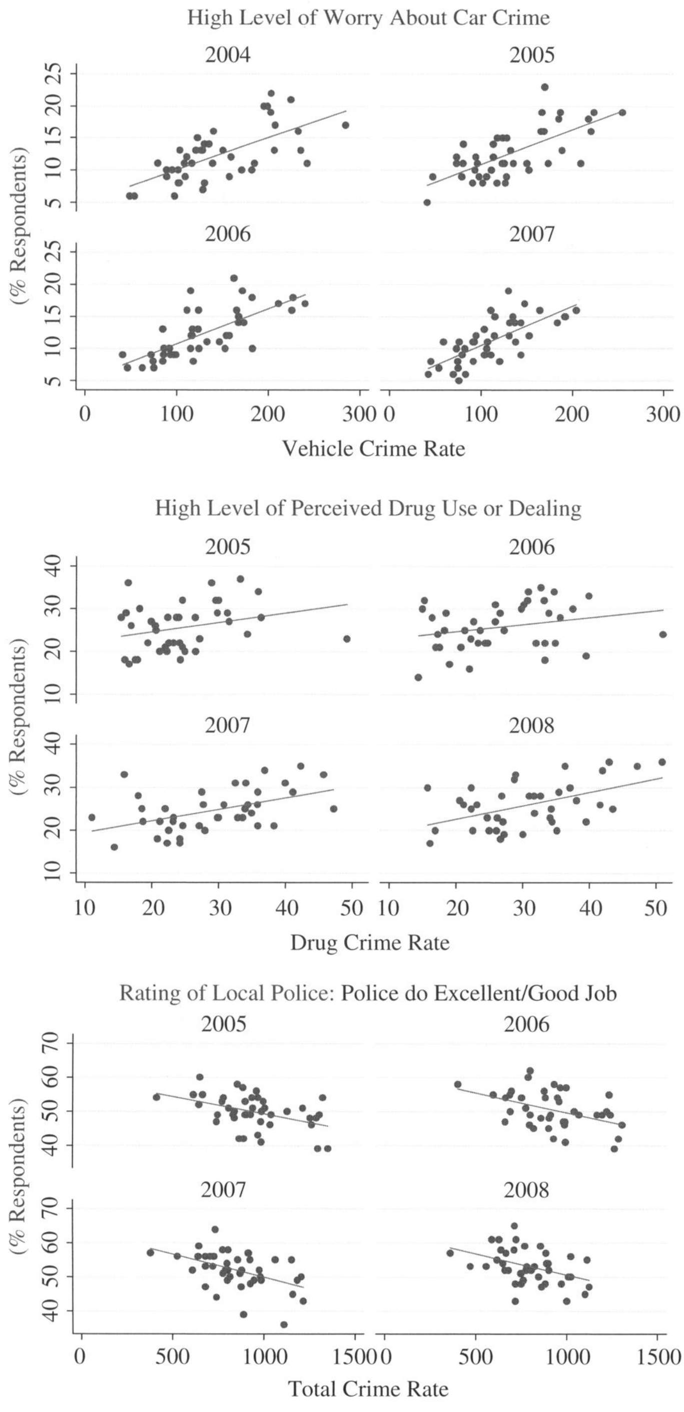

Fig. A1. *(Continued)*

A.4. *Appendix Tables*

Table A5

Mental Health (GHQ) and Crime: Individual and LA Controls

GHQ – Overall	1	2	3	4
	LA crime		PFA crime	
log (total crime rate)	0.008**	0.008**	0.014***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004
Marital status (excluded category: married/civil partnership)				
Separated	0.027*	0.026*	0.027*	0.027*
	(0.015)	(0.015)	(0.015)	(0.015)
Divorced	−0.008	−0.008	−0.008	−0.008
	(0.011)	(0.011)	(0.010)	(0.010)
Widowed	0.070***	0.070***	0.070***	0.070***
	(0.016)	(0.016)	(0.020)	(0.020)
Never married	0.008	0.008	0.008	0.008
	(0.009)	(0.009)	(0.010)	(0.010)
Employment status (excluded category: employed)				
Self-employed	0.006	0.006	0.006	0.006
	(0.006)	(0.006)	(0.006)	(0.006)
Unemployed	0.057***	0.057***	0.057***	0.057***
	(0.007)	(0.007)	(0.007)	(0.007)
Retired	0.012*	0.012*	0.012*	0.012*
	(0.007)	(0.007)	(0.006)	(0.006)
Maternity leave	−0.002	−0.002	−0.002	−0.002
	(0.011)	(0.011)	(0.010)	(0.010)
Family care	0.027***	0.027***	0.027***	0.027***
	(0.007)	(0.007)	(0.005)	(0.005)
Full time student	0.009	0.009	0.009	0.009
	(0.008)	(0.008)	(0.008)	(0.008)
Sick, disabled	0.064***	0.064***	0.064***	0.064***
	(0.011)	(0.011)	(0.010)	(0.010)
Government training scheme	−0.005	−0.005	−0.006	−0.006
	(0.033)	(0.033)	(0.020)	(0.021)
Other	0.037**	0.037**	0.037***	0.037***
	(0.014)	(0.014)	(0.013)	(0.013)
LA controls				
Employment rate	−0.070*	−0.080*	−0.069**	−0.078**
	(0.040)	(0.042)	(0.033)	(0.035)
Share of benefit claimants		−0.434		−0.431
		(0.380)		(0.485)
Share of residents aged 15–24		−0.688*		−0.653*
		(0.379)		(0.375)
Share of immigrants		0.062		0.068
		(0.071)		(0.060)
Police officer *per capita*		−0.506		−0.307
		(0.594)		(0.506)
log (resident population)		0.014		−0.001
		(0.133)		(0.125)
Other individual controls	X	X	X	X
Year-quarter dummies	X	X	X	X
Observations	25,647	25,647	25,647	25,647

Notes. This Table reports FD estimates of GHQ index on log crime rates recorded during the quarter before the interview in, respectively, the LA (columns 1–2) or PFA (columns 3–4) of residence. The GHQ index has been normalised to vary between 0 (least distressed) and 1 (most distressed). 'Other individual controls' are: age, age squared, a dummy for children in the household, categorical variables for education level and log household income. Sample: BHPS data. Urban LAs. Standard errors: robust and clustered by LA (upper part of the Table; 165 clusters) or by PFA (lower part of the Table; 41 clusters); *significant at 10%; **significant at 5%; ***significant at 1%.

Table A6

Mental Health (GHQ) and Crime: Trends and Initial Conditions

	1	2	3	4	5	6	7	8	9
				LA crime					
log (total crime rate)	0.008**	0.007*	0.007	0.008**	0.008**	0.007*	0.007*	0.007*	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
log (violent crime rate)	0.001	0.001	0.001	0.002	0.001	0.001	0.002	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log (property crime rate)	0.008**	0.007*	0.007*	0.009**	0.008**	0.007*	0.007*	0.007*	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
				PFA crime					
log (total crime rate)	0.014***	0.014***	0.013***	0.015***	0.015***	0.014***	0.014**	0.014**	0.013**
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
log (violent crime rate)	0.006**	0.006*	0.006*	0.006**	0.006**	0.005	0.005	0.005	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
log (property crime rate)	0.015***	0.015**	0.014**	0.016***	0.016***	0.016***	0.015**	0.015**	0.015**
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
PFA linear trend		X						X	
LA linear trend			X						X
Initial LA crime rates				X	X	X	X	X	X
Initial avg GHQ (LA)					X	X	X	X	X
Initial avg BHPS controls (LA)						X	X	X	X
Initial LA controls							X	X	X
Individual controls	X	X	X	X	X	X	X	X	X
Year-quarter dummies	X	X	X	X	X	X	X	X	X
All LA controls	X	X	X	X	X	X	X	X	X
Observations	25,647	25,647	25,647	25,647	25,635	25,635	24,661	24,661	24,661

Notes. This Table reports FD estimates of GHQ index on log crime rates recorded during the quarter before the interview in, respectively, the LA (upper part of the Table) or PFA (lower part of the Table) of residence. The GHQ index has been normalised to vary between 0 (least distressed) and 1 (most distressed). A linear trend is included at the PFA level (columns 2 and 8) or at the LA level (columns 3 and 9). 'Initial LA crime rates' is the average crime rate (respectively, total, property and violent) in the LA of residence in year 2002 interacted with year dummies. '*Initial avg GHQ (LA)*' is the average GHQ in the LA of residence measured over the period 1999–2001 and interacted with year dummies. 'Initial avg BHPS controls (LA)' are the averages of individual controls in the LA of residence measured over the period 1999–2001 and interacted with year dummies. 'Initial LA controls' are the average LA controls measured over the period 1999–2001 and interacted with year dummies. Other controls are: individual controls (age, age squared, a dummy for children in the household, dummies for marital status, for employment status and for education level, and log household income); a full set of year-quarter dummies; employment rate in the LA of residence (yearly average); all LA controls (employment rate, share of residents receiving welfare benefits, share of individuals aged 15–24 over total adult population, immigrants share, number of policemen *per capita* and log population size). Each cell reports results from a separate regression, with total crime, violent crime and property crime included alternatively in the regression. Sample: BHPS data. Urban LAs. Standard errors: robust and clustered by LA (upper part of the Table; 165 clusters) or by PFA (lower part of the Table; 41 clusters); *significant at 10%; **significant at 5%; ***significant at 1%.

Table A7

Mental Health and Crime: Single GHQ Items

GHQ item	(1) Unable to concentrate	(3) Not playing useful role	(5) Constantly under strain	(6) Unable to overcome difficulties	(7) Not enjoying day-to-day activities	(9) Feeling unhappy or depressed	(11) Feeling worthless	(12) Not feeling reasonably happy
log (total crime rate)	0.017*	0.017**	0.016**	0.021***	0.017**	0.022**	0.012*	0.016**
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.010)	(0.007)	(0.006)
log (violent crime rate)	0.005	0.005	0.004	0.011**	0.006	0.011**	0.007**	0.008**
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)
log (property crime rate)	0.020**	0.019**	0.019**	0.020**	0.017**	0.023*	0.011	0.014**
	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.012)	(0.008)	(0.007)
Individual controls	X	X	X	X	X	X	X	X
Year-quarter dummies	X	X	X	X	X	X	X	X
All LA controls	X	X	X	X	X	X	X	X
Observations	25,647	25,647	25,647	25,647	25,647	25,647	25,647	25,647

Notes. This Table reports FD estimates of single GHQ items on log crime rates recorded during the quarter before the interview in the PFA of residence. Each of the GHQ items has been normalised to vary between 0 (least distressed) and 1 (most distressed). Other controls are: individual controls (age, age squared, a dummy for children in the household, dummies for marital status, for employment status and for education level and log household income); a full set of year-quarter dummies; employment rate in the LA of residence (yearly average); all LA controls (employment rate, share of residents receiving welfare benefits, share of individuals aged 15–24 over total adult population, immigrants share, number of policemen *per capita* and log population size). Each cell reports estimation results from a separate regression. Sample: BHPS data. Urban LAs. Standard errors: robust and clustered by PFA (41 clusters); *significant at 10%; **significant at 5%; ***significant at 1%.

Table A8

Mental Health and Crime: Different Crime Types

	1	2	3	4
	GHQ – overall	GHQ – anxiety and depression	GHQ – social dysfunction	GHQ – confidence loss
Total crime				
Violent crime				
ln (robbery rate)	0.003	0.008	−0.001	0.003
	(0.005)	(0.008)	(0.005)	(0.010)
ln (sexual crime rate)	−0.000	0.001	−0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.004)
ln (violence rate)	0.005**	0.007**	0.003	0.005**
	(0.002)	(0.003)	(0.003)	(0.002)
Property crime				
ln (burglary rate)	0.012**	0.017**	0.010**	0.005
	(0.004)	(0.006)	(0.004)	(0.006)
ln (criminal damage rate)	0.006*	0.007	0.005	0.006
	(0.003)	(0.005)	(0.003)	(0.005)
ln (fraud and forgery rate)	0.004	0.005	0.003	0.005
	(0.003)	(0.005)	(0.002)	(0.005)
ln (vehicle crime rate)	0.008**	0.010	0.008*	0.003
	(0.004)	(0.006)	(0.004)	(0.007)
ln (other theft rate)	0.014**	0.019**	0.013**	0.005
	(0.005)	(0.007)	(0.005)	(0.007)
Other crime				
ln (drug crime rate)	0.001	0.001	0.001	0.001
	(0.002)	(0.003)	(0.003)	(0.004)
ln (any other crime rate)	0.004	0.006	0.001	0.008**
	(0.003)	(0.004)	(0.003)	(0.004)
Individual controls	X	X	X	X
Year-quarter dummies	X	X	X	X
All LA controls	X	X	X	X
Observations	25,647	25,647	25,647	25,647

Notes. This Table reports FD estimates of the four GHQ indices (Overall, Anxiety and Depression, Social Dysfunction; Confidence Loss) on log crime rates recorded during the quarter before the interview in the PFA of residence. All four GHQ indices have been normalised to vary between 0 (least distressed) and 1 (most distressed). Other controls are: individual controls (age, age squared, a dummy for children in the household, dummies for marital status, for employment status and for education level, and log household income); a full set of year-quarter dummies; employment rate in the LA of residence (yearly average); all LA controls (employment rate, share of residents receiving welfare benefits, share of individuals aged 15–24 over total adult population, immigrants share, number of policemen *per capita* and log population size). Each cell reports estimation results from a separate regression. Sample: BHPS data. Urban LAs. Standard errors: robust and clustered by PFA (41 clusters); *significant at 10%; **significant at 5%; ***significant at 1%.

Table A9

BHPS: Number of Interviews by Year and Month

Interview month	Year 2004	Wave	Year 2005	Wave	Year 2006	Wave
January	84	14	167	15	131	16
February	42	14	58	15	23	16
March	17	14	12	15	19	16
April	9	14	6	15	1	16
May	0	14	3	15	0	16
Total (January–May)	152		246		174	
September	4,168	15	4,952	16	5,226	17
October	3,196	15	3,064	16	2,976	17
November	1,291	15	931	16	789	17
December	272	15	176	16	127	17
Total (September–December)	8,927		9,123		9,118	

Note. Authors' calculations from BHPS data.

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Additional Supporting Information may be found in the online version of this article:

Appendix B. Alternative Channels and Further Results.
Data S1.

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