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The effect of neighbourhood and spatial crime rates on mental wellbeing

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Abstract
This paper attempts to provide new evidence on the indirect cost of neighbourhood crime rates on mental wellbeing of residents. Crime places a heavy burden on the economy, and it receives significant attention from the public. Yet, the connection between crime and health for victims and non-victims is not well captured in the literature. Using spatial methodology, we differentiate the effect on mental wellbeing of residents due to the crime rates in their immediate neighbourhood (local) and crime rates in the surrounding areas (spatial). The main innovation of the paper is to use these crime rates at small geographical level (around 8500 residents) to better translate the changes in crime in the neighbourhoods and their effects on a person's mental wellbeing. This is different to other studies that looked at crime incidences in larger geographical units. Our estimation results show that the increase in local and spatial crime rates against the property negatively affect the mental wellbeing of residents. The negative impact of spatial crime rates against the person is also present and is 6.7 times larger than the effect of property crime rates.

Keywords Crime · Mental health · Neighbourhood effects · Spatial effects

1 Introduction

In many developed and developing countries, issues of crime are of major concerns in the political agenda due to their high societal cost (McCollister et al. 2010). Even in the countries with low crime rates, the incidence of crime does not only produce

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monetary and/or health damages to a victim's wellbeing but also often associates with considerable psychological distress in non-victims leading to alterations in their behaviour due to the changes in perceived risks for their safety (Brunton-Smith and Sturgis 2011; Dustmann and Fasani 2016; Braakmann 2012). Yet, the connection between crime and its effect on the health of non-victims is not well captured in the literature. This paper contributes to this literature in multiple ways.

We examine the effect of crime incidences on mental wellbeing of individuals in the local area of residence and surrounding neighbourhoods. Using fixed effects estimators with multiple robustness checks, we draw inferences from our results about the existence and magnitude of the effect of *local neighbourhood* crime rates (at the suburb level) on mental wellbeing of residents. These localised crime rates may better translate the changes in crime in the neighbourhoods and their effect on a person's mental wellbeing in comparison with other studies that looked at crime incidences in larger geographical units. Furthermore, we specifically contribute to the literature by estimating the effect of the crime rates in the surrounding neighbourhoods on mental wellbeing of individuals by using spatial methodology. This approach helps evaluate the relevance of distance in estimating the indirect impact of crime rates. In this paper, we also provide new evidence on the impact of victimisation from different types of crimes on mental wellbeing and examine whether people who previously experienced victimisation are more sensitive to the crime levels and perceive them differently than non-victims.

The estimation of non-monetary costs of crime is important due to its high impact on society (Dolan and Peasgood 2007). The indirect impact (psychological distress and anxiety) generated from the fear of crime and victimisation risks is significant, and Cornaglia et al. (2014) suggest they may be larger than the direct impact of crime. Braakmann (2012) also provides evidence of changes in behaviour like choosing a different mode of transportation, improving house protection, and making a decision to carry a weapon due to victimisation risks.

The importance of *local* neighbourhood characteristics, in particular crime rates, on mental wellbeing has been also emphasised in sociology and public health literature. Several studies provide evidence of the association between neighbourhood characteristics, such as local crime rates, physical and social infrastructure, and subjective wellbeing of individuals, who reside in those neighbourhoods or pass through them (Morenoff 2003; Cohen and Felson 1979). The study on neighbourhood context and mental health by Aneshensel and Sucoff (1996) draws on structural factors like socioeconomic characteristics of neighbourhoods and social cohesion. They find that adolescents from low socioeconomic backgrounds living in neighbourhoods with high exposure to ambient hazards like crime, violence, and drug use are more likely to experience mental health problems. In particular, perception of a threatening neighbourhood leads to higher probabilities of having depression, anxiety, and conduct disorder.

Neighbourhood crime rates impact the perception of victimisation risks of individuals that is connected to mental wellbeing through the channels of stress and anxiety. Furthermore, the individual's mental wellbeing may be affected not only by the crime rates in local neighbourhood but also by the crime conditions pertaining to other, especially contiguous, neighbourhoods. This approach relates to the Chicago School of urban sociological studies that investigates neighbourhoods through their interconnections as part of the larger social environment (Park et al. 1967, p. 7). Spatially connected neighbourhoods widen the concept of the neighbourhood effects on an individual and account for the impact of adjacent neighbourhoods on a person's living environment. Although we expect the effects of crime incidences in adjacent neighbourhoods to be weaker as the distance from where crime occurs is larger. Following the dissipation of crime hotspots framework by Short et al. (2010), these spatial effects of crime may generate additional anxiety and stress. This rests on the assumption that residents are more aware about crime incidences in their neighbourhood and areas nearby (Brantingham and Brantingham 1993). For example, local community organisations across Queensland, such as Neighbourhood Watch groups, provide information and issue newsletters to share information on neighbourhood safety activities, local areas' crime incidences, and police information.

The research on measuring the effect of crime on mental health/subjective wellbeing is limited in the economics literature [see recent book chapter (Bindler et al. 2020)] with studies looking at the psychological effects of direct victimisation (i.e. the changes in mental health due to being victimised) (Mahuteau and Zhu 2016; Johnston et al. 2018), the effect of local crime rates on the mental wellbeing of individuals living in the respective communities (Dustmann and Fasani 2016), and both effects combined (Cornaglia et al. 2014). Our study is related to the works by Dustmann and Fasani (2016) and Cornaglia et al. (2014). Both papers estimate the effects of violent and property crime on mental wellbeing of individuals using panel data estimators, although the studies diverge in conclusions. While Dustmann and Fasani (2016) find significant negative effect of property crime rates on mental wellbeing, Cornaglia et al. (2014) provide evidence of the deterioration of subjective wellbeing due to violent crime rather than crime incidences against property. Authors in these two papers use a relatively large urban geographical area definition for testing the effect of crime statistics on mental wellbeing of residents. In the case of Dustmann and Fasani (2016), the crime statistics are presented at the Local Authority (LA) level in England and Wales with an average population of 180,000 individuals in one urban LA. Cornaglia et al. (2014) use the Local Government Area (LGA) level to tabulate crime statistics. The authors use data on 110 urban LGAs with an average population of 215,000 individuals.

In both studies, the authors provide empirical estimates of the impact of local crime rates on subjective wellbeing of individuals residing in those areas. However, the use of a large geographical unit for the analysis of local crime statistics may not facilitate obtaining a good (precise) estimate of the effect on person's subjective wellbeing. For example, crime incidences such as theft or robbery may predominantly occur in a small number of neighbourhoods with high concentration of entertainment, food and drinking facilities, but by using the crime rates at LA or LGA levels, the authors attribute the effect evenly of those crime incidences to each residents living in these large geographical units with no regard to how close one lives to high crime neighbourhoods. We hypothesise this use of crime rates in large geographical areas and estimation of its effect on wellbeing of residents to be insufficient to uncover the influence of the *local* crime rates on mental wellbeing of individuals. Furthermore, Cornaglia et al. (2014) note that due to the crime data constraints they were unable to capture the within-LGA variation in crime rates and estimate the "very" local effect on individuals' mental wellbeing.

This paper attempts to provide new evidence on the indirect cost of neighbourhood crime rates on mental wellbeing of residents. We use a multi-year panel data study of households merged with detailed monthly crime statistics at a suburb level to identify which types of crimes are more distressing. We also show the importance of the distance where crime occurs and measure the impact of crime rates at the suburbs located further away from home. Our findings suggest that crime rates have adverse consequences for mental wellbeing of residents. Not surprisingly, the impact is heterogeneous for different types of crime rates and with respect to the distance. For example, a 1 standard deviation increase in property crime rate (including unlawful entry, theft, fraud or property damage) in a local area where a person resides reduces the resident's mental wellbeing by 1 point or 1.5% with respect to the mean value of mental wellbeing. The effect on mental wellbeing is only half as large (0.5%) for a 1 standard deviation increase in property crime rates in contiguous neighbourhoods. The results for the violent crimes (include homicide, robbery, assault, and sexual offence) are significant only for contiguous neighbourhoods with the impact of 1 standard deviation on mental wellbeing being similar (0.5%) to the effect of the spatial property crime. Furthermore, using information on crime victimisation, we find that individuals suffer a substantial decrease in mental wellbeing from violent crime victimisation. The impact is statistically significant and reduces the mental wellbeing by 7.2%. The results also suggest that while the victims of violent crimes suffer significant immediate impact to their mental health and wellbeing, the impact is likely to be non-lasting and tends to dissipate after 3 months of the victimisation event.

2 Data description

2.1 Data on individual characteristics and mental wellbeing

The data on individuals for this study are from the Household, Income, Labour Dynamics (HILDA) panel dataset covering 15 waves of the study from 2001 to 2015.[1] Although the information in HILDA is available for all of Australia, we restrict our analysis to only one state—Queensland,[2] because of the availability of the detailed neighbourhood crime statistics, which we obtained from the Queensland Police Service. The scope of HILDA covers all members of the selected household, but only individuals that are over 15 years of age are interviewed and asked to fill out the self-completion questionnaire. The interview and questionnaire completion dates are available in HILDA, and we use this information to match it with the crime statis-

[1] We use the unconfidentialised version of HILDA for all waves in our analysis that contain detailed geography of the neighbourhood where a household resides. At the time of writing, there are 15 waves of HILDA available.

[2] Queensland is the second largest state in Australia with a population of approximately 4.9 million people. In terms of socio-demographic characteristics, Queensland population is largely representative of Australian population. Queensland has a diversified economy, and main sectors include mining, tourism, agriculture, and a range of service industries: banking, insurance, education.

tics data. The use of HILDA in empirical research of subjective/mental wellbeing has been extensive and largely due to the availability of data generated by the 36-Item Short Form Health Survey (SF-36) that respondents fill out as a component of their self-completion questionnaire in each wave. The SF-36 is a widely used multidimensional generic measure of individuals' health-related quality of life, and it provides instruments that have been successfully describing subjective wellbeing. The literature suggests that the measures of mental wellbeing constructed using SF-36 perform well in terms of validity and consistency and have well-established psychometric properties (Butterworth and Crosier 2004; McHorney et al. 1993).

Our main outcome measure of mental wellbeing is a mental wellbeing index (MWI)[3] that is constructed similarly to Frijters et al. (2014) by combining 9 items in mental health and vitality components. Both components contain similar scoring information. The mental health component includes questions on how much of the time during the past 4 weeks a respondent has felt: (i) nervous; (ii) down in the dumps; (iii) calm and peaceful; (iv) sad, and (v) happy. The vitality component includes questions on how much of the time during the past 4 weeks a respondent has felt: (i) full of life; (ii) having a lot of energy; (iii) worn out, (iv) tired. Each of the 9 questions uses the following scale: 1—"All of the time", 2—"Most of the time", 3—"A good bit of the time", 4—"Some of the time", 5—"A little bit of the time", 6—"None of the time". Before constructing the index, we apply reverse coding to some of the items, so that overall a higher score indicates a better state of mental wellbeing. Using the methodology presented in Ware et al. (2000), we compute the index of mental wellbeing by performing algebraic summation of all responses and then transforming the score to a 0–100 scale with higher values representing better mental wellbeing status. The index is calculated if a respondent answered at least 5 out of 9 questions, and in the cases when some of the questions were left unanswered (maximum 4 questions could be left unanswered), we substitute the missing values with the individual's average for the items that were answered.[4]

Table 1 reports the descriptive statistics for the mental wellbeing by socioeconomic and demographic variables calculated using MWI as a main variable of interest. This preliminary analysis shows that on average the presence of heterogeneity in mental wellbeing is not pronounced for the majority of the individual characteristics. However, the larger differences in means between groups and higher standard deviations are present in the victimisation category. Particularly, residents who experienced violent crime victimisation in the previous 12 months express lower levels of mental wellbeing, which is associated with the reduction in MWI on average by 10.59 points (or 15.6% when compared to the mean of MWI). At the same time, the difference in MWI means between non-victims and victims of property crimes is relatively small.

[3] We do not use mental component score (MCS) as a measure of mental wellbeing, which is constructed using principal component analysis, because there is a negative weighting that needs to be assigned to the scales of physical health.

[4] This procedure is recommended in Ware et al. (2000). Total number of imputed observations is 523 representing 2.3% of the estimation sample. The majority of observations (415 out of 523) required imputation only for one question.

Table 1 Summary statistics for Mental Wellbeing Index

	Mean	Overall SD	Within SD	*N* obs.
Mental wellbeing index	67.70	16.60	9.14	22,224
Mental health component	74.31	16.95	9.90	22,224
Gender				
Male	69.13	16.24	8.58	10,243
Female	66.47	16.80	9.59	11,981
Age group				
15–30	66.79	16.30	9.13	5736
31–45	66.89	16.31	8.60	6815
46–60	68.91	17.04	8.70	5573
61–75	69.94	16.74	7.99	3007
Over 75	65.09	16.16	8.47	1093
Education				
Year 11 or below	66.70	17.31	9.26	7081
Year 12	67.27	16.56	8.76	3428
Certificate/Diploma	68.22	16.41	8.71	6868
Bachelor/Masters/Doctorate	68.71	15.71	8.89	4847
Marriage status				
Married or De Facto	68.37	16.06	8.69	14,419
Separated or Divorced	65.95	19.16	9.60	2281
Widowed	68.17	15.06	8.39	844
Single	66.38	17.02	9.48	4680
Employment status				
Employed	69.13	15.53	8.57	14,960
Unemployed	64.27	18.50	6.09	779
Not in labour force	64.80	18.23	8.75	6485
*Victimisation status**				
Non-victim	67.91	16.44	8.87	19,989
Violent crime victim**	57.11	21.14	6.57	274
Property crime victim**	65.24	17.11	4.97	873

*Victimisation questions were not asked in wave 1

**Victimised in the past 12 months since questionnaire completion date

In our analysis, we match the local crime rates and observations in HILDA in accordance with their reported residential areas by using Statistical Areas 2 (SA2s) in the 2011 Australian Standard Geographical Classification (ASGC). SA2s are the third smallest geographical units that cover all of Australia without gaps and, according to the Australian Bureau of Statistics (ABS), Queensland is divided into 526 SA2s with an average population size of approximately 8500 residents in 2011.

In the major cities, SA2s often correspond to the established suburb areas. However, some smaller (larger) suburbs have been clustered together (broken up) to account for the differences in suburb size. Our HILDA sample consists of households that reside in 310 SA2 in major urban areas[5] (average population size in Queensland urban SA2 was 9563 people in 2011) and represent over 63% of all households residing in Queensland. Urban specification is selected for two reasons. First, in major urban SA2s we have more individuals surveyed per SA2 in comparison with other areas, which helps mitigate the measurement issue arising from averaging the impact across a small number of residents in an area. And second, most of the variation in crime levels happens in cities; thus benefitting our identification strategy. This specification is similar to the one in Cornaglia et al. (2014) and Dustmann and Fasani (2016).

2.2 Neighbourhood crime statistics

Our SA2 definition of the neighbourhood is advantageous in comparison with the studies that use larger geographical areas for the definition of neighbourhoods, allowing testing neighbourhood's crime rate effects on a more granular level. We obtained the crime statistics for all 526 SA2 from the Queensland Police Service. All crime incidences that had been registered by police divisions were categorised in accordance with the Australian Standard Offence Classification and aggregated by Queensland Police Service on a monthly basis from January 2001 to December 2015 for each SA2 using dates and locations of crime events. In this study, we use two crime categories: crimes against the property (property crimes) and crimes against the person (violent crimes) to examine their effects on mental wellbeing of individuals. To construct the crimes against the property, we follow Queensland Police crime statistics broad offence division and aggregate crime incidences from the following categories: arson, unlawful entry, other property damage, unlawful use of motor vehicle, other theft, and fraud. Crimes against the person include homicide (murder), other homicide, robbery, assaults, sexual offences, and other offences against the person. Due to their high costs to physical and mental health or financial wellbeing, crimes against the person and crimes against the property are less likely remain unreported if compared with other crimes category which includes noise complaints, traffic and drug-related offences. Our taxonomy of crime categories also aligns with the studies of Cornaglia et al. (2014) and Dustmann and Fasani (2016) which helps the results comparison.

Using crime statistics and annual mid-year resident population statistics for each SA2 reported by the Queensland Government, we calculate biannual property crime rates and person crime rates per 10,000 residents for each SA2. We present summary statistics in Table 2. Offences against property are the most common among crime types in Queensland between 2001 and 2015. More than 43% of crimes in that category relate to theft followed by unlawful entries and other property damages. Overall, those three categories account for more than 82% of registered property crimes in Queensland. In the "offences against the person" category, most of the crime incidences and variation in crime rates relate to assaults and sexual offences, while the cases of homicide are extremely rare. For example, more than 90% of SA2s in the sample never had any homicide case between 2001 and 2015, but if we include adjacent neighbourhoods the number decreases to 61%. This is not surprising. While the chance of a homicide case

[5] Major urban areas are defined as population clusters or cities with 100,000 people or more. This definition follows the Australian Statistical Geography Standard Section of State classification.

Table 2 Biannual crime rates per 10,000 residents for Queensland urban SA2

	Mean	Overall SD	Within SD	% of crime in category	% of SA2s with no crime in any period
SA2 crime statistics					
Total crime	380.3	627.1	408.6	n.a.	0.0
Homicide (murder)	0.1	0.4	0.4	0.2	95.5
Other homicide	0.2	0.7	0.7	0.4	90.8
Robbery	3.2	8.2	5.7	8.6	32.8
Assaults	22.3	45.5	21.6	59.4	1.8
Sexual offences	6.7	22.9	21.8	17.8	14.3
Other offences	5.1	8.1	5.9	13.6	14.2
Person offences	37.5	68.9	39.9	100.0	0.4
Arson	1.8	3.2	2.3	0.5	43.5
Unlawful entry	75.0	68.8	51.4	21.9	0.0
Other property damage	61.6	82.4	60.0	18.0	0.0
Unlawful use of vehicle	20.4	29.3	22.5	5.9	1.8
Other theft	147.5	288.6	178.4	43.0	0.0
Fraud	36.6	154.6	120.5	10.7	5.9
Property offences	342.9	566.9	377.8	100.0	0.0
Spatial crime statistics					
Total crime	470.3	762.9	310.3	n.a.	0.0
Homicide (murder)	0.1	0.2	0.2	0.2	78.8
Other homicide	0.2	1.2	1.1	0.5	61.1
Robbery	3.3	5.3	3.7	8.1	2.5
Assaults	24.9	33.9	16.6	60.2	0.0
Sexual offences	6.9	9.7	8.8	16.8	0.2
Other offences	5.9	9.9	7.7	14.3	0.2
Person offences	41.4	49.5	26.7	100.0	0.0
Arson	2.8	6.5	4.5	0.7	5.0
Unlawful entry	79.9	65.6	47.5	18.6	0.0
Other property damage	69.2	81.5	51.4	16.1	0.0
Unlawful use of vehicle	29.1	74.6	37.2	6.8	0.0
Other theft	202.4	456.6	156.4	47.2	0.0
Fraud	45.4	107.4	74.7	10.6	0.0
Property offences	428.9	722.4	290.0	100.0	0.0

happening in one's own immediate neighbourhood is quite small, the probability of this event when including contiguous areas increases significantly. Naturally, for the more common crime types we expect the percentage of SA2s with no crime in any period to be 0. The rates and prevalence of violent crimes are approximately 1/10 of the property crimes, and we expect the effects of violent and property crime rates on mental wellbeing of individuals to be heterogeneous due to (i) the perceptions of the likelihood of being a victim of a violent crime and a victim of a property crime are not likely to be the same, and (ii) the perceived differences in potential health damages.

2.3 Spatial crime rates

We consider that people do not spend time solely in their SA2 neighbourhood of residence and perform their daily routines in other suburbs like commuting to and from work, going shopping, or visiting family and friends. Unlike examining the effect of SA2 crime rates in isolation, spatial dependence between neighbourhood crime rates becomes a matter of interest and allows us to measure the effect of crime rates in s's surrounding neighbourhoods on mental wellbeing of individuals who reside in s's neighbourhood. We account for the effects of the crime rates in the surrounding neighbourhoods using a contiguous spatial matrix. The choice of the weighting matrix is driven by two factors that form residents' perception about the crime environment: (i) residents pass through the contiguous neighbourhood more frequently than through the regions located farther away, and (ii) crimes in contiguous-to-s SA2s are more likely to have spillover effects in terms of crime incidences on the s's SA2. Furthermore, in "Appendix A" we present information on SA2 crime rates for the Greater Brisbane Area and Cairns Region, first and fifth most populous urban areas in the state of Queensland. The mapping of average 6-month SA2 property and violent crime rates provides support for the contiguous spatial connections between the neighbourhoods' crime patterns. Violent and property crimes seem to be clustered forming high and low crime areas in both cities.

We construct a first-order "queen" contiguity matrix, in which we determine that a spatial unit is contiguous with other neighbourhoods if it shares a border with them or has a common vertex. The spatial weight matrix is often denoted by W. W matrix is row-standardised and is of the following structure:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1S} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ w_{S1} & w_{S2} & \cdots & w_{SS} \end{bmatrix} \tag{1}$$

In our study, the size of the W matrix is $S \times S$, where $S = 526$ is the number of rural and urban SA2s in Queensland. We construct the spatial matrix for all available SA2s to account for the border cases when non-urban SA2s' crime rates have spatial influence on the crime rates in urban SA2s. In W matrix presented in (1), a row of the matrix shows spatial dependence between the area s and all other areas $(s', \ldots, S)$. The relationship between them depends on the underlying neighbourhood location structure between the area s and the other areas s'. Those areas that share a border or a common vertex with s's neighbourhood have nonzero weights w (calculated using (2)) in the spatial matrix. The nonzero weights are computed as inverse of the number of neighbourhoods that abut neighbourhood s. Thus, the spatial weights for s's neighbourhood along the row are identical with each contiguous area influencing the target area s equally. The average number of contiguous neighbourhoods for an urban SA2 is 5.

$$w_{ss'} = \begin{cases} \frac{1}{\sum_{\substack{s'=1 \\ s' \neq s}}^{S} I(w_{ss'} \neq 0)}, & \text{if } s' \text{ is contiguous to } s \\ 0, & \text{if } s' \text{ is not contiguous to } s \end{cases} \tag{2}$$

We use this spatial weight matrix to construct biannual spatial rates for violent and property crime rates for each SA2 and then, estimate the effect on the mental wellbeing of individuals. Spatial violent crime rates are largely similar on average to the rates in SA2 neighbourhoods, while spatial property crime rates are higher than the ones in SA2s. As expected, the largest differences between spatial and SA2 crime rates are in overall and within standard deviations with spatial statistics reporting generally smaller values. This is because the calculation of spatial statistics involves crime rates from multiple SA2s, so the effect of the extreme values in some areas is smoothed when those crime rates are adjusted using the spatial weighting matrix.

3 Methodology

We model the relationship between crime rates and mental wellbeing through a fixed effects regression model. We estimate the following equation:

$$\begin{aligned} \mathrm{MH}_{ist} = {} & \theta_1 \mathrm{VC}_{st} + \theta_2 \mathrm{PC}_{st} + \theta_3 \mathrm{SVC}_{st} + \theta_4 \mathrm{SPC}_{st} \\ & + x_{it}^{'} \beta + z_{st}^{'} \psi + \alpha_i + \mathrm{SA2}_s + T_t + \mathrm{ST}_{\hat{s}t} + \epsilon_{ist} \end{aligned} \tag{3}$$

Our dependent variable MH_{ist} is a measure of mental wellbeing of individual i, residing in the s SA2 in interview year t. The parameters of interest θ_1, θ_2, θ_3, and θ_4 represent the effects of crime rates on mental wellbeing. θ_1 (for crimes against the person, VC_{st}) and θ_2 (for the crimes against the property, PC_{st}) capture the influence of the crime rates that happened in the prior 6 months to the month in which SF-36 was completed. For example, if an individual residing in the suburb of Fairfield completed the questionnaire in October 2014, then this information is matched with crime rates that occurred in Fairfield between May and October 2014. Spatial crime statistics for violent and property crime (SVC_{st} and SPC_{st}) are constructed using a spatial contiguous weighting matrix with corresponding 6-month SA2 crime rates, and the effects of spatial crime rates are measured by θ_3 and θ_4, respectively. α_i and $\mathrm{SA2}_s$ denote individual and SA2 neighbourhood fixed effects. The vector T_t represents both year and year-quarter time fixed effects. We also control in our models for temporal trends in larger regions by including Statistical Areas 4 (SA4)[6] fixed effects interacted with time fixed effects. This is represented by $\mathrm{ST}_{\hat{s}t}$ with the $\hat{s}$ and t indexing SA4 areas and year, respectively. The vector x_{it} includes individual time-varying variables such as age, age squared, employment, marital status, education level, presence of children

6 There are 19 SA4 regions covering the whole of Queensland without gaps or overlaps.

in the household, and log of income. The vector z_{st} represents quarterly median sold house prices and log of population in SA2s. ϵ_{ist} denotes an error term.

In a spatial econometric framework, this regression model follows a spatial lag of X model (SLX) in which X represents a matrix of neighbourhood crime rates. This modelling approach presents an "externalities-based motivation" advocated by LeSage and Pace (2009, p. 30). We assume that crime incidences in surrounding neighbourhoods act as a contributing factor in explaining mental wellbeing outcomes due to the stress and anxiety of potential victimisation. While the effect of the crime rate in the residence neighbourhood shows a direct influence on mental wellbeing (for example, if property crime rates are constantly high in the area, then we assume that people worry more about being a victim of a break-in or their property being damaged), the spatial crime rates indirectly influence the mental wellbeing level of residents due to the property crime spillovers between neighbourhoods. For the violent crime rates, the level of crime in contiguous neighbourhoods that residents pass through may exert the spatial influence on their mental condition. Furthermore, accounting for the effects of spatial crime rates is relevant as the empirical evidence suggests that crime incidences are not randomly distributed over space but rather concentrated in particular areas identified in the literature as "hot spots" (Sherman et al. 1989). In our case, the use of SLX model provides intuitive economic reasoning. In comparison with the spatial autoregressive model (SAR) or spatial error model (SEM), the implementation and identification of parameters under SLX are straightforward once we construct the W matrix. Gibbons and Overman (2012) advocate the use of SLX-type models and provide a summary of identification nuances related to SAR- and SEM-type models that includes the additional exclusion restrictions necessary for identification and the estimation of autocorrelation coefficient ρ.

Under the SLX model, we evaluate the effects of local spillovers due to the neighbourhood property and violent crime rates. Although the additional spatial dependence may be present because of the correlation in nearby suburbs' amenities, facilities, or socioeconomic characteristics, accounting for this dependence explicitly is not feasible due to the data limitations on SA2-level variables. To accommodate the error correlation arising from the common shocks affecting individuals living in the same geographical areas, we adjust the calculation of standard errors using two-way cluster robust procedure. We apply the idea proposed by Cameron et al. (2011) to estimate the robust standard errors that will accommodate the possible correlations within two non-nested groups: (i) within suburb autocorrelation is captured by using SA2 as a category, and (ii) within individual autocorrelation is captured by the individual identifiers.

One of the key concerns in the application of the SLX model is the endogeneity issue of neighbourhood crime rates and spatial crime rates. Our estimation relies on the validity of treating SA2 crime rates as exogenous to the changes in mental wellbeing of residents. This assumption is reasonable, as it is highly unlikely that unobserved individual time-varying events at period t that affect mental wellbeing of individuals also lead to the significant changes in contemporaneous or future periods' crime rates in the area. At the same time, we are unable to control for multiple SA2 time-varying characteristics that may have an impact on mental wellbeing of residents and be associated with the crime rates. This would contaminate our estimates for the crime rates due to the omitted variable problem. For example, if SA2 unemployment rate has a negative effect on the mental wellbeing of the residents and is positively correlated with crime incidences in SA2, our estimates for the crime rates would be negatively biased. One of the options to account for SA2-specific variables is to allow a more flexible time trend with respect to SA2s. But this specification is not without a disadvantage. By including an interaction term of SA2 and time variables the identification of the effects of SA2 crime rates becomes problematic due to insufficient variation in crime rates after controlling for SA2-year fixed effects. Instead, we include SA4s interacted with time fixed effects in the regressions. Because SA4s have been designed to represent the labour markets and other regional outputs (Australian Bureau of Statistics 2016), SA4-year fixed effects act as good proxies for unemployment and macroeconomic trends in the areas that may be correlated with crime levels and mental wellbeing. We also control for the dynamics of general economic health of SA2 areas by including resident population and median sold house prices for the SA2s in the quarters when resident s participated in the survey waves.

Furthermore, as explained in Elhorst (2013, p. 19) and Corrado and Fingleton (2012) the structure of W is critical to obtain unbiased and consistent estimates for the influence of spatial variables on the outcome. However, in reality we do not know the true W and can only provide an estimate of it relying on economic reasoning of the linkages. To construct the W matrix, we a priori assume that only the crime rates in contiguous suburbs influence the mental wellbeing of individuals and have the same spatial weights. W matrix does not vary over time as there are no geographical changes in neighbourhoods' locations, and we consistently apply SA2 geographical classification for all waves (1 through 15).

Under our estimation framework, we address the issues of sorting and selection bias in estimating the parameters of interest. The sorting problem may arise if there is correlation between the crime statistics for SA2 areas and mental wellbeing of individuals. For the issue of sorting, we expect that people that are more distressed live in the areas where crime is more prevalent. Using fixed effects estimation, we control for sorting by exploiting only within SA2 and within individual variations.

To avoid the bias in estimating the effects of SA2 crime rates on mental wellbeing of individuals, we also account for the people who changed their neighbourhood of residence resulting in the different influence of the SA2 crime rates and SA2 characteristics. We treat the individuals that moved between SA2s separately: (i) we select those that spend in the "new" neighbourhood of residence at least 2 periods, and (ii) we assign them with new ID and treat them as new individuals in our sample. This procedure is similar to the one applied in Dustmann and Fasani (2016).

4 Results

Table 3 reports the estimates of $\theta_1, \theta_2, \theta_3$, and θ_4 from the linear fixed effects regression model. We use MWI and the mental health component as our dependent variables to represent mental wellbeing of residents. The results across the models show no significant effect of the SA2 crime rates against the person per 10,000 residents on individual mental wellbeing. Although these results are surprising, we note that the

Table 3 Estimates of the effect of SA2 crime rates on mental wellbeing outcomes

	1	2	3	4	5	6	7
Mental wellbeing index							
Violent crime	0.0064				0.0108		0.0111
	(0.0078)				(0.0081)		(0.0080)
Spatial violent		−0.0205***				−0.0158**	−0.0151**
		(0.0066)				(0.0077)	(0.0076)
Property crime			−0.0030***		−0.0032***		−0.0027**
			(0.0011)		(0.0012)		(0.0012)
Spatial property				−0.0018***		−0.0013**	−0.0011*
				(0.0005)		(0.0005)	(0.0006)
Controls							
Individual	Y	Y	Y	Y	Y	Y	Y
SA2	Y	Y	Y	Y	Y	Y	Y

Table 3 continued

	1	2	3	4	5	6	7
Mental health component							
Violent crime	0.0105				0.0146		0.0149
	(0.0086)				(0.0091)		(0.0091)
Spatial violent		−0.0189**				−0.0170*	−0.0163*
		(0.0086)				(0.0098)	(0.0098)
Property crime			−0.0026**		−0.0030**		−0.0026**
			(0.0012)		(0.0012)		(0.0013)
Spatial property				−0.0011**		−0.0005	−0.0003
				(0.0005)		(0.0006)	(0.0006)
Controls							
Individual	Y	Y	Y	Y	Y	Y	Y
SA2	Y	Y	Y	Y	Y	Y	Y

Total number of observations in all models is equal to 22,224. Columns 1–7 report the results from the linear fixed effects model. Individual controls include age, age squared, log of household income, level of education, marital status, presence of children in the household and employment status. SA2 controls include median sold house price and log of population. SA4-year fixed effects control for temporal trends. A full set of time dummies, SA2 areas and individual fixed effects are included in all models. Standard errors (in parentheses) are clustered at SA2 geographical level and individual identifier

***Significant at 1%; ** significant at 5%; * significant at 10%

number of SA2 violent crime incidences is small and crimes like homicide, robbery, assaults, or sexual offences are relatively rare, especially at the small geographical area like SA2. Due to the small variations in the *very local* violent crimes rates, residents may find it hard to observe them and form the perception of victimisation risks corresponding to the real crime situation in their immediate neighbourhood. On the other hand, averaging violent crime rates over contiguous areas improves the correlation between the violent crime situation and the perception of crime rates and makes the measurement issue less salient. We suggest that the perception about victimisation risks and its impact on mental wellbeing is formed by the crime rates in larger areas, as more information is taken into account from different news outlets, work commute, or social activities that happen outside of the suburb of residence. In support of this argument, we find a statistically significant negative influence of the crime rates in non-*i* neighbourhoods on mental wellbeing of individuals residing in *i* SA2. Presented in the column 2, the effect of the spatial violent crime is highly significant and an increase in 1 violent crime incident in spatial crime is associated with a 0.0205 units decrease in MWI. Using standard deviations for interpretation, the increase by 1 within standard deviations in spatial violent crime rates decreases MWI by 0.55 (0.8% if evaluated at the mean of MWI) units, comparable to the difference (0.69) between MWIs of married and single individuals. We find similar results for the effects of violent crime and spatial violent crime rates on the mental health component. Next, we report estimates for the property crime and spatial property crime rates. The results in the column 3 and column 4 show that the SA2 property crime rate and spatial property crime rate are highly significant and negatively associated with MWI and mental health. The magnitude of the effect of property crimes is significant, and 1 within standard deviation in SA2 property crimes rates is associated with the decrease of 1.13 units in MWI (or approximately 2% if evaluated at the mean of MWI).

Since crime rates are likely to be geospatially correlated and hence, may create some multicollinearity, we examine in column 5 the impact of *very local* violent and property crime rates on mental wellbeing. We run a separate analysis for spatial violent and property crime rates (i.e. crimes in contiguous non-*i* neighbourhoods for individuals residing in *i*) and present the results in column 6. The results from the full model with both SA2 neighbourhood and spatial crime rates are presented in column 7. Across the models, the estimates for spatial violent, property, and spatial property crime rates are negative and statistically different from zero. The analysis of the estimates across the models shows that there is some correlation between the neighbourhood crime rates and the spatial crime rates. Nevertheless, the impact of that correlation is relatively small. Using the full model coefficients (column 7), we interpret that an increase by 1 standard deviation in spatial violent crime rates is associated with the decline in MWI of individuals by approximately 0.40 points (0.5% if evaluated at the mean of MWI), while a 1 standard deviation increase in property crime and spatial property crime rates reduces MWI by 1.02 (1.5%) and 0.319 (0.5%), respectively. Contrary to the residents' higher concern about violent crime rates in contiguous SA2s, for the property crime rates people potentially worry more about what happens inside their immediate neighbourhoods where most crimes in that category are theft, unlawful entries, and property damages.

We now look at the effect of crime rates on mental wellbeing accounting for the victimisation status of individuals. A positive correlation may exist between the people being victimised (as reported in HILDA) and the crime rates in their SA2 of residences—translating the higher crime rates into the higher likelihood of victimisation. If this is the case, then our estimates for the crime rates may be understated as the effects of the omitted victimisation variables are attributed to the crime rates.

The results in Table 4 show that including victimisation binary variables is important to get more accurate estimates of crime rates. Although the effect of the violent crime rate in the residing neighbourhood on mental wellbeing continues to be not significant, the estimates for the property, spatial property, and particularly the spatial violent crime rates are different in magnitude than the ones in Table 3. Across all models, there is a strong negative effect of victimisation on mental wellbeing, but the effect is only significant for the recent (in the last three months) victims of physical violence. Suffering from violent crime, although large in magnitude (from 7.1 to 7.2% if compared to the mean of MWI) distorts mental wellbeing on average only for a short period (up to 3 months). This result is consistent with the evidence in Cornaglia et al. (2014) which suggests that victims of violent crimes experience significant immediate impact on their mental health, but the impact is likely to dissipate after 3 months of an event.

In contrast to the violent crime victimisation results, the effects of property crime victimisation across all specifications are smaller in magnitude and are not statistically significant regardless of the time that passed from victimisation. The results for the mental health component as an outcome variable are presented in "Appendix B.1", and they are similar qualitatively and quantitatively to the ones for MWI. Furthermore, if we assume that property crime rates, theft, and reported property damages are predominantly committed by people who do not know the victim, we find surprising that the effect of the property rates on mental wellbeing is significant (as shown in Tables 3, 4), but the effect of property victimisation in Table 4 is not. Since property crimes tend to be concentrated in specific neighbourhoods, it may be the case that our neighbourhood regressors pick up some of the effect of property victimisation rendering the identification problematic. Another possible explanation of these results lies in human psychology when people worry about being potential victims, especially if they live in a high crime SA2, but once experienced an outcome like a theft or unlawful entry, they may adapt quickly and handle the situation much better than initially predicted. The literature provides some evidence of this phenomenon. LaGrange and Ferraro (1989) and Cook and Fox (2011) found that the perception of the likelihood of victimisation with respect to property crime rates is a significant predictor of the fear of crime. This fear of crime translates to anxiety, worrisome, and stress affecting the mental wellbeing of individuals. On the other hand, Shapland and Hall (2007) report that the victims of property offences experience smaller decline in happiness levels in comparison with the victims of violent crimes, and the effect of property crime victimisation is short-lived and lasts around 2 weeks. This may explain why we do not observe the statistically significant impact of property crime victimisation as victims of theft crimes quickly recover and have no lasting impact on their mental wellbeing.

Previous literature also suggests that people who previously experienced victimisation are expected to be more sensitive to the crime levels and perceive them differently

Table 4 Estimates of the effect of SA2 crime rates and victimisation on mental wellbeing

	1	2	3	4	5	6	7
Violent crime	0.0062				0.0101		0.0106
	(0.0078)				(0.0079)		(0.0078)
Spatial violent		− 0.0216***				− 0.0181**	− 0.0175**
		(0.0074)				(0.0082)	(0.0081)
Property crime			− 0.0028**		− 0.0030**		− 0.0026**
			(0.0012)		(0.0012)		(0.0012)
Spatial property				− 0.0017***		− 0.0012**	− 0.0011**
				(0.0005)		(0.0005)	(0.0005)
VV (− 1 quarter)	− 4.85***	− 4.87***	− 4.83***	− 4.86***	− 4.79***	− 4.87***	− 4.85***
	(1.62)	(1.62)	(1.62)	(1.62)	(1.62)	(1.62)	(1.62)
VV (− 2 quarter)	− 2.83	− 2.87	− 2.83	− 2.81	− 2.86	− 2.85	− 2.87
	(2.48)	(2.48)	(2.48)	(2.48)	(2.48)	(2.48)	(2.49)
VV (− 3 quarter)	− 0.20	− 0.17	− 0.17	− 0.02	− 0.22	− 0.05	− 0.05
	(2.56)	(2.55)	(2.55)	(2.57)	(2.55)	(2.56)	(2.57)
VV (− 4 quarter)	− 3.55	− 3.54	− 3.54	− 3.51	− 3.61	− 3.53	− 3.60
	(2.61)	(2.62)	(2.61)	(2.61)	(2.60)	(2.62)	(2.61)

Table 4 continued

	1	2	3	4	5	6	7
PV (− 1 quarter)	0.47	0.48	0.45	0.46	0.46	0.47	0.48
	(0.84)	(0.84)	(0.84)	(0.84)	(0.84)	(0.84)	(0.84)
PV (− 2 quarter)	− 1.02	− 1.01	− 1.00	− 1.02	− 1.00	− 1.01	− 1.00
	(0.81)	(0.81)	(0.81)	(0.81)	(0.81)	(0.81)	(0.81)
PV (− 3 quarter)	− 1.13	− 1.16	− 1.16	− 1.12	− 1.15	− 1.15	− 1.18
	(1.17)	(1.17)	(1.17)	(1.17)	(1.17)	(1.17)	(1.17)
PV (− 4 quarter)	− 0.24	− 0.25	− 0.28	− 0.27	− 0.25	− 0.26	− 0.28
	(1.04)	(1.04)	(1.04)	(1.04)	(1.03)	(1.04)	(1.04)
Controls							
Individual	Y	Y	Y	Y	Y	Y	Y
SA2	Y	Y	Y	Y	Y	Y	Y

Total number of observations in all models is equal to 20,832. The outcome variable in all models is MWI. Columns 1–7 report the results from the linear fixed effects model. VV and PV are dummy variables representing violent and property victimisation. The estimates for the effects of victimisation variables on mental wellbeing are reported with regard to the time (for example, "− 3 months" means victimisation occurred in the past 3 months) that passed since a person being victimised. Individual controls include age, age squared, log of household income, level of education, marital status, presence of children in the household and employment status. SA2 controls include median sold house price and log of population. SA4-year fixed effects control for temporal trends. A full set of time dummies, SA2 areas and individual fixed effects are included in all models. Standard errors (in parentheses) are clustered at SA2 geographical level and individual identifier. The reduction in the number of observations is mainly driven by the absence of data on victimisation variables in wave 1

***Significant at 1%; ** significant at 5%

to those who have not been victimised (Ferraro 1995). However, empirically the connection between victimisation and fear of crime remains unresolved with authors providing mixed results (see Wilcox et al. 2007; Dull and Wint 1997). To explore the potential heterogeneity in the crime effects on mental wellbeing, we interact the violent and property crime rates with corresponding victimisation status. Our results in “Appendix B.2” show no evidence of heterogeneity in responses among victims and non-victims as in all models these interaction terms are not statistically significant. This may be explained by the effects of victimisation on mental wellbeing being short-lived which do not significantly change residents’ perception about crime levels around their places of residence.

Females and older individuals may also respond differently to the changes in crime levels and the fear of crime due to their physical vulnerability and relative risk of falling a victim compared to other social groups (Warr 1984; Ferraro and LaGrange 1987). For example, one of the reasons elderly people are more afraid of crime than younger adults is related to their limited ability to protect themselves (McKee and Milner 2000). The literature also suggests that higher rates of fear expressed by women are associated with a broader concern of sexual harassment and assault crimes (Pain 2001; Ferraro 1996). We report the heterogeneous effects of crime rates with respect to gender and age in “Appendix B.3”. While the crime rates variable for the male sample shows significant results similar to the full sample outcomes, only the effect of the spatial violent crime on mental wellbeing is found significant for the female sample. Furthermore, the results for age-related heterogeneity show statistically significant effects of crime rates mostly for the younger sample ($<$ 60 years). These lack of significance in the effects of crime rates for female and older adults samples may be related to the mismatch between actual and perceived crime rates by these two groups. Using Australian survey data (Davis and Dossetor 2010; Indermaur and Roberts 2005) provide evidence that crime perceptions reported by females, older people, and poorly educated people are significantly less accurate than the perceptions reported by males, younger adults, and people with higher education.

Another explanation of the heterogeneous effects of crime rates on mental wellbeing due to gender can be partly attributed to the victimisation statistics with males generally experiencing higher rates of victimisation accounting for non-reported cases (Australian Bureau of Statistics 2019). In our sample, victimisation rates are also slightly higher for males than females for both violent and property crime victimisation. The results from victimisation variables for male and female samples in “Appendix B.3” suggest that while the effect of violent crime victimisation for males is slightly larger than for females, the impact tends to be short-lived for both cohorts and the period of adaptation lasts up to 3 months. The results of victimisation for older adults are generally not significant which can be explained by a measurement error due to the small number (20) of older people being victimised across all waves.

5 Discussion and robustness checks

In this section, we assess the robustness of our results with respect to (i) the measurement error due to SA2s with small samples, (ii) the choice of spatial weighting matrix, and (iii) the construction of violent and property crime rates. Additionally, we investigate the possibility of selection bias in the estimates for the crime rates that is generated by people who move between SA2s because of the high crime rates in their SA2 of residence. Although the number of those who provided the answer "To live in a better neighbourhood"[7] is small relative to the total number of people who moved (less than 5%), we test whether our estimates for the effects of crime statistics on mental wellbeing would be different once we exclude those observations. We find the estimates quantitatively and qualitatively to be largely similar to the results from the original sample (see "Appendix B.4"). There is also a possibility of endogenous selection within the neighbourhood area. This may happen if individuals face family and work constraints that prevent them from moving from one area to another and move within the area they already reside to a location with less crime exposure. This concern is more likely to materialise if the geographical areas are large (see Dustmann and Fasani, 2016; Cornaglia et al., 2014) and selection within the areas may reduce victimisation risk. We believe that using a small geographical area, such as SA2, avoids this type of endogenous selection to a large extent, as moving within the SA2 would not help much to avoid high crime areas if the crime hotspots are in the neighbourhood. To test whether this is true, we exclude individuals who moved within the SA2 and stated "To live in a better neighbourhood" as the main reason of changing residence. In "Appendix B.5", the results for the spatial violent, property, and spatial property crime rates remain statistically significant and the size of the effects is similar to the main results presented in Table 4.

Identifying the effect of crime in a small geographical area on mental wellbeing may come at the risk of the measurement error, as we cannot be sure how the perceptions about the local and spatial neighbourhood crime rates are built. Furthermore, using survey data (rather than administrative for deriving mental wellbeing measures) and having a small sample problem in some neighbourhood areas may exacerbate the issue of identification. One way to mitigate the identification concern is to constrain the analysis only to those areas that have sufficient number of observations. We run our regressions using the data from the SA2s that have at least 50 observations.[8] The results from this sample specification are presented in "Appendix B.6", and they are highly consistent with the results from the main models.

Previously, we mentioned that the estimates of the effects of crime and spatial crime are subject to the correct specification of the W matrix. In this robustness exercise, we account for the effects of the crime rates in the surrounding neighbourhoods using a diffusion framework based on Tobler's first law of geography, "which states that everything is related to everything else, but near things are more related than distant things" (Tobler 1970). In contrast to examining the spatial effects using SA2 crime rates in contiguous neighbourhoods, the diffusion treats spatial dependence between them as the matter of interest and allows us to measure the effect of crime rates in s's surrounding neighbourhoods on individual's mental wellbeing residing in s's neighbourhood. Here, the frequency of passing through the surrounding neighbourhood is

[7] This is the best (closest) reason associated with crime level in the neighbourhood in HILDA.

[8] We have also tried selecting the SA2s with 100 and 150 observations. While the total sample size reduces, the results generally remain consistent.

seen as distance dependent, and the neighbourhoods' crime rates that are closer to the individual's residence SA2 have more influence, and hence larger weights, than those farther away.

To represent such dependencies, we generate a distance decay spatial weight matrix that is based on the inverse distance decay function following (4). The magnitude of the spatial dependence between the area s (i.e. the SA2 area where an individual i resides) and all other areas depends on the distance between the area s's centroid and centroids of the areas $(s', \ldots, S)$ that lie within threshold distance value, $d_{\max}$. $d_{\max}$ represents the radius for each area centroid and is used to identify how close the surrounding areas should be in order to exert spatial influence. We select 10 km as our threshold value for $d_{\max}$ based on residence-work commuting patterns in urban Queensland (BITRE 2015), and the median number of spatial SA2s used to construct spatial crime rates is 19.5.

$$w_{ss'} = \begin{cases} \frac{1}{d_{ss'}}, & \text{if } d_{ss'} < d_{\max} \\ 0, & \text{if } d_{ss'} > d_{\max} \end{cases} \tag{4}$$

The use of the threshold value $d_{\max}$ is driven by two points. First, we rely on the assumption that the influence of the crime rates in the areas that are far away from where an individual resides is negligible. Second, by limiting the number of neighbourhoods that exert spatial influence in crime rates, we create a largely sparse weighting matrix, which is computationally advantageous, especially in the large S cases. In Table 5, we provide evidence of the similar negative relationship between crime variables and mental wellbeing of individuals. Overall, the results for the full models are robust to the selection of spatial weight matrix.

With respect to the construction of the crime rates, the variables are based on crimes that happened in the prior 6 months from the month of the survey. As the perception of crime may fade over time with crimes that took place 5–6 months ago may influence individuals' mental wellbeing differently than more recent crime events occurring 1–2 months ago, we perform sensitivity analysis and present the estimates of 3-month crime rates on mental wellbeing in Table 6. The coefficients for the spatial violent, property and spatial property crime rates continue to be highly significant and, as expected, are larger in magnitude corresponding potentially to more accurate perception of crime events that occurred more recently. The impact of violent crime victimisation is similar to the main results in Table 4, and it remained to be short-lived. Overall, these results suggest that our original estimates of local and spatial crime rates on mental wellbeing are robust to the SA2 crime construction.

We also investigate the relationship between the crime rates aggregated using larger geographical level (SA3) and mental wellbeing of individuals. In comparison with our main analysis on 310 urban SA2s, there are 52 SA3 areas in which individuals from our sample reside with the average population of approximately 57,000 people. The disadvantage of using the crime rates over large geographical areas, such as SA3, is that the effect of the crime incidences does not take into account how close a resident lives to the crime events. The estimation of the effect will be measured with less precision, especially in the neighbourhoods in which there are only small areas

Table 5 Estimates of the effects of SA2 crime rates on mental wellbeing using inverse distance spatial matrix

	1	2	3	4	5	6	7
Violent crime	0.0062				0.0101		0.0105
	(0.0084)				(0.0085)		(0.0085)
Spatial violent		−0.0192**				−0.0173**	−0.0166**
		(0.0082)				(0.0082)	(0.0081)
Property crime			−0.0028***		−0.0030***		−0.0028**
			(0.0011)		(0.0011)		(0.0011)
Spatial property				−0.0038*		−0.0035	−0.0029
				(0.0021)		(0.0022)	(0.0022)
Controls							
Victimisation	Y	Y	Y	Y	Y	Y	Y
Individual	Y	Y	Y	Y	Y	Y	Y
SA2	Y	Y	Y	Y	Y	Y	Y

Total number of observations in all models is equal to 20,832. The outcome variable in all models is MWI. Columns 1–7 report the results from the linear fixed effects model. VV and PV are dummy variables representing violent and property victimisation. The estimates for the effects of victimisation variables on mental wellbeing are reported with regard to the time (for example, "− 3 months" means victimisation occurred in the past 3 months) that passed since a person being victimised. Individual controls include age, age squared, log of household income, level of education, marital status, presence of children in the household and employment status. SA2 controls include median sold house price and log of population. SA4-year fixed effects control for temporal trends. A full set of time dummies, SA2 areas and individual fixed effects are included in all models. Standard errors (in parentheses) are clustered at SA2 geographical level and individual identifier

***Significant at 1%; ** significant at 5%; * significant at 10%

Table 6 Estimates of the effect of 3-month SA2 crime rates on mental wellbeing

	1	2	3	4	5	6	7
Violent crime	0.0074				0.0095		0.0097
	(0.0104)				(0.0105)		(0.0105)
Spatial violent		− 0.0320***				− 0.0259**	− 0.0249**
		(0.0123)				(0.0126)	(0.0126)
Property crime			− 0.0028*		− 0.0029*		− 0.0025*
			(0.0015)		(0.0015)		(0.0015)
Spatial property				− 0.0036***		− 0.0032***	− 0.0031***
				(0.0011)		(0.0012)	(0.0012)
VV (− 1 quarter)	− 4.85***	− 4.86***	− 4.85***	− 4.88***	− 4.81***	− 4.89***	− 4.88***
	(1.71)	(1.71)	(1.71)	(1.71)	(1.71)	(1.72)	(1.72)
VV (− 2 quarter)	− 2.84	− 2.85	− 2.81	− 2.81	− 2.84	− 2.83	− 2.83
	(2.28)	(2.28)	(2.28)	(2.28)	(2.28)	(2.28)	(2.28)
VV (− 3 quarter)	− 0.20	− 0.13	− 0.17	− 0.02	− 0.21	0.01	0.02
	(2.65)	(2.64)	(2.64)	(2.66)	(2.64)	(2.65)	(2.65)
VV (− 4 quarter)	− 3.55	− 3.53	− 3.53	− 3.50	− 3.59	− 3.51	− 3.56

Table 6 continued

	1	2	3	4	5	6	7
	(2.73)	(2.73)	(2.73)	(2.73)	(2.72)	(2.73)	(2.73)
PV (− 1 quarter)	0.47	0.47	0.46	0.46	0.45	0.47	0.48
	(0.79)	(0.79)	(0.79)	(0.79)	(0.79)	(0.78)	(0.79)
PV (− 2 quarter)	− 1.02	− 1.01	− 1.01	− 1.02	− 1.02	− 1.01	− 1.01
	(0.83)	(0.82)	(0.83)	(0.83)	(0.82)	(0.82)	(0.82)
PV (− 3 quarter)	− 1.13	− 1.15	− 1.14	− 1.11	− 1.14	− 1.13	− 1.14
	(1.11)	(1.11)	(1.11)	(1.11)	(1.11)	(1.11)	(1.11)
PV (− 4 quarter)	− 0.25	− 0.25	− 0.27	− 0.26	− 0.23	− 0.26	− 0.27
	(1.09)	(1.09)	(1.09)	(1.09)	(1.08)	(1.09)	(1.09)
Controls							
Individual	Y	Y	Y	Y	Y	Y	Y
SA2	Y	Y	Y	Y	Y	Y	Y

Total number of observations in all models is equal to 20,832. The outcome variable in all models is MWI. Columns 1–7 report the results from the linear fixed effects model. VV and PV are dummy variables representing violent and property victimisation. The estimates for the effects of victimisation variables on mental wellbeing are reported with regard to the time (for example, "− 3 months" means victimisation occurred in the past 3 months) that passed since a person being victimised. Individual controls include age, age squared, log of household income, level of education, marital status, presence of children in the household and employment status. SA2 controls include median sold house price and log of population. SA4-year fixed effects control for temporal trends. A full set of time dummies, SA2 areas and individual fixed effects are included in all models. Standard errors (in parentheses) are clustered at SA2 geographical level and individual identifier

***Significant at 1%; ** significant at 5%; * significant at 10%

Table 7 Estimates of the effects of SA3 crime rates on mental wellbeing

	1	2	3	4	5	6
Violent crime	− 0.0153	− 0.0243**			− 0.0079	− 0.0201*
	(0.0125)	(0.0121)			(0.0101)	(0.0117)
Property crime			− 0.0046**	− 0.0031*	− 0.0043**	− 0.0024
			(0.0018)	(0.0019)	(0.0018)	(0.0019)
Controls						
Victimisation	Y	Y	Y	Y	Y	Y
Individual	Y	Y	Y	Y	Y	Y

Total number of observations in all models is equal to 20,832. Columns 1, 3, 5 present the results for the MWI as an outcome variable. Columns 2, 4, 6 present the results for the Mental health component as an outcome variable. Columns 1–6 report the results from the linear fixed effects model. Individual controls include age, age squared, log of household income, level of education, marital status, presence of children in the household and employment status. Victimisation controls include dummy variables representing violent and property victimisation. SA4-wave fixed effects control for temporal trends. A full set of wave dummies, SA3 areas and individual fixed effects are included in all models. Standard errors (in parentheses) are clustered at SA3 geographical level and individual identifier

** significant at 5%; * significant at 10%

with high crime prevalence. Additionally, if a person only considers SA3 crime environment, the perception of victimisation risks, and hence anxiety about it, may be evaluated incorrectly, especially for property crimes. The effect of the violent crime rates on MWI, although negative, is not statistically significant. However, the association between the violent crime rates and the mental health component is consistently negative and significant across the models. The estimate for the SA3 property crime rate is significant and larger in magnitude than the sum of coefficients for property and spatial property crime rates from Table 4. This analysis supports the use of SA2 crime rates and spatial crime rates instead of crime rates in larger areas. Using SA2 crime rates potentially provides not only more accurate estimates of the crime environment on mental wellbeing of individuals but also helps uncover how residents perceive the risks of victimisation depending on the distance to crime incidences.

6 Conclusion

This study contributes to the literature by exploring the connection between mental wellbeing and crime that is currently not well-captured. Using 15 waves of HILDA panel survey and the "very" local neighbourhood crime statistics, we have investigated the effects of the crime rates against the person and against the property on the mental wellbeing outcomes of the Queensland urban residents. The translational mechanism of neighbourhood crime rates lies in the perception of the victimisation likelihood that is connected to mental wellbeing of individuals through the channels of stress and anxiety. We find robust evidence that the residents living in a neighbourhood with a high prevalence of property crime experience a decrease in their mental wellbeing. Furthermore, the individual's mental wellbeing is affected by the property crime conditions pertaining to surrounding, especially contiguous, neighbourhoods. Our findings suggest that people worry more about the property crime situation in the area where they live, and the effect of crime rates against property in the contiguous neighbourhoods is about 42% smaller. While the effects of property crime rates in immediate and surrounding neighbourhoods are both significant, the violent crime rates are only relevant in the contiguous areas to the mental wellbeing of residents.

Importantly, comparing to the studies of Cornaglia et al. (2014) and Dustmann and Fasani (2016) in which the authors used crime statistics at a large urban geographical definition, our approach of segregating the crime rate in a large geographical area into the "residing" SA2 crime rate and the crime rate in the contiguous areas validates the importance of the distance between the neighbourhoods' crime rates and the effect on mental wellbeing. Furthermore, including the effects of spatial crime rates is very relevant as our findings suggest that crime incidences are not randomly distributed over space but rather clustered across neighbourhoods. The results for the effects of the crime rates on mental wellbeing are strongly significant and sustain multiple robustness checks, such as modifying the spatial weight matrix, calculating crime rates using different time interval, and using crime rates at a larger geographical level.

The results from this study have significant policy relevance for the government, police services, and mental health professionals. Intangible costs of neighbourhood crimes, such as the decrease in mental wellbeing of residents living in or near the areas with high crime prevalence, should be taken into policy considerations as this societal burden of crime may be much larger than the pecuniary costs to the victims. Furthermore, the findings suggest that professional mental health support, especially in the areas of high crime rates, could be beneficial to the residents in order to offset the negative impact from the high exposure to ambient hazards like crime.

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Availability of data and materials This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA survey data is one of the Australian Government Department of Social Services (DSS) longitudinal datasets housed by the National Centre for Longitudinal Data (NCLD) and managed by the Australian Data Archive (ADA). The datasets analysed and/or generated during the current study are subject to the Confidentiality Deed signed with the Commonwealth of Australia (as represented by the Department of Social Services) and to the Commonwealth privacy laws. Data are accessible from the NCLD by application https://www.dss.gov.au/national-centre-for-longitudinal-data-ncld/access-to-dss-longitudinal-datasets, and any questions about applying for the DSS longitudinal datasets should be addressed to NCLD ncld@dss.gov.au.

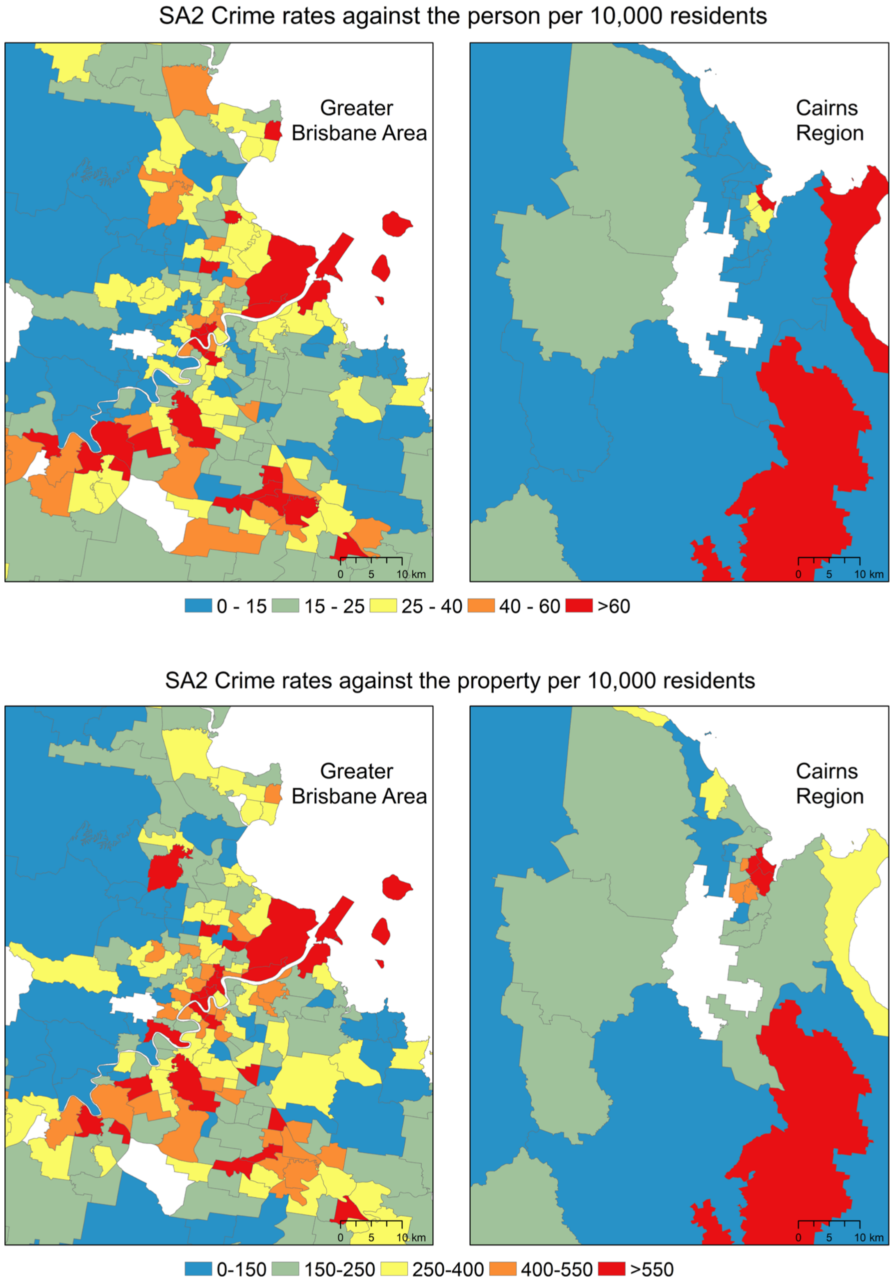
Declarations

Conflict of interest The authors declare that there is no conflict of interests.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards.

Appendix A: Distribution of crime rates across SA2s

In this "Appendix A", we present the distribution of crime rates across SA2s in the Greater Brisbane area and Cairns region. Crime rates in other urban areas show similar spatial dependence. Colour coded cut-off levels approximately represent 20th, 40th, 60th and 80th percentiles.


SA2 Crime rates against the person per 10,000 residents
Greater Brisbane Area
Cairns Region
0 5 10 km
0 - 15
15 - 25
25 - 40
40 - 60
>60
SA2 Crime rates against the property per 10,000 residents
Greater Brisbane Area
Cairns Region
0 5 10 km
0-150
150-250
250-400
400-550
>550

Appendix B: Results from robustness checks

B.1 The effects of SA2 crime rates and victimisation status on mental wellbeing

	1	2	3	4	5	6	7
Violent crime	0.0072				0.0111		0.0114
	(0.0085)				(0.0087)		(0.0087)
Spatial violent		− 0.0189**				− 0.0173*	− 0.0167
		(0.0095)				(0.0104)	(0.0103)
Property crime			− 0.0027**		− 0.0029**		− 0.0026**
			(0.0013)		(0.0013)		(0.0013)
Spatial property				− 0.0011**		− 0.0006	− 0.0004
				(0.0005)		(0.0006)	(0.0006)
VV (− 1 quarter)	− 5.73***	− 5.75***	− 5.71***	− 5.74***	− 5.70***	− 5.75***	− 5.73***
	(1.77)	(1.77)	(1.77)	(1.77)	(1.77)	(1.77)	(1.77)
VV (− 2 quarter)	− 3.92	− 3.94	− 3.91	− 3.90	− 3.93	− 3.93	− 3.95
	(2.74)	(2.74)	(2.74)	(2.74)	(2.74)	(2.74)	(2.74)
VV (− 3 quarter)	0.53	0.56	0.56	0.64	0.54	0.62	0.61
	(2.72)	(2.71)	(2.72)	(2.73)	(2.72)	(2.72)	(2.73)
VV (− 4 quarter)	− 2.29	− 2.27	− 2.28	− 2.25	− 2.34	− 2.27	− 2.34
	(3.06)	(3.06)	(3.06)	(3.06)	(3.06)	(3.06)	(3.06)
PV (− 1 quarter)	0.39	0.40	0.37	0.38	0.39	0.39	0.40
	(0.90)	(0.90)	(0.90)	(0.90)	(0.90)	(0.90)	(0.90)
PV (− 2 quarter)	− 1.42	− 1.41	− 1.40	− 1.42	− 1.40	− 1.41	− 1.40
	(0.94)	(0.94)	(0.94)	(0.94)	(0.94)	(0.94)	(0.93)
PV (− 3 quarter)	− 0.19	− 0.22	− 0.22	− 0.19	− 0.22	− 0.22	− 0.25
	(1.46)	(1.46)	(1.46)	(1.46)	(1.46)	(1.46)	(1.46)
PV (− 4 quarter)	− 0.71	− 0.71	− 0.74	− 0.72	− 0.73	− 0.72	− 0.74
	(1.26)	(1.27)	(1.26)	(1.27)	(1.26)	(1.27)	(1.26)
Controls							
Individual	Y	Y	Y	Y	Y	Y	
SA2	Y	Y	Y	Y	Y	Y	

Total number of observations in all models is equal to 20,832. The outcome variable in all models is MWI. Columns 1–7 report the results from the linear fixed effects model. VV and PV are dummy variables representing violent and property victimisation. The estimates for the effects of victimisation variables on mental wellbeing are reported with regard to the time (for example, "− 3 months" means victimisation occurred in the past 3 months) that passed since a person being victimised. Individual controls include age, age squared, log of household income, level of education, marital status, presence of children in the household and employment status. SA2 controls include median sold house price and log of population. SA4-year fixed effects control for temporal trends. A full set of time dummies, SA2 areas and individual fixed effects are included in all models. Standard errors (in parentheses) are clustered at SA2 geographical level and individual identifier

** significant at 5%

B.2 Heterogeneous effects of crime rates with respect to victimisation status on mental wellbeing

	1	2	3	4
Violent crime	0.0101	0.0103	0.0108	0.0110
	(0.0079)	(0.0079)	(0.0088)	(0.0088)
Spatial violent		− 0.0172**		− 0.0165
		(0.0080)		(0.0102)
Property crime	− 0.0031**	− 0.0026**	− 0.0029**	− 0.0026**
	(0.0012)	(0.0012)	(0.0013)	(0.0013)
Spatial property		− 0.0011**		− 0.0004
		(0.0005)		(0.0007)
Violent crime * VV	0.0051	0.0051	0.0231	0.0234
	(0.0262)	(0.0264)	(0.0256)	(0.0262)
Spatial violent * VV		− 0.0005		− 0.0014
		(0.0239)		(0.0275)
Property crime * PV	− 0.0024	− 0.0024	− 0.0016	− 0.0018
	(0.0016)	(0.0016)	(0.0022)	(0.0023)
Spatial property * PV		0.0002		0.0005
		(0.0006)		(0.0006)
VV (12 months)	− 3.49**	− 3.47**	− 4.28**	− 4.24**
	(1.58)	(1.63)	(1.75)	(1.75)
PV (12 months)	0.42	0.34	0.11	− 0.02
	(0.78)	(0.79)	(0.96)	(0.97)
Controls				
Individual	Y	Y	Y	Y
SA2	Y	Y	Y	Y

Total number of observations in all models is equal to 20,832. Columns 1 and 2 present the results for the MWI as an outcome variable. Columns 3 and 4 present the results for the Mental health component as an outcome variable. Columns 1–4 report the results from the linear fixed effects model. Individual controls include age, age squared, log of household income, level of education, marital status, presence of children in the household and employment status. SA2 controls include median sold house price and log of population. SA4-year fixed effects control for temporal trends. A full set of time dummies, SA2 areas and individual fixed effects are included in all models. Standard errors (in parentheses) are clustered at SA2 geographical level and individual identifier

***Significant at 1%; ** significant at 5%; * significant at 10%

B.3 Gender and age heterogeneous effects of crime rates on mental wellbeing

	Male	Female	< 60 years	≥ 60 years
Violent crime	0.0267	− 0.0025	0.0106	0.0139
	(0.0160)	(0.0116)	(0.0088)	(0.0148)
Spatial violent	− 0.0142*	− 0.0192*	− 0.0226***	− 0.0001
	(0.0079)	(0.0116)	(0.0085)	(0.0135)
Property crime	− 0.0027*	− 0.0025	− 0.0030**	− 0.0009
	(0.0014)	(0.0016)	(0.0013)	(0.0023)
Spatial property	− 0.0014**	− 0.0008	− 0.0011**	− 0.0012
	(0.0007)	(0.0007)	(0.0005)	(0.0008)
VV (− 1 quarter)	− 5.11**	− 4.70*	− 4.74***	− 0.24
	(2.22)	(2.45)	(1.65)	(3.24)
VV (− 2 quarter)	0.39	− 5.05	− 3.06	1.79
	(2.95)	(3.33)	(2.50)	(2.93)
VV (− 3 quarter)	1.06	− 0.66	1.03	− 18.90
	(3.69)	(3.90)	(2.46)	(8.03)
VV (− 4 quarter)	2.26	− 7.14	− 2.64	− 5.69
	(3.80)	(2.92)	(2.79)	(6.65)
PV (− 1 quarter)	0.69	0.20	0.68	− 1.42
	(0.99)	(1.18)	(0.90)	(1.68)
PV (− 2 quarter)	− 0.31	− 1.86	− 0.56	− 1.15
	(1.06)	(1.19)	(0.94)	(1.75)
PV (− 3 quarter)	− 2.03	− 0.33	− 0.67	− 4.26
	(1.28)	(1.86)	(1.20)	(2.49)
PV (− 4 quarter)	− 0.77	− 0.05	− 0.42	− 1.54
	(1.53)	(1.45)	(1.21)	(2.34)
Controls				
Individual	Y	Y	Y	Y
SA2	Y	Y	Y	Y

Total number of observations in gender and age models is equal to 20,832 and 20,756, respectively. The outcome variable in all models is MWI. The number of females in the sample is 11,243, and the number of males is 9589. The number of people whose age is less than 60 years is 16,634, and the number of people whose age is 60 years or older is 4,122. Columns 1–4 report the results from the linear fixed effects model. Individual controls include age, age squared, log of household income, level of education, marital status, presence of children in the household and employment status. SA2 controls include median sold house price and log of population. SA4-year fixed effects control for temporal trends. A full set of time dummies, SA2 areas and individual fixed effects are included in all models. Standard errors (in parentheses) are clustered at SA2 geographical level and individual identifier

***Significant at 1%; ** significant at 5%; * significant at 10%

B.4 The effects of SA2 crime rates on mental wellbeing excluding individuals who moved between SA2s

	1	2	3	4	5	6	7
Violent crime	0.0071				0.0101		0.0104
	(0.0077)				(0.0078)		(0.0077)
Spatial violent		− 0.0207**				− 0.0171*	− 0.0166*
		(0.0085)				(0.0098)	(0.0097)
Property crime			− 0.0022*		− 0.0024**		− 0.0020*
			(0.0012)		(0.0012)		(0.0012)
Spatial property				− 0.0018***		− 0.0013*	− 0.0012*
				(0.0006)		(0.0007)	(0.0007)
Controls							
Victimisation	Y	Y	Y	Y	Y	Y	Y
Individual	Y	Y	Y	Y	Y	Y	Y
SA2	Y	Y	Y	Y	Y	Y	Y

Total number of observations in all models is equal to 20,075. The outcome variable in all models is MWI. We exclude individuals from the sample who moved between SA2s and stated "To live in a better neighbourhood" as the main reason of changing residence. Columns 1–6 report the results from the linear fixed effects model. Individual controls include age, age squared, log of household income, level of education, marital status, presence of children in the household and employment status. SA2 controls include median sold house price and log of population. Victimisation controls include dummy variables representing violent and property victimisation. SA4-year fixed effects control for temporal trends. A full set of time dummies, SA2 areas and individual fixed effects are included in all models. Standard errors (in parentheses) are clustered at SA2 geographical level and individual identifier

***Significant at 1%; ** significant at 5%; * significant at 10%

B.5 The effects of SA2 crime rates on mental wellbeing excluding individuals who moved within SA2s

	1	2	3	4	5	6	7
Violent crime	0.0058				0.0098		0.0103
	(0.0078)				(0.0079)		(0.0078)
Spatial violent		– 0.0218***				– 0.0185**	– 0.0179**
		(0.0074)				(0.0083)	(0.0082)
Property crime			– 0.0029**		– 0.0030**		– 0.0026**
			(0.0012)		(0.0012)		(0.0012)
Spatial property				– 0.0017***		– 0.0012**	– 0.0010*
				(0.0005)		(0.0005)	(0.0005)
Controls							
Victimisation	Y	Y	Y	Y	Y	Y	Y
Individual	Y	Y	Y	Y	Y	Y	Y
SA2	Y	Y	Y	Y	Y	Y	Y

Total number of observations in all models is equal to 20,715. The outcome variable in all models is MWI. We exclude individuals from the sample who moved within SA2s and stated "To live in a better neighbourhood" as the main reason of changing residence. Columns 1–6 report the results from the linear fixed effects model. Individual controls include age, age squared, log of household income, level of education, marital status, presence of children in the household and employment status. SA2 controls include median sold house price and log of population. Victimisation controls include dummy variables representing violent and property victimisation. SA4-year fixed effects control for temporal trends. A full set of time dummies, SA2 areas and individual fixed effects are included in all models. Standard errors (in parentheses) are clustered at SA2 geographical level and individual identifier

***Significant at 1%; ** significant at 5%; * significant at 10%

B.6 The effects of crime rates on mental wellbeing using SA2s with at least 50 obs

	1	2	3	4	5	6	7
Violent crime	0.0030				0.0089		0.0089
	(0.0079)				(0.0083)		(0.0081)
Spatial violent		– 0.0245***				– 0.0202**	– 0.0196**
		(0.0082)				(0.0094)	(0.0093)
Property crime			– 0.0043***		– 0.0045***		– 0.0038**
			(0.0016)		(0.0017)		(0.0017)
Spatial property				– 0.0020***		– 0.0013**	– 0.0011
				(0.0006)		(0.0007)	(0.0007)
Controls							
Victimisation	Y	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y	Y
SA2 control	Y	Y	Y	Y	Y	Y	Y

Total number of observations in all models is equal to 16,820. The outcome variable in all models is MWI. Columns 1–6 report the results from the linear fixed effects model. Individual controls include age, age squared, log of household income, level of education, marital status, presence of children in the household and employment status. SA2 controls include median sold house price and log of population. Victimisation controls include dummy variables representing violent and property victimisation. SA4-year fixed effects control for temporal trends. A full set of time dummies, SA2 areas and individual fixed effects are included in all models. Standard errors (in parentheses) are clustered at SA2 geographical level and individual identifier

***Significant at 1%; ** significant at 5%

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