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Crime and Mental Wellbeing

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ABSTRACT

Crime and Mental Wellbeing*

We provide empirical evidence of crime's impact on the mental wellbeing of both victims and non-victims. We differentiate between the direct impact to victims and the indirect impact to society due to the fear of crime. The results show a decrease in mental wellbeing after violent crime victimization and that the violent crime rate has a negative impact on mental wellbeing of non-victims. Property crime victimization and property crime rates show no such comparable impact. Finally, we estimate that society-wide compensation due to increasing the crime rate by one victim is about 80 times more than the direct impact on the victim.

JEL Classification: I31, R28

Keywords: crime, mental wellbeing, neighbourhood effects, non-victims

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I. Introduction

In 2006, the US Senate Judiciary Committee heard evidence from two sources on the economic cost of crime. The director of the Bureau of Justice Statistics told the committee that according to victimization surveys, the financial cost of crime to victims and their families is $16 billion annually. Immediately afterwards, economist Jens Ludwig told the committee that, based on survey respondents' willingness to pay to reduce crime in their communities, the cost of crime to victims is $694 billion per year. This 40-fold disparity between direct victimization costs and willingness to pay to reduce crime highlights the fact that much of the social cost of crime is intangible and is not suffered by victims, but by nonvictims.

The notion that crime costs to nonvictims may be important is not new. The English jurist and philosopher Jeremy Bentham (1748-1832), provided the example of a man who is robbed on a road. The "primary mischief," wrote Bentham, arise from the physical harm and loss of possessions occurring from the robbery. But the crime also has a "secondary mischief."

"The report of this robbery circulates from hand to hand, and spreads itself in the neighbourhood. It finds its way into the newspapers, and is propagated over the whole country. Various people, on this occasion, call to mind the danger which they and their friends, as it appears from this example, stand exposed to in traveling; especially such as may have occasion to travel the same road."

[" *An Introduction to the Principles of Morals and Legislation*," (1781) Ch. XII.6]

What is important about this aspect of crime (which Bentham referred to as "the alarm") is that it affects a much larger number of people than the direct impact would suggest. As Wolff (2005) points out, even if the probability of harm is very low, "the fear can be ever-present for a great number of people, depressing their lives."

In this paper, we provide the first empirical estimates of crime's impact on the mental health of both victims and nonvictims using a unique dataset that allows us to measure the same individual's mental wellbeing over successive years.[1] Because we have data on victimization status, we are able to measure the "direct" impact to victims and the "indirect" impact to victims and nonvictims that occurs through the crime rate. Moreover, we are also able to measure the impact of violent crimes separately from property crimes. Our outcome measure is based on detailed and repeated survey information that allows distinction of different dimensions of mental wellbeing. By matching each individual to detailed local-area crime statistics for various types of crimes, and using repeated information of area criminal activity, victimization and measures of mental wellbeing, we are able to assess the effect that different types of crimes have on the mental wellbeing of victims and nonvictims.

We find that an individual suffers a decrease in mental wellbeing in the immediate three months after violent crime victimization occurs with the largest negative effect of 9.8 percentage points (13 percent) on social functioning – the mental wellbeing measure that captures the ability to perform normal social activities without emotional problems. Overall, the negative effects of victimization are fairly robust across the numerous mental wellbeing measures. The effect generally remains, but is economically and statistically weaker, when we measure the impact of victimization in the four to 12 months prior to interview. Likewise, the violent crime rate has a negative impact on some measures of mental wellbeing for both victims and nonvictims, with the largest effect again on social functioning. Property crime victimization, alternatively, shows no

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[1] To the best of our knowledge, only Dustmann and Fasani (2013), using UK data, have looked at the detrimental impact of exposure to changes in local crime on mental wellbeing of residents. However, they do not distinguish between victims and non-victims.

statistically significant impact on mental wellbeing once controlling for individual fixed effects. Nor does the property crime rate.

We also find that local area geographic size matters. On one hand, the effect of violent crime victimization is fairly larger and more robust in larger geographic areas while, on the other hand, crime rates have a stronger negative impact on mental wellbeing in smaller geographic areas. We hypothesize that in larger areas, conditional on a particular crime rate, individuals may feel that the odds of being victimized are lower than they actually are and therefore, when it does happen, the impact is all the more severe. Crime rates are more probabilistic. In smaller geographic areas, the recorded crime rate is more likely to represent the actual crime rate where a person lives and accordingly reacts.

Finally, we quantify the dollar value of the benefits from reductions in crime. Two well-known strategies exist to perform this exercise: an ex post perspective, which focuses on calculating the cost to society of crimes that have already taken place, and an ex ante approach that reflects the willingness to pay (WTP) of the public for a reduction in the risk of crime victimization in the future.

We estimate that the average victim requires ex post compensation of about $930 Australian Dollars (AUD) and that all local area residents' WTP to reduce crime rate by one victim is $76,600 AUD.[1] Thus, society wide level ex ante cost is about 80 times more than the direct ex post impact on the victim herself. While the certainty of victimhood is worth paying about $930 to avoid (in terms of mental wellbeing–there are, of course, other costs that are beyond the scope of our paper), the WTP for small reductions in the risk of victimhood, as captured by the violent crime rate, is smaller for the average individual. Multiplying this amount by the population gives us the "value of a statistical victim" – the amount society would spend to reduce the number of victims by one person. This finding is similar in concept to the "value of a statistical life" that Cook and Ludwig (2000) discuss in their book on gun violence.[2]

The reminder of the paper is structured as follows. In Section 2, we present related literature on the topic and in Section 3, we describe the mental health and crime data. In Section 4, we discuss the methodology we follow for our analysis and present the results for both victims and nonvictims in Section 5. Section 6 presents robustness tests and model extensions and Section 7 investigates threats to identification. Section 8 discusses the monetary impact of the loss in mental wellbeing and the final section reviews the implications of our findings and concludes.

II. Literature

Our research is related to two distinct literatures. First, a number of studies that look at the effect of neighborhoods on individuals' mental wellbeing show that individuals in disadvantaged neighborhoods tend to have worse mental health outcomes (see, for example, Aneshensel and Sucoff 1996; Schulz et al. 2000; Ross 2000 and 2001; Strafford and Marmot 2003; Strafford, Chandola and Marmot 2007). However, most of these studies lack a convincing research design to establish the causality of any measured relationship. As Propper et al. (2006) point out, it is difficult to know whether these studies reflect the impact of places on people, or merely the correlation between neighborhood choice and mental wellbeing. One way of disentangling this issue is by exploiting some random variation in the neighborhoods where individuals live. Based on the Moving to Opportunity (MTO) experiment, Katz, Kling and Liebman (2001); Kling, Liebman and Katz (2001) and Kling et al. (2004) do just that. Their findings suggest that a primary reason that participants wished to move out of public housing was fear of crime. And indeed, one of the major impacts of receiving a housing voucher to move into a low-poverty neighborhood was a reduction in crime victimization and improved mental wellbeing. We add to this literature by providing a direct assessment of the effect of victimization status and area crime on mental wellbeing. Although we do not have a randomized experiment, panel data on both mental wellbeing and crime allow us to eliminate sorting effects.

The second literature is a number of economic studies that have attempted to identify the net cost of crime (to victims and nonvictims) by using revealed preference techniques. Assessment of these net costs is particularly important from a policy perspective. One approach has been to look at the effect of changes in crime risk on house prices (Thaler 1978; Schwartz, Susin and Voicu 2003; Gibbons 2004; Linden and Rockoff 2008). The amount that an individual would be willing to pay for a house that reduces the future risk of victimization underestimates the willingness to pay to reduce the overall crime rate in the neighborhood, since the latter also includes the added value that the individual places on a reduction in crime risk to the rest of society. Our approach focuses on the total effect when estimating the impact of reducing crime rates on mental health.

III. Background

Our empirical analysis is for Australia. By developed country standards, crime rates in Australia are high. The aggravated assault rate (the most common violent crime) stood at 724 victims per 100,000 individuals in 2000, peaked at a crime rate of 840 in 2007 and has since slightly declined. In comparison, the aggravated assault rate in the United States stood at 324 per 100,000 individuals in 2000 and has been in decline since then.[3] In the 2000 International Crime Victims Survey, covering 17 countries, a higher share of Australians reported that they had been the victim of a crime in the previous 12 months than in any other nation, including the United States (Kesteren, van Mayhew and Nieuwbeerta 2000). Despite that fact that the homicide rate is lower in Australia than in the United States, these statistics suggest that Australia provides a rich context in which to explore the relationship between crime and mental wellbeing.

A. Data on Mental Wellbeing

The data on mental wellbeing, as well as respondents' background information, are drawn from the Australian "Household, Income and Labour Dynamics in Australia" (HILDA) survey, a household-based panel study which began in 2001. Our observation window is from 2002-2006 as the questions on victimization were not asked in 2001. The survey is unique in that it administers in each wave a detailed measure of mental wellbeing, based on the 36-Item Short Form Health Survey (SF-36). Alternative measures of the subjective perception of mental health (for example, the GHQ) perform similarly (Failde, Ramos and Fernandez-Palacin 2000) but the SF-36 has become the most widely used health measure in clinical studies throughout the world.

The SF-36 is a multi-purpose, short-form health survey. It is a generic measure, as opposed to one that targets a specific age, disease, or treatment group and its reliability in terms of internal consistency and stability over time has been tested and found to meet psychometric criteria. These measures rely upon patient self-reporting and are now widely utilized by managed care organizations and by Medicare in the United States for routine monitoring and assessment of care outcomes in adult patients. Because the SF-36 is such a reliable measure of health status, it is commonly used in health economics as a variable in the quality-adjusted life year calculation to determine the cost-effectiveness of a health treatment (see Räsänen et al 2006 for a literature review). The mental health measures in the SF-36 have been used to answer economic questions such as the relationship between mental health and labor market participation (Frijters, Johnston and Shields 2010), between the feeling of safety and mental health (Green, Gilbertson and Grimsley 2002) and between the external environment and mental wellbeing (Guite, Clark and

Ackrill 2009). However, to our knowledge, no study examines the direct relationship between local area crime and different mental health measures for both victims and nonvictims of crime.

The 36 items can be grouped into two broad sub-groups: “physical health” and “mental health.” Within each sub-group, questions are combined to reflect more detailed expressions of wellbeing. Here, we will focus on mental health outcomes (and will later consider the physical measures in robustness tests). The 14 questions that refer to mental health are used to construct four multi-item scales, each of which measures a particular aspect of mental wellbeing. These are: 1. The Vitality scale, a measure of tiredness (constructed using four items); 2. The Social Functioning score (constructed using two items), which picks up the interference of emotional problems with normal social activities; 3. The Role Emotional scale (constructed using three items), a measure of the difficulties with daily activities because of emotional problems; and 4. The Mental Health scale (constructed using five items), a measure of nervousness and depression.

These scales can be aggregated into a summary measure of mental wellbeing - the Mental Component Summary (MCS) - using a standard scoring algorithm. As the different measures capture various symptoms, for the purpose of our study, these are likely to pick up different types of disturbances that may be caused by crime incidents. Unsurprisingly, they are highly correlated. Excluding the summary measure that is correlated with the four measures mechanically, the correlations among the four measures range from .47 (between Role Emotional and Vitality) to .68 (between Mental Health and Vitality).

The top panel of Table 1 provides definitions of the lowest and highest possible scores of the four SF-36’s mental health scales and reports the means and standard deviations of each of the measures. Most of the variation in the data is cross sectional, though, roughly a quarter of the variation is within an individual over time.

B. Data on Crime

Local area crime statistics are tabulated at the Local Government Area (LGA) level. LGAs in Australia are the third and lowest tier of government, administered by the states and territories, which, in turn, are beneath the Commonwealth or federal tier. Unlike the US or the UK, there is only one level of local government in all states, with no distinction such as counties and cities. We separately approached each state and territory government to request crime data. In some cases, this involved filing requests under the relevant Freedom of Information Acts, although these really served only to prompt the relevant data-holders, and ultimately none of the data were obtained in this manner. Eventually, we were able to obtain data for seven of the eight states and territories, covering 99 percent of the Australian population. Since the states do not apply a uniform crime classification system, we recoded crimes into 16 categories using the Australian Standard Offence Classification (ASOC), though, throughout the paper, our results are based on further aggregating these categories into violent and property crime.[4]

With the restricted use version of the HILDA dataset (which contains information on the respondent's postcode and the date of interview), we are able to match each individual to the crime rate in their local government area during the 12 month period before answering the questionnaire. In addition, the survey interviews individuals in each wave about whether they have been victims of crime, which allows us to distinguish the responses of victims and nonvictims.

In the bottom panel of Table 1, we present summary statistics on crime rates for the years 2002 - 2006. We distinguish between property crimes and violent crimes - a distinction which we will follow in our empirical specifications. Violent crimes include homicide, assault, sexual assault, abduction and robbery. Property crimes include burglary and theft. Crime rates represent the crime incidents per 100,000 individuals in Australian metropolitan areas in the 12 months prior to the interview date.[5] As the first row shows, the average violent crime rate in our data is 921 incidents per 100,000 individuals and 90 percent of the variation in crimes rates is across individuals that derives from differences in interview date and LGA. The remaining 10 percent is within individual over time. Property crime shows more variation at the individual level where 17 percent derives from changes within individual over time and the remaining 83 percent reflects cross sectional variation. While not shown in this Table, property crime fell quite considerably over 2001-2006.[6] The criminology literature has not reached a consensus on the factors that explain this drop, though possible explanations include changes in the age structure, shifts in heroin supply, reduced availability of firearms, and improved antitheft devices in new motor vehicles (see, for example, Moffatt and Poynton 2006; Brickell 2008). Violent crime shows no such pattern.

The next four rows of Table 1 present the fraction of respondents that were victimized during the quarter before the interview and/or during the two to four quarters prior to the interview. Roughly 0.6 percent of our observations are violent crime victimization incidents within the previous quarter. Another 1.1 percent are victims two to four quarters before the interview. Property crime is more prevalent with 2.1 percent of individuals having suffered a property crime in the previous quarter and another 3.9 percent in the two to four quarters before the interview. The identifying variation for these variables is roughly equally divided between cross-section and time and the crime rate from these self-reported surveys is of a similar magnitude to police-reported crime rates.

C. Data on Individual Characteristics

In Table 2 we summarize the individual characteristics of the respondents in our data, where we report in the first column means and standard deviations for individuals in the sample that are never victimized. We then distinguish between those who are victims of violent or property crime (not necessarily mutually exclusive) at some point during 2001 - 2006. For the last two columns, all demographic and mental health measures apply to pre-victimization periods, that is, using only the data prior to becoming a victim as we consider mental health endogenous to victimization status.

The Table entries suggest that, generally speaking, nonvictims and victims differ on a number of dimensions. Nonvictims are more likely to be older, have children between 5 - 24 and are less likely to move out of their LGA. When breaking victims down into violent and property it becomes clearer that victims of violent crimes differ much more from nonvictims than do victims of property crimes. This is particularly true for the mental wellbeing variables. Victims of violent crimes have, on average, lower mental wellbeing. We can also see that there are significant differences between the two types of victims. Victims of violent crimes are younger, less educated, have fewer children and lower mental and physical wellbeing than victims of property crimes. This table illustrates the importance of controlling for demographics in the empirical analysis as well as focusing on changes in mental health rather than cross-sectional differences.

Our analysis also accounts for other time-varying characteristics known to affect mental wellbeing: the local area unemployment rate, local area average total income, and the share of rainy days. The unemployment rate is included in order to capture the possibility that local economic booms or busts may affect both crime and mental wellbeing (see, for example, Kapuscinski, Braithwaite, and Chapman 1998; Raphael and Winter Ebmer 2001). Average incomes may capture degrees of financial stress as well as being correlated with crime. Finally, the number of rainy days is included on the basis that good or bad weather may have a direct impact on both crime and mental wellbeing (see, for example, Cohn 1990; Jacob, Lefgren, and Moretti 2007). The unemployment rate and rainy days are measured over the same period as the crime rate (the 12 months prior to the interview) whereas average income is measured over the calendar year due to data availability.[7] As Table 2 shows, both property and violent crime victims live in LGAs with higher unemployment, lower average earnings, and higher violent and property crime rates.

IV. Empirical Methodology

In our analysis, we concentrate on individuals living in metropolitan Australia, such as Sydney, Melbourne, and Canberra as nearly all variation in crime rates is derived from urban areas. Since Australians mainly live in cities, by restricting the analysis to metropolitan areas, we use around 67 percent of the overall Australian population and 63 percent of our data. The typical respondent in our survey lived in an LGA with a population of approximately 215,000 people (the interquartile range is 95,000 to 945,000 people). The total number of LGAs in our analysis is 110.

Our estimation equation is given by

$$\begin{aligned}(1)\qquad M_{irt} &= \alpha_0 + \beta_1 VC_{irt}^{q_1} + \beta_2 VC_{irt}^{q_{2-4}} + \beta_3 PC_{irt}^{q_1} + \beta_4 PC_{irt}^{q_{2-4}} \\ &+ \beta_5 VCR_{irt} + \beta_6 PCR_{irt} + \gamma_{1'} X_{it} + \gamma_{2'} Z_{rt} + T_t + \alpha_i + LGA_r + \varepsilon_{irt}\end{aligned}$$

where M_{irt} is the mental wellbeing index of individual i in area r in interview year t. VC^{q_1} and PC^{q_1} are binary indicators equal to one, zero otherwise, if individual i has been a victim of a violent or property crime during the quarter (3 months) prior to the interview. Thus, while both the mental health index and the victimization variables are both indexed by time t, it should be clear that there is a built in lag for the victimization variables, crime and other relevant variables. Similarly, $VC^{q_{2-4}}$ and $PC^{q_{2-4}}$ are binary indicators equal to one if the individual has been a victim of a violent or property crime two to four quarters prior to the interview, respectively. We view VC^{q_1} and PC^{q_1} as capturing the more immediate impacts of victimization whereas $VC^{q_{2-4}}$ and $PC^{q_{2-4}}$ capture longer run results. The variables VCR_{irt} and PCR_{irt} represent the violent and property crime rates in the 12 months prior to the interview date. X_{it} are individual characteristics as previously described: age, age squared, sex, education, number of children and binary indicators for month of interview, Z consists of the LGA level time varying characteristics of the number of rainy days, the unemployment rate and the log of average earnings. T_t, α_i and LGA_r represent time, individual and area fixed effects, respectively and ε_{irt} represents the idiosyncratic error term.[8] Our preferred estimation is by individual fixed effects estimation and standard OLS is provided for comparison. Standard errors are clustered by LGA.[9]

V. Results

A. Victimization

Table 3 presents the results for each of the five measures of mental wellbeing. The odd numbered columns present results from the OLS models and the even numbered columns present the individual fixed effects models. Consider the first row. Generally speaking, the estimates show that victimization within a quarter prior to interview is strongly and significantly related to a deterioration of mental wellbeing for all mental categories we consider here. For instance, to have been a victim of a violent crime is associated with a mental health outcome (measured by the Mental Component Summary Measure - MCS) that is about 8.4 percentage points (or 19 percent when evaluated at the mean) lower in the OLS specification and 3.3 percentage points (or 7.5 percent when evaluated at the mean) lower in the fixed effects specification. The OLS estimates are likely biased as victims of crime are arguably a selected subgroup with larger mental health issues. The estimated associations of crime with the four mental health scales that make up the mental component summary measure (Vitality, Role Emotional, Social Functioning and Mental Health) are generally even larger (columns 3 - 10). All results are significant at the one percent level with the exceptions of Vitality (FE specification) that is significant at the ten percent level and Role Emotional (FE specification) that is not statistically significant. In particular, focusing on the fixed effects specifications, the effects of victimization are largest for social functioning where the reduction is 9.8 percentage points (or about 13 percent) in the quarter after victimization. According to literature in psychology, the largest impact of victimization on mental health is reflected in the tendency of victims towards avoidance (see for instance Kilpatrick and Acierno 2003). This may be in the form of behavioral or cognitive escape from thoughts, feelings, individuals, or places associated with the trauma, as well as the experience of feelings of detachment, and restricted affect. This tendency towards increased avoidance is in our data best captured by the social functioning measure of mental wellbeing. This scale tells us how well the victim can perform normal social activities without interference due to emotional problems.

The longer run impacts of victimization are less straightforward. Focusing on the FE specifications in the second row (victim of violent crime in 4 - 12 months before the interview date), at best the results are significant at 10 percent and are fairly smaller in magnitude than the corresponding coefficient in the row above. For example, the estimated coefficient for MCS (column 2) drops from -3.3 percentage points to -1.3 percentage points. These results suggest that violent crime victimization has an immediate impact on mental health that is fairly large but this impact dissipates fairly quickly after a quarter. One particularly interesting result is that mental health (column 8) is the one measure that is significant in the quarter prior to interview but not in the 4 - 12 months prior to interview, conditional on the former being significant. Based on this, it appears that feelings of depression (what the Mental Health measure captures) are shorter lived that those areas of mental wellbeing that involve interaction with society (aspects of which the three remaining measures capture).

In contrast to the violent crime victimization results, the effect of being a victim of a property crime on mental wellbeing is smaller across all specifications and statistically weaker. Once we control for individual fixed effects, there is no statistically significant impact of being a victim of a property crime on mental wellbeing. This holds for both the immediate quarter prior to interview as well as longer lags.

B. Interpretation of the Magnitudes

Overall, the effect of violent crime victimization on mental wellbeing is fairly large when we compare it to other events that impact mental wellbeing that we included as controls in our regressions. For example, the effect of accomplishing a low level of education[10] is associated with 1.03 percentage points (unreported) lower MCS compared to those who achieve at least a bachelor degree–roughly one-third the impact of violent crime victimization. If the number of rainy days were to increase from zero to 100 percent, MCS would be estimated to be 1.86 percentage points lower (unreported)–still only just more than half the impact of violent crime victimization in the previous quarter. Another way of conceptualising the size of the effects we observe is to compare them with the impact on mental wellbeing for New Yorkers of being explosed to the September 11 attacks. Comparing our results with those of that of Adams and Boscarino (2005), we estimate that the effect of falling victim to a violent crime is 2 1/2 times larger than each unit increase in exposure to the September 11 attacks on New York City.[11]

C. Crime Rates

We next consider the impact of crime rates on mental wellbeing. Violent crime rates show a fairly consistent and robust negative effect on mental wellbeing (with the exceptions of the fixed effects estimations for Vitality and Mental Health). An increase of one unit in the crime rate (equivalent to one more victim in an LGA with population of 100,000) is associated with a .0021 and .0015 percentage point decline in MCS in the OLS and fixed effects specifications, respectively.[12] Overall, the OLS results are larger with higher statistical significance. Again, this difference may be partially explained by sorting. Individuals may sort according to their mental well-being and this may be correlated with area characteristics such as crime rates. If we treat this problem as simply one that affects the levels of mental wellbeing then controlling for individual and LGA fixed effects will correct the endogeneity problem.[13] In contrast to these results, the effect of property crime on mental health is economically and statistically zero.

For an alternative interpretation of the crime rate results, we calculated the normalized versions of the crime rates and used those instead of the level crime rates in a regression where all other variables remained the same. The estimated results of the two crime rate variables are presented below the line. As is expected, statistical significance is not impacted by the transformation but the normalization allows us to measure the impact of a one standard deviation change in the crime rates on mental wellbeing. Increasing the crime rate by one standard deviation is associated with .86 percentage points lower MCS (column 2), 2.08 percentage points lower Social Functioning (column 4), and 2.64 percentage points lower Role Emotional (column 8). We calculate that a two standard deviation increase in the violent crime rate has roughly the same effect on MCS over the course of a year as does violent crime victimization (where we calculate the effect of violent crime victimization over the course of a year as the weighted average of the two estimated victimization coefficients). As before, property crime shows no such similar impact on mental wellbeing.

Finally, we note that we also estimated an expanded model where we allowed the effect of crime rates on mental wellbeing to differ between victims and nonvictims (by including interaction terms). The results across the board showed that the estimated coefficients on the interaction effects were economically small and not statistically significant at conventional levels.[14] Thus, after conditioning on victimization status, we do not reject the hypothesis that crime rates themselves impact the mental health of victims and nonvictims alike.

VI. Extensions of the Baseline Model and Robustness Tests

Crime rates are defined at the local government area but due to heterogeneity in the geographic size of LGAs, one may imagine that the impact of crime rates may very well depend upon variation within an LGA. More precisely, the crime rate in a LGA captures the average of crime rates in smaller neighborhoods within the LGA. The larger the geographic size of the LGA, the more the average may be less representative of the actual crime rate where a person lives. Thus, LGA level crime rates may not reflect the reality of day-to-day existence for an individual as the size of the LGA grows. A literature in psychology has stressed the important role played by the perception of the level of violence on mental health. Building upon this, sociological literature has stressed that in order to understand the effect of the fear of crime on anxiety it is not enough to know who individuals are (looking at observable characteristics) but, rather, to account for the characteristics of the area where they live (Pain 2000; Smith 1987).

Due to data constraints, we cannot capture the within-LGA variation in "very" local crime rates. However, under the assumption that smaller LGAs are likely to have less internal variance in crime rates we can break the data into two groups–those below the median LGA size and those above. Doing this, we repeated our fixed effects analysis for each of the five mental wellbeing measures with results presented in Table 4. The table reveals an interesting pattern. When we consider the first five columns (below median area), the statistically significant negative effect of victimization on mental health that we saw in Table 3 nearly completely disappears. The one exception is social functioning where the effect is negative and significant at the five percent level for victimization in the previous quarter (column 2, row 1). On the other hand, the second five columns (above median area) show an effect of victimization on mental wellbeing that is comparable to that found in Table 3. We hypothesize that larger geographical areas may make residents feel artificially safe even conditional on the crime rate. Because residents may mentally minimize the true risks of victimization, when it does occur the effect is particularly acute. This being said, while there appears to be noticeable statistical difference between LGAs above and below the median size, many of the point estimates are similar in magnitude. We tested whether each estimated coefficient in the "Below Median" regressions (columns 1-5) was statistically different from its counterpart in the "Above Median" regressions (columns 6-10). For the most part, there is no statistical difference between the coefficients with the exception of the estimated coefficients on the violent crime victimization two to four quarters prior to the interview (VC^{q2-4}) variables and similarly for property crime victimization (PC^{q2-4}) for MCS and Social Functioning.

Turning next to crime rates in the same Table, violent crime rates show the opposite pattern of victimization. While the statistical significance is a bit weaker as compared to Table 3, crime rates in smaller LGAs have negative impacts on mental wellbeing whereas they do not appear to impact mental wellbeing in larger LGAs. This is consistent with hypothesis that the crime rates for a larger LGA may be weakly correlated with the true neighborhood crime rate in which the individual lives. In contrast to Table 3, property crime victimization shows some impact on mental wellbeing in relatively large geographic areas where MCS and three of the four primary measures are negatively impacted. Again, this may be because residents in larger geographic areas mentally downplay the risks (or do not believe that actual crime rates apply to their "very" local area). Property crime rates, alternatively, continue to show no association with mental wellbeing. Similar to the victimization variables, there is no statistical difference in the estimated coefficients above and below the median.

Next, as a placebo test, we repeated our baseline specification using two physical health measures that we obtained from the SF-36. These are Physical Function and Role Physical (see Table 1 for definitions).[15] The results are reported in Table 5. The even columns (OLS) show that victimization–both violent and property–is associated with lower physical wellbeing, though, like mental wellbeing, it is likely that those individuals with lower physical ability are more likely to become victims. Controlling for individual fixed effects, the odd numbered columns show that there is no impact of victimization on physical wellbeing. While it may be somewhat surprising that a violent attack has no effect on physical wellbeing, we note that the types of activities that comprise the Physical Function and Role Physical measures are fairly basic in nature. For example, the ability to lift a bag of groceries, bend at the knee or difficulty performing work due to physical reasons. In line with our expectations, there is no correlation between violent and property crime rates and physical wellbeing.

Finally, we investigated whether there is any spillover effect on other household members. That is, when one person in the household is victimized, how does this impact the other family members? We find that there is a negative impact but statistical significance is generally weak (unreported but available upon request.)[16]

VII. Threats to Identification

There are a number of issues that challenge our identification assumptions. One such challenge is omitted variable bias. If a deterioration in socioeconomic conditions leads to an increase in crime, we may be attributing decreases in mental wellbeing to increases in crime when, more accurately, they are due in large part to these broader socioeconomic changes. One way to address this concern is to allow for a more flexible time trend at the LGA level. While this solution addresses the identification concern for the effect of victimization, it is less satisfactory for the crime rate variables. Because the crime rate variables capture LGA level crime rates in the 12 month prior to interview we technically have additional variation within the LGA-year because individuals were interviewed at different months during the year. Thus, two individuals, both living in the same LGA in year t but interviewed in different months during year t will have different crime rates. Given that crime rates do not vary a great deal within such short time spans (and that most respondents are interviewed at the same time of the year) the additional variation it provides at the LGA-year level is relatively minor and likely insufficient to identify the effect of crime rates on mental wellbeing once controlling for LGA-year fixed effects. The results from this specification are provided in Table 6. Broadly speaking, the effect of violent crime victimization in the quarter prior to interview is negative and robust across the various mental wellbeing measures (consistent with the results in Table 3). With the exception of Vitality and Role Emotional, all FE estimates are statistically significant at a minimum significance level of one percent. The lagged victimization variable shows a weaker effect, though significant at the ten percent level, in a number of the FE specifications. Property crime victimization, like in Table 3, shows no significant impact on mental wellbeing once controlling for individual fixed effects.

As anticipated, the property and violent crime rate variables show virtually no significance. Due to the weak variation once controlling for LGA-time fixed effects, little weight should be placed on these latter findings. While we attempt to control for a number of these socioeconomic changes at the LGA-year level in our baseline model, such as number of rainy days, unemployment rates and average incomes in our baseline specifications, we acknowledge that it is difficult to account for all relevant changes in socioeconomic conditions and these may be correlated with crime rates. If exogenous shocks (which are not captured in our socioeconomic controls) cause mental wellbeing to fall and crime to rise then our estimated coefficients on crime may be downward biased, that is, we are attributing too large of a negative impact to crime. Conversely, if exogenous changes in crime affect mental wellbeing via one of our controls (eg. by raising unemployment or lowering income), then we may be failing to capture part of the negative impact of crime on mental wellbeing.

A second identification concern is that of reverse causality. One could imagine that given some negative shock to mental health the probability of becoming a victim may increase. Thus, what we estimate as crime's affect on mental health is simply capturing this reverse causality between victimization and mental health. Given the discrete nature of our data, we cannot completely eliminate this alternative explanation.[17] Nonetheless, there are tests that we can undertake to alleviate some of the concern that reverse causality is a primary driver of our findings. Table 7 presents the results from a regression of our mental wellbeing measures on binary indicators for a two-year window around the year of victimization (violent crime). The omitted category in this case is the year prior to victimization. In particular, we are concerned that prior to victimization there is a dip down in mental health. We can see from the results in the first row of the Table that there is no statistical difference between years $t=-2$ and $t=-1$ suggesting that mental wellbeing is not significantly lower just prior to victimization. Moreover, this Table also shows that there is a fairly robust and large statistical difference between the year prior to and the year of ($VC_{t=0}$) victimization. We interpret this as the impact of victimization. Subsequent years show some rebound in mental health, where we no longer reject equality between the year prior to victimization and the one or two years after.[18]

In a similar vein, we estimated the effect of changes in mental health on the probability of violent crime victimization in the subsequent year. The results (unreported, but available upon request) do not indicate any correlation between changes in mental health in year t and violent crime victimization in $t+1$.[19]

VIII. Discussion

In this paper we investigate the effects area crime may have on both victims and nonvictims of crime. As we discuss in the Introduction, the difference between direct victimization costs and WTP to reduce crime suggests that most of the social cost of crime is suffered by nonvictims. We now quantify the mental wellbeing cost to the victim and society at large in monetary terms. We start with asking how much do victims need be compensated in order to return their mental wellbeing to the levels prior to victimization and, likewise, nonvictims for the increased crime rate that impacts the probability of future victimization.[20] In order to obtain this information we first converted the SF-36 data into an SF-6D health state for each observation in our dataset using an algorithm based on Brazier and Roberts (2004) adapted to HILDA by researchers at Monash University.[21] The SF-6D is a generic preference-based single index measure of health that can be used to generate QALYs and, hence, can be used in cost-utility analysis. We then multiplied the SF-6D measure by $50,000, which is the rough estimate given to the “value of a high-quality life" in Australia and estimate that each percentage point loss in Social Functioning is worth $211 (se 0.98).[22] Taking our baseline results from column 4 of Table 3, the percentage point loss in Social Function over the year is equal to -4.59 (s.e. 1.03) for victims and -0.0035 (se 0.0014) for nonvictims.[23] That is, the average nonvictim living in an LGA with a population of 100,000 experiences a decline of 0.0035 percentage points in Social Functioning with a one victim increase in the crime rate. Using these estimates, we can calculate the amount of income that would be necessary to compensate the victim as well as the rest of society for the increase in crime rate. We bootstrap the estimation procedure using 1000 bootstrap replications to take into account the uncertainty in the previous estimates. We estimate an ex post monetary loss to a victim of $928 (se $287) and an ex ante amount society would pay to reduce crimes by one of $76,583 (se $29,534) – roughly 80 times the ex post cost to the victim. In line with Cook and Ludwig (2000), we call this the “value of a statistical victim” – the amount society would sacrifice to reduce the number of victims by one person and maintain mental wellbeing at its previous level.

We also point out that total nonvictim compensation is independent of the number of victims and population. LGAs with larger populations will tend to have per victim amounts that are lower (because increasing the number of victims by one has a smaller impact on the overall crime rate and therefore a lower impact on mental wellbeing) but these lower amounts are then multiplied by larger population values. The opposite is true for low population LGAs. Increasing the number of victims by one has a much larger impact on the crime rate and a larger negative impact on mental wellbeing. These larger numbers, however, are then multiplied by a smaller population number.

IX. Conclusion

In this paper, we combine detailed crime statistics with panel survey data that provides a detailed set of mental wellbeing indicators for the same individuals over a six-year period. We find that even when controlling for individual and local area fixed effects, an individual suffers a decrease in mental wellbeing in the immediate three months after violent crime victimization occurs. This effect is fairly robust across the numerous mental wellbeing measures and ranges between 2.8 to 9.8 percentage points with the strongest effect on social functioning–the ability to perform normal social activities without emotional problems. The effect generally remains, but is economically and statistically weaker, when we measure the impact of victimization in the four to 12 months prior to interview. Likewise, the violent crime rate has a negative impact on mental wellbeing for both victims and nonvictims with the largest effect again on social functioning. Property crime victimization, alternatively, shows no statistically significant impact on mental wellbeing once controlling for individual fixed effects. Nor does the property crime rate. As a placebo test, we replace our mental health measures with physical health measures and find no impact of victimization and crime rates on physical wellbeing once controlling for individual fixed effects. Moreover, we subject our main findings to a number of robustness tests and resolve that neither reverse causality nor omitted variables are the likely drivers of our main findings.

The impact of victimization and crime rates also vary by geographic size of the area. Our baseline victimization results are driven primarily by larger local areas. We hypothesize that larger geographical areas may make residents feel artificially safe even conditional on the crime rate. Because residents may mentally minimize the true risks of victimization, when it does occur the effect is particularly acute. Interestingly, violent crime rates show the opposite pattern of victimization. While the statistical significance is a bit weaker, crime rates in smaller LGAs have negative impacts on mental wellbeing whereas they do not appear to impact mental wellbeing in larger LGAs. This is consistent with the hypothesis that crime rates in larger LGAs may be weakly correlated with the true neighborhood crime rate in which the individual lives.

Finally, we estimate that the average victim requires compensation of about $930 Australian Dollars (AUD) and that all local area residents place ex ante negative valuation on mental wellbeing of about $76,600 from the increase in the crime rate due to one additional victim. Thus, society wide level compensation is about 80 times more than the direct impact on the victim herself.

X. References

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Table 1
Crime and Mental Wellbeing Variables

Variable	Mean	Standard Deviation (Overall)	Standard Deviation (Between)	Standard Deviation (Within)	V_B/V_W	Description
SF	82.95	22.85	20.27	13.1	0.71	Social Functioning: 0 = extreme and frequent interference with normal social activities due to physical or emotional problems; 100 = Performs normal social activities without interference due to physical or emotional problems.
VT	60.62	19.46	17.52	9.69	0.77	Vitality: 0 = Feels tired and worn out all of the time; 100 = Feels full of pep and energy all of the time.
RE	83.42	32.21	27.72	20.09	0.66	Role Emotional: 0 = Problems with work or other daily activities as a result of emotional problems, 100 = No problems with work or other daily activities as a result of emotional problems.
MH	74	16.98	15.44	8.84	0.75	Mental Health: 0 = Feelings of nervousness and depression all of the time. 100 = Feels peaceful, happy, and calm all of the time.
MCS	48.57	10.29	9.27	5.51	0.74	Mental Component Summary: Summary measure of mental wellbeing comprised of a weighted average of the four measures defined above and then normalized to be between 1 - 100.
PF	84.58	22.16	21.08	10.52	0.80	Physical Function: 0 = Extremely limited in performing all physical function activities because of physical health; 100 = Performs physical function activities with ease

RP	80.92	34.42	29.39	20.29	0.68	Role Physical: 0 = no problem with work or regular daily activities due to physical problems; 100 = extreme difficulty in performing work or regular daily activities due to physical problems.
VCR	921.03	588.41	574.69	187.89	0.90	Violent Crime Rate: Violent crime incidents per 100,000 individuals in the 12 months prior to interview.
PCR	5811.52	3067.07	2904.8	1299.87	0.83	Property Crime Rate: Property crime incidents per 100,000 individuals in the 12 months prior to interview.
VC^{q1}	0.0063	0.08	0.062	0.063	0.50	=1 if victim of violent crime during previous 3 months, zero otherwise.
$VC^{q2\text{-}4}$	0.011	0.104	0.088	0.078	0.56	=1 if victim of violent crime during previous 4 to 12 months, zero otherwise.
PC^{q1}	0.021	0.145	0.104	0.117	0.44	=1 if victim of property crime during previous 3 months, zero otherwise.
$PC^{q2\text{-}4}$	0.039	0.194	0.147	0.152	0.48	=1 if victim of property crime during previous 4 to 12 months, zero otherwise.

Notes: V_B/V_W represents the fraction of the variance that is due to between (or cross-sectional) variation compared to within (over time) variation. Sources: See Data Appendix for crime rate data. Mental and physical wellbeing data and victimization obtained from HILDA (2001-2006).

Table 2
Summary Statistics

Variable	Nonvictims	Victim of Violent Crime	Victim of Property Crime	Description
Age	43.72	33.52*	38.69*†	Age in years
	(17.83)	(14.80)	(15.99)	
Sex	0.54	0.51	0.51*	Male = 0, Female=1
	(0.50)	(0.50)	(0.50)	
Education				
Low	0.50	0.55*	0.47*†	= 1 if maximum education is Certificate I/II or High School Diploma, 0 otherwise.
	(0.50)	(0.50)	(0.50)	
Medium	0.26	0.25	0.27	= 1 if maximum education is Certificate III/IV or Advanced diploma, 0 otherwise.
	(0.44)	(0.44)	(0.44)	
High	0.24	0.20*	0.26†	= 1 if maximum education is Bachelor degree or above, 0 otherwise.
	(0.43)	(0.40)	(0.44)	
Children				
Age 0 -4	0.12	0.12	0.15*	= 1 if there are children between 0 - 4 years old in the household, zero otherwise.
	(0.32)	(0.33)	(0.35)	
Age 5 -14	0.20	0.15*	0.20†	= 1 if there are children between 5 - 14 years old in the household, zero otherwise.
	(0.40)	(0.36)	(0.40)	
Age 15-24	0.15	0.10*	0.12*	= 1 if there are children between 15 - 24 years old in the household, zero otherwise.
	(0.35)	(0.30)	(0.32)	
Mover	0.10	0.16*	0.14*	= 1 if moved from LGA to another, 0 otherwise
	(0.24)	(0.32)	(0.31)	
Mental Health				
MCS	49.02	43.98*	48.33* †	See Table 1
	(10.00)	(12.09)	(10.39)	

Vitality	61.13	55.89*	60.84†	See Table 1
	(19.30)	(20.22)	(19.33)	
Social Functioning	83.59	75.62*	83.76†	See Table 1
	(22.47)	(26.32)	(22.08)	
Role Emotional	84.41	71.54*	83.59†	See Table 1
	(31.44)	(37.72)	(31.28)	
Mental Health	74.55	67.25*	74.35†	See Table 1
	(16.71)	(19.64)	(16.33)	
Physical Health				
Physical Functioning	84.06	84.91	87.62*†	See Table 1
	(22.58)	(22.15)	(19.23)	
Raw Physical	81.14	76.24*	83.59*†	See Table 1
	(34.30)	(36.34)	(32.01)	
VCR	908.00	977*	988*	See Table 1
	(576)	(664)	(674)	
PCR	5664.00	6497*	7186*†	See Table 1
	(2966)	(3441)	(3769)	
Rainy Days	0.33	0.33	0.33	The fraction of rainy days over the previous year.
	(.04)	(.04)	(.04)	
Unemployment Rate	5.50	6.25*	6.34*	The unemployment rate over the previous year.
	(2.71)	(2.91)	(3.18)	
Average Total Income	19441.00	18726*	18323*†	LGA level average total income (labor plus other sources) per fiscal year (July-June). Includes nonworkers.
	(2949)	(2967)	(2895)	
Interview Month (modal response)	September	September	September	
Observations	25,408	465	1682	

Notes: * different from column 1 at a minimum 5 percent level of significance. † different from column 2 at a minimum 5 percent level of significance. Education: Certificate I/II provides basic vocational skills and knowledge (6 - 12 months of secondary education). Certificate III/IV provides training in more advanced skills and knowledge. A Certificate IV is generally accepted by universities to be the equivalent of six to twelve months of a Bachelor's degree, and credit towards studies may be granted accordingly. Courses at Diploma, Advanced Diploma level take between two to three years to complete, and are generally considered to be equivalent to one to two years of study at degree level. Source: HILDA except for crime rates, rainy days and unemployment rate (see Data Appendix).

Table 3
The Effect of Crime on Mental Wellbeing

	MCS		Social Functioning		Vitality		Role Emotional		Mental Health	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VC^{q1}	-8.389	-3.306	-20.627	-9.844	-10.543	-2.776	-20.171	-4.261	-12.833	-5.388
	(1.021)***	(1.082)***	(2.092)***	(2.234)***	(1.602)***	(1.460)*	(3.490)***	(3.897)	(1.579)***	(1.661)***
$VC^{q2\text{-}4}$	-7.162	-1.287	-15.909	-2.669	-9.862	-1.970	-21.987	-4.407	-10.821	-1.791
	(0.781)***	(0.757)*	(1.518)***	(1.417)*	(1.262)***	(1.085)*	(2.335)***	(2.696)	(1.173)***	(1.178)
PC^{q1}	-1.780	-0.483	-3.888	-0.973	-2.793	-0.849	-5.799	-1.687	-2.422	-0.766
	(0.468)***	(0.409)	(0.858)***	(0.823)	(0.791)***	(0.629)	(1.473)***	(1.585)	(0.751)***	(0.635)
$PC^{q2\text{-}4}$	-1.267	-0.115	-2.713	-0.623	-2.459	-0.675	-4.386	-1.058	-1.201	0.204
	(0.359)***	(0.280)	(0.741)***	(0.647)	(0.614)***	(0.465)	(1.085)***	(1.017)	(.534)**	(0.432)
$VCR^{\dagger}$	-2.093	-1.453	-4.021	-3.525	-2.333	-1.512	-5.273	-4.472	-2.644	-1.076
	(0.721)***	(0.628)**	(1.446)***	(1.390)**	(1.245)*	(1.025)	(2.430)**	(2.459)*	(1.015)***	(0.861)
$PCR^{\dagger}$	0.020	-0.029	-0.081	0.006	0.127	0.048	0.284	0.195	-0.058	-0.153
	(0.088)	(0.084)	(0.163)	(0.152)	(0.149)	(0.134)	(0.284)	(0.312)	(0.130)	(0.115)
Constant	43.027	59.225	66.896	146.211	50.973	149.994	32.829	74.387	72.061	84.285
	(16.256)***	(19.656)***	(34.147)*	(59.327)**	(48.554)	(26.704)***	(61.702)	(59.000)	(26.167)***	(32.915)**
$VCR^{\S}$	-1.243	-.860	-2.379	-2.084	-1.362	-.885	-3.118	-2.637	-1.579	-.645
	(.372)***	(.381)**	(.810)***	(.878)**	(.672)**	(.677)	(1.221)**	(1.383)*	(.598)***	(.602)
$PCR^{\S}$	.069	-.088	-.234	.023	.394	.145	.889	.592	-.166	-.470
	(.249)	(.262)	(.538)	(.590)	(.462)	(.468)	(.797)	(.927)	(.403)	(.421)
R^2	.053	.717	.049	.675	.042	.755	.040	.615	.047	.732

Notes: OLS columns include age, age squared, sex, education, number of children, number of rainy days, the unemployment rate, log of average total income, binary indicators for month of interview, year, and LGA. FE columns include the same but exclude age (linear over time) and sex (fixed over time) and include individual fixed effects. Standard errors are clustered by LGA. †: estimated coefficients multiplied by 1000 for aesthetic purposes. §: normalized. Observations: 32,594. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 4
The Effect of Crime on Mental Wellbeing by LGA size

	MCS (1)	Social Functioning (2)	Vitality (3)	Role Emotional (4)	Mental Health (5)	MCS (6)	Social Functioning (7)	Vitality (8)	Role Emotional (9)	Mental Health (10)
*VC^q1^*	-1.723	-8.919	-2.831	-1.539	-2.474	-3.945	-9.523	-2.818	-5.512	-6.543
	-2.039	(3.486)**	-3.029	-7.094	-2.889	(1.250)***	(2.985)***	(1.647)*	-4.663	(1.988)***
*VC^q2-4^*	1.232	1.763	-0.089	2.885	1.448	-2.759	-4.989	-3.248	-8.108	-3.963
	(1.390)†	(2.385)†	(1.906)†	(5.079)†	(2.079)†	(.981)***	(1.905)***	(1.471)**	(3.429)**	(1.548)**
*PC^q1^*	-0.18	-0.807	-0.205	-2.571	-0.166	-0.656	-1.091	-1.344	-0.705	-1.223
	-0.739	-1.473	-1.082	-2.024	-1.156	-0.544	-1.06	(.784)*	-2.488	-0.796
*PC^q2-4^*	0.481	0.545	0.214	1.095	0.606	-0.514	-1.365	-1.252	-2.207	-0.133
	(.478)†	(1.174)†	-0.744	-1.672	-0.679	(.301)*	(.689)**	(.556)**	(1.225)*	-0.562
*VCR^†^*	-1.495	-3.776	-0.492	-6.908	-0.939	-1.219	-2.277	-1.54	-2.327	-0.872
	(.877)*	(2.158)*	-1.525	(3.571)*	-1.251	-1.03	-2.199	-1.519	-3.144	-1.508
*PCR^†^*	-0.007	0.082	-0.121	0.61	-0.201	-0.086	-0.087	0.167	-0.526	0.023
	-0.109	-0.212	-0.194	-0.426	-0.164	-0.178	-0.355	-0.257	-0.571	-0.258
Constant	61.797	215.338	127.894	303.276	26.834	69.513	163.669	162.535	58.432	106.157
	-60.74	-139.568	-103.4	-208.632	-102.509	(21.201)***	(57.148)***	(30.096)***	-60.784	(35.666)***
Observations	12464	12464	12464	12464	12464	20025	20025	20025	20025	20025
R^2	0.728	0.675	0.764	0.622	0.741	0.724	0.686	0.761	0.626	0.738

Notes: Columns 1 - 5 use the subsample of LGAs with area below the median. Columns 6 - 10 use the subsample of LGAs with area above the median. Fixed Effects estimation. All columns control for time variant individual characteristics (age squared, education, number of children), LGA level variables (rainy days, unemployment rate and log of average total income) and month of interview, year, LGA, and individual fixed effects. Standard errors are clustered by LGA. *** significant at 1%; ** significant at 5%; *significant at 10%. †represents a statistically significant difference at a minimum 10% level between the estimated coefficients in the Below and Above Median regressions. For example, the estimated coefficient of 1.232 in the second row of column 1 is statistically significantly different from its corresponding estimate in the second row of column 6 of -2.759.

Table 5
Physical Health

	Physical Function		Role Physical	
	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)
VC^{q1}	-5.931	-0.371	-14.226	-4.850
	(1.599)***	(1.535)	(2.789)***	(2.9755)
$VC^{q2\text{-}4}$	-6.150	-1.479	-15.710	-0.461
	(1.225)***	(1.318)	(2.241)***	(2.583)
PC^{q1}	-1.343	-0.760	-4.033	-1.198
	(0.772)*	(0.757)	(1.254)***	(1.409)
$PC^{q2\text{-}4}$	0.054	-0.152	-4.616	-1.987
	(0.529)	(0.532)	(1.015)***	(1.099)*
$VCR^{\dagger}$	0.617	0.197	-1.731	-0.419
	(0.678)	(0.735)	(1.169)	(1.376)
$PCR^{\dagger}$	-0.264	0.061	0.961	1.157
	(0.466)	(0.538)	(0.790)	(0.947)
Constant	63.664	109.116	38.017	247.153
	(48.126)	(37.023)***	(68.806)	(71.100)***
Observations	32594	32594	32370	32370
R^2	0.239	0.777	0.126	0.655

Notes: OLS columns include age, age squared, sex, education, number of children, number of rainy days, the unemployment rate, log of average total income, binary indicators for month of interview, year, and LGA. FE columns include the same but exclude age (linear over time) and sex (fixed over time) and include individual fixed effects. Standard errors are clustered by LGA. †: estimated coefficients multiplied by 1000 for aesthetic purposes.

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

Table 6

The Effect of Crime on Mental Wellbeing (Random Trend Models: LGA-year FE)

	MCS		Social Functioning		Vitality		Role Emotional		Mental Health	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VC^{q1}	-8.461	-3.367	-20.694	-9.955	-10.808	-2.885	-20.419	-4.657	-12.895	-5.405
	(1.030)***	(1.106)***	(2.121)***	(2.337)***	(1.603)***	(1.479)*	(3.516)***	(3.999)	(1.584)***	(1.694)***
VC^{q2-4}	-7.165	-1.260	-15.989	-2.738	-9.876	-2.021	-22.034	-4.145	-10.756	-1.691
	(0.780)***	(0.761)*	(1.520)***	(1.405)*	(1.268)***	(1.111)*	(2.342)***	(2.663)	(1.184)***	(1.205)
PC^{q1}	-1.647	-0.379	-3.688	-0.984	-2.521	-0.696	-5.546	-1.590	-2.221	-0.588
	(0.485)***	(0.422)	(0.883)***	(0.855)	(0.815)***	(0.627)	(1.524)***	(1.667)	(0.781)***	(0.642)
PC^{q2-4}	-1.319	-0.172	-2.837	-0.862	-2.482	-0.673	-4.484	-1.288	-1.272	0.161
	(0.373)***	(0.284)	(0.766)***	(0.640)	(0.634)***	(0.484)	(1.095)***	(1.023)	(0.554)**	(0.437)
*VCR^*	2.009	1.859	0.972	-1.925	2.363	1.392	-0.150	6.057	0.279	2.650
	(2.579)	(2.362)	(5.121)	(5.423)	(4.639)	(3.276)	(9.752)	(10.422)	(4.312)	(3.474)
*PCR^*	4.405	0.115	7.113	0.746	6.123	-0.783	19.459	10.707	3.013	-2.276
	(2.509)*	(2.811)	(3.996)*	(5.067)	(4.390)	(4.049)	(9.214)**	(9.481)	(3.864)	(4.179)
Constant	-0.357	12.22	-47.105	-64.852	-47.375	95.784	-59.518	-100.664	18.026	30.580
	(23.294)	(55.890)	(23.870)**	(140.611)	(73.846)	(92.708)	(109.170)	(78.195)	(36.861)	(59.054)
R^2	0.064	0.724	0.059	0.681	0.051	0.759	0.051	0.623	0.057	0.738

Notes: OLS columns include age, age squared, sex, education, number of children, number of rainy days, the unemployment rate, log of average total income, binary indicators for month of interview, year, LGA and the interaction between year indicators and LGA indicators. FE columns include the same but exclude age (linear over time) and sex (fixed over time) and include individual fixed effects. ∧: estimated coefficients multiplied by 1000 for aesthetic purposes. Standard errors are clustered by LGA. Observations: 32,594. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 7
Mental Wellbeing in a Two-Year Window Around Victimization

	MCS	Role Emotional	Social Functioning	Vitality	Mental Health
	(1)	(2)	(3)	(4)	(5)
$VC_{t=-2}$	0.329	2.033	0.053	1.956	0.670
	(1.086)	(3.933)	(2.757)	(2.107)	(1.749)
$VC_{t=0}$	-2.310	-4.837	-8.862	-3.552	-3.447
	(1.006)**	(3.226)	(1.909)***	(1.645)**	(1.727)**
$VC_{t=1}$	-0.128	1.393	-1.756	-1.597	0.380
	(1.335)	(3.248)	(2.539)	(2.141)	(2.411)
$VC_{t=2}$	-0.217	2.889	-5.542	-2.869	-0.741
	(1.399)	(4.150)	(2.959)*	(2.622)	(2.546)
Constant	-41.978	-241.351	-108.283	9.237	-153.198
	(54.282)	(274.706)	(99.762)	(116.254)	(103.354)
Observations	1208	1208	1208	1208	1208
R^2	0.238	0.212	0.232	0.222	0.233

Notes: Omitted base is t = -1. Sample is restricted to individuals with only one victimization event within the two year window in order to eliminate confounding impacts on mental health in t ≥ 1. Controls include age, age squared, sex, education, number of children, number of rainy days, the unemployment rate, log of average total income, binary indicators for month of interview, year and LGA. Standard errors clustered by LGA. *** significant at 1%; ** significant at 5%; * significant at 10%.

Appendix I

A. Crime Statistics

In Australia, the collation of crime statistics is a state government responsibility. Although some data are routinely provided to the Australian Institute of Criminology, this does not include the high-frequency, regionally disaggregated data that we use in this paper.

After repeated contact with the governments of the six states and two territories that comprise Australia, we were able to obtain crime statistics data for all areas except the Northern Territory. In some cases, this contact also included lodging Freedom of Information requests, though ultimately none of the data were provided through this channel. Only Victoria required us to pay for the data while the other states provided it free of charge. Since only 0.9 percent of Australians live in the Northern Territory, our crime data theoretically covers 99.1 percent of the Australian population. We are also unable to match data for a small number of observations in our dataset, so end up with crime data for 98.7 percent of our survey sample.

In the Australian Capital Territory, New South Wales, South Australia, and Victoria, crime data are coded by police stations on a Local Government Area (LGA) basis (the Australian Capital Territory is a single LGA). In Tasmania, crime data are coded on a suburb basis, and matched to postcodes using a crosswalk supplied by the Australian Bureau of Statistics. In Western Australia, crime data are coded on by locality, and we match them to postcodes using a crosswalk supplied by the Western Australian Police. Both suburbs (Tasmania) and localities (Western Australia) are a finer geographic coding than postcodes.

Geographically matching crime data to regional areas is more complicated in Queensland, whose crime data are coded to geographic areas known as Police Divisions. These Police Divisions were then matched to LGAs for us by the Queensland Police Service. The

Queensland crime data spanned 328 police divisions, and 128 LGAs. The Queensland Police Service also provided information on the match quality. The median Police Division was matched to an LGA containing 99.7 percent of its population (the mean was 91.4 percent).

In the case of Victoria, the data was confidentialized, such that cells containing between 1 and 3 crimes were replaced with an asterisk. In addition, the statistics contained data on the total number of crimes (across all categories) for each month. Using these totals, we imputed values for the confidentialized cells using the following procedure:

- If the total was confidentialized, assume the total was 2
- Calculate the gap between the total and the sum of the non-confidentialized cells
- Divide this gap by the number of confidentialized cells, and assign that number to each of the confidentialized cells.

For all states and territories except the Australian Capital Territory, crime statistics are reported on a monthly basis. For the Australian Capital Territory, data are tabulated on a quarterly basis, and we assign the same crime rate to each month in the quarter. Criminal incidents are classified by the date that they were reported to or detected by police. We expect that in most cases this will correspond to the date on which the offence occurred, but we have no way of verifying this.

Population data are drawn from the Australian Bureau of Statistics publication Regional Population Growth (Cat No 3218.0). This provides the population for each LGA as at June in each year. We linearly interpolate population figures for intervening months. In a small number of cases, the ABS does not report population statistics for an LGA, but we still have crime statistics for that area. In these instances, we assume the population is unchanged from the closest date for which we have population statistics. (In other words, we do not extrapolate beyond the available population data.)

The states do not apply a uniform crime classification system. The number of different crime categories in which the data were provided was 16 for the Australian Capital Territory, 60 for New South Wales, 87 for Queensland, 119 for South Australia, 206 for Tasmania, 27 for Victoria, and 24 for Western Australia. We recoded crimes into 16 categories using the Australian Standard Offence Classification (ASOC). These categories are described in Table A1.

Table A1
Major Crime Categories (Australian Standard Offence Classification)

Abbreviated Name	Description	Examples
Homicide	Homicide and related offences	murder, conspiracy to murder, manslaughter
Assault	Acts intended to cause injury	assault, aggravated assault
Sexual Assault	Sexual assault and related offences	aggravated sexual assault, sexual offences against a child
Dangerous Acts	Dangerous or negligent acts endangering persons	dangerous or negligent driving, neglect of person under care
Abduction	Abduction and related offences	abduction, kidnapping, deprivation of liberty
Robbery	Robbery, extortion and related offences	robbery, blackmail
Burglary	Unlawful entry with intent/burglary, break and enter	burglary, break and enter
Theft	Theft and related offences	theft of a motor vehicle, receiving stolen property
Deception	Deception and related offences	credit card fraud, bribery, counterfeiting
Drug Offences	Illicit drug offences	traffic in illicit drugs, possess illicit drug
Weapons Offences	Weapons and explosives offences	sell prohibited weapons, possess prohibited explosives
Property Damage	Property damage and environmental pollution	graffiti, noise pollution
Public Order Offences	Public order offences	trespass, offensive language, prostitution
Traffic Offences	Road traffic and motor vehicle regulatory offences	speeding, driving without a licence
Justice Offences	Offences against justice procedures and government	breach of parole, breach of domestic violence order
Miscellaneous Offences	Miscellaneous offences	defamation, threatening behavior, public health offences

B. Unemployment

Unemployment statistics are produced on a quarterly basis for each Statistical Local Area (SLA) by the Department of Employment and Workplace Relations. This is the finest level of aggregation at which we are able to obtain unemployment rate data. These estimates are based on data from the monthly Labour Force Survey conducted by the Australian Bureau of Statistics, adjusted using Centrelink data on the number of Newstart and Youth Allowance (Other) recipients and Census data. The Department of Employment and Workplace Relations have smoothed these data by averaging over four quarters.

The unemployment rate is not available for all SLAs. Where it is available in some later months, but not earlier months, we use the later months to estimate the ratio of unemployment in that SLA to the national unemployment rate, and multiply the national unemployment rate by this ratio to impute missing values for earlier months. Where the unemployment rate is missing in all quarters, we assign the national unemployment rate. In some cases, unemployment rates are based on labor force estimates of less than 100 people. In these cases, we assume that measurement error renders them unusable, and instead assign the unemployment rate of the nearest SLA.

There are 932 SLAs in Australia (in many cases SLAs cover the same area as LGAs). We match each respondent to their SLA using a crosswalk prepared by the ABS. This crosswalk does not contain information on the proportion of the population in each postcode area who live in the SLA.

When analyzing crime in the month or quarter of interview, we use the unemployment rate in the quarter of interview. When analyzing the effect of crime in the previous six months, we use the average unemployment rate over the current and previous quarter. And when analyzing crime in the previous twelve months, we use the average unemployment rate over the current quarter and the previous three quarters.

C. Rain Days

Using daily data provided by the Bureau of Meteorology, and taken from weather stations in the capital cities, we calculate the share of rain days in a given month. For example, if some rainfall was recorded on ten days in a 30-day month, the share of rain days would be 0.33. We also calculate the share of rain days over the previous quarter, half-year and year.

D. Matching

Matching Crime Statistics to Mental Health Data Mental health questions are answered using a self-completion questionnaire. Although the HILDA dataset does not contain the date on which the self-completion questionnaire was filled out, it does contain the date on which the person was interviewed (xHHIDATE), and whether the self-completion questionnaire was picked up at that time (xHGS). For example, in the 2004 wave, the interviewer collected the self-completion questionnaire from two-thirds of respondents at the time of the interview. We therefore code the mental health questions as relating to the date on which the person was interviewed. Where that variable is missing, we use the date of the household interview instead (xHHHQIVW). From this point on, we refer to this as the interview date.

Since our crime data are only monthly, we assume that crime is spread evenly across the month. Where the interview date is on or after the 15th day of the month, we assign that month's crime rate to the respondent. Where the interview date is before the 15th day of the month, we assign the previous month's crime rate to the respondent.

For example, suppose the interview date for a respondent living in the center of Brisbane was 13 March 2004. In that case, the current quarter crime rate assigned to her would be the average crime rate in the Brisbane Local Government Area (LGA) from December 2003 to February 2004, the previous quarter rate would be the average crime rate for that LGA from September 2003 to November 2003, and so on.

The finest geographic coding available in HILDA is the respondent's postcode (zipcode). The match from postcodes to LGAs is updated by the Small Area Population Unit of the Australian Bureau of Statistics. Since both sets of boundaries occasionally change, we use the crosswalk closest in time to the collection of the data (which means that we sometimes use multiple crosswalks).

Postcodes are a finer level of aggregation than LGAs. In the areas covered by this analysis, there are 2409 postcode areas, and 622 LGAs. The median LGA contains 8 postcode areas (the mean is 10.4). We match postcodes to the LGA in which the majority of that postcode lives. The median postcode is 100 percent contained within an LGA (the mean is 95.6 percent).

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1 At the time our article was accepted for publication, the Australian dollar was around parity with the US dollar. We estimate that each person in a community of 100,000 people would in fact pay up to $0.77 to reduce the number of victims by one and thereby maintain his or her level of mental wellbeing.

2 From a policy perspective, the ex ante approach is preferable as it allows to more accurately compare benefits to costs in dollar terms whereas the ex post approach attempts to monetize intangible values such as the loss to quality of life after such a loss has occurred. This latter approach, otherwise known as the "willingness to accept" (WTA) can be problematic

because in practice individuals often feel that there is no sum of money that can compensate for their loss.

3 Sources: Australian Institute of Criminology: Fact and Figures 1994-2010 (www.aic.gov.au) and The Disaster Center: US Crime Rates, 1960 -2010 (www.diastercenter.com/crime/uscrime).

4 See Data Appendix.

5 Note that this is not necessarily the same thing as LGA-year as individuals were interviewed at different points during the year.

6 This stands in contrast to the US, where property crime over this period did not change substantially.

7 Average total income is calculated as the weighted average of all households within an LGA using the HILDA data. The Data Appendix contains more precise details on data sources and how the other variables were calculated.

8 Eleven percent of our observations represent individuals that move from one LGA to another, which allows us to separately identify both individual and LGA effects.

9 Alternative clustering by individual provided nearly identical results.

10 At most a high school diploma.

11 A unit increase in exposure was associated with 0.53 percentage points lower MCS scores where each unit involves answering yes to a question such as "Were you in the WTC at the time of the attacks?"; "Did you have difficulty breathing due to the smoke?" or "Did you lose your job because of the disaster?" As their study was done a year after the event, we use the longer run estimated effect in row 3 of column 2 as a comparison.

12 Note that the estimated crime rate coefficients in Table 3 are multiplied by 1000 for aesthetic purposes.

13 One may imagine that there is a positive correlation between high crime LGAs and low mental health individuals. However, given that people may freely sort, it may be that the most resilient individuals stay in high crime rate areas and weaker individuals tend to move out of high crime rate areas. The latter effect would lead to a downward bias in our OLS estimates.

14 Unreported but available upon request.

15 There are two other measures of physical fitness–Bodily Pain and General Health–in addition to a summary measure analogous to MCS. However, because there is often a fine line between mental and physical wellbeing, these latter two measures (and hence the summary measure) have been found to be fairly correlated with mental wellbeing. If one wants to measure pure physical wellbeing, Physical Function and Role Physical are superior measures that are virtually uncorrelated with mental wellbeing. See Ware, Kosinski and Keller (1994) for additional details.

16 In earlier work, we found some evidence that the effect of crime on mental wellbeing was magnified by newspaper reports (Cornaglia and Leigh 2011). However, given declining newspaper readership rates, we believe a proper analysis of crime reporting should also include other media. We have therefore dropped this aspect of the discussion from the paper.

17 What we would ideally like to have is a more continuous measure of mental health and victimization. A case we cannot rule out is a negative shock to mental health on day one that increases the probability of victimization on day two and interviewed for the survey on day three. We imagine that this sort of timing, while exaggerated, is of relatively low probability.

18 Roy and Schurer (2012) in their paper on the persistence of mental health shocks find that mental welling tends to revert to its prior level in 2 - 3 years after a shock.

19 This is also true if we consider only victimization in the quarter after the interview date rather than the full year after the interview date.

20 The latter compensation may also internalize the additional value that one places on the increased risk to family members and others in society, not just one's own self.

21 Coded by Janel Hanmer (July 2005) and later updated by John Brazier and Quality Metric, and Jenny Beuchner.

22 The use of $50,000 as a benchmark for assessing the cost-effectiveness of an intervention first emerged in 1992 and became widely used after 1996. Similar measures for the UK and the USA are £20,000 and $50,000, respectively. We focus on social functioning because it is the mental wellbeing measure that is consistently impacted by crime in our analysis.

23 The -4.59 estimate is derived from a weighted average of the two violent crime victimization estimates and recall that for aesthetic reasons, the estimated coefficient on the violent crime rate was multiplied by 1000.