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Crime Victimisation Over Time and Sleep Quality

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Abstract: We here consider the relationship between the individual time profile of crime victimisation and sleep quality. Sleep quality worsens with contemporaneous crime victimisation, with physical violence having a larger effect than property crime. But crime history also matters, and past victimisation experience continues to reduce current sleep quality. Last, there is some evidence that the order of victimisation spells plays a role: consecutive years of crime victimisation affect sleep quality more adversely than the same number of years when not contiguous.

Keywords: Crime, time, physical violence, property crimes, sleep quality.

Victimisation criminelle au travers du temps and qualité du sommeil

Abstract : Nous adressons ici la question du lien entre le profil temporel de la victimisation criminelle et la qualité du sommeil à l'échelle individuelle. La qualité du sommeil se dégrade instantanément en cas de victimisation criminelle et l'effet de violences physiques est plus fort que l'effet de crimes liés à la propriété. Cependant, les expériences de victimisation criminelles passées comptent également au sens où elles affectent toujours la qualité actuelle du sommeil. Finalement, nous mettons en avant le fait que l'ordre des épisodes de victimisation criminelle est important : des années de victimisation criminelles consécutives ont un impact négatif plus fort sur la qualité du sommeil que le même nombre d'années de victimisation criminelle non-consécutives.

Mots-clefs : Crime, temps, violence physique, crime lies à la propriété, qualité du sommeil.

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1 Introduction

Crime is a long-standing societal concern, and results in a variety of pecuniary costs such as financial losses, days off work and medical expenses. However, recent contributions in this area have highlighted that the non-pecuniary costs of crime may substantially outweigh these associated pecuniary costs. A number of papers have found that crime reduces subjective well-being and mental health (Norris and Kaniasty, 1992; Moller, 2005; Powdthavee, 2005; Cohen, 2008; Hanslmaier, 2013; Cornaglia et al., 2014; Dustmann and Fasani, 2016; Mahuteau and Zhu, 2016; Johnston et al., 2018; Brenig and Proeger, 2018). In this spirit, we here consider another type of non-pecuniary cost of crime: sleep quality. While poor sleep is associated with worse psychological well-being, its adverse consequences may extend far beyond this variable. In the medical literature, poor sleep quality is considered as a major risk factor for many health conditions, such as diabetes (Kawakami et al., 2004), obesity (Marshall et al., 2008), cardiovascular disease and hypertension (Kasasbeh et al., 2006), and malfunctions of the immune system (Opp and Toth, 2003). However, sleep quality has received only limited attention in this context in the health-economics literature.

We here analyse the empirical link between individual crime victimisation and sleep quality using panel data from the Household Income and Labour Dynamics in Australia (HILDA) Survey. Australia is a developed country with relatively severe crime problems. According to OECD (2010), Australia had the ninth-highest victimisation rate for assaults or threats (3.4%) and the fifth-highest rate for burglary with entry (2.5%) of OECD countries in 2005.[1] The HILDA data distinguishes between two types of crimes: those with physical violence (e.g. assault) and property crimes (e.g. theft or housebreaking). We in particular appeal to this panel data to focus on the time profiles of crime victimisation in determining current sleep quality, conditional on contemporaneous crime victimisation. We consider two types of influence from the past. First, a scarring effect of past crime implies that any past crime experience will continue to reduce current well-being conditional on the current crime experience. Second, the order of past victimisation may also matter, with consecutive events mattering more given total past crime exposure. Section 2 below will show that, for both types

[1]The OECD average rates were 2.9% and 1.8%, respectively.

of crimes considered here, 30 percent of victims experienced the crime more than once. For these victims, contiguous victimisation years may affect current sleep quality.

Our empirical analyses thus relate sleep quality at time t to contemporaneous victimisation experience and past victimisation values up to t–1. We characterise the latter using two measures from the recent literature on economic inequality over time: (i) the *chronicity* index of Foster (2009) (which measures the frequency of victimisation over the past observational period in HILDA) and (ii) the *persistence* index of Bossert et al. (2012) (which considers the continuity of victimisation spells). We find that both the contemporaneous incidence and the past profile of crime victimisation reduce current sleep quality.

2 Data and descriptive statistics

2.1 Data and variables

We use data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, the first wave of which appeared in 2001. HILDA is an annual nationally-representative Australian household panel survey that collects information on economic well-being, life events and labour-market dynamics, amongst other topics. As the first wave (2001) does not include information on crime victimisation, we use HILDA waves 2002–2013 to construct the individual's victimisation history.[2] Starting in 2002, HILDA respondents were asked at each wave which major life events from a list of 21 had occurred to them over the past 12 months. Two of these 21 refer to crime victimisation: (i) "*victim of physical violence (e.g., assault)*" (which we will denote by PV_{it}) and (ii) "*victim of a property crime (e.g., theft, housebreaking)*" (denoted by PC_{it}). Our two key crime variables PV_{it} and PC_{it} are thus dummies generated from recent self-reported events.

In addition to recent events, the individual's history of victimisation (the past values of PV_{it} and PC_{it}) may also continue to affect individual sleep quality, conditional on current victimisation. We include past victimisation in a number of different ways. We first calculate two dummy variables for

[2]HILDA waves 2014–2016 are also available. We do not use these here as we estimate the effects of victimisation profiles on sleep quality, and information on the latter is only available in the 2013 wave.

ever having been a victim of physical violence or property crimes in previous HILDA waves from the first period in which the individual was observed up to period t–1: these are denoted by $Past_{it-1}^{PV}$ and $Past_{it-1}^{PC}$.

We also distinguish *chronic* crime victimisation from what we think of as being in a state of *persistent* victimisation. The former refers to the frequency of occurrence (Clark et al., 2001; Foster, 2009), while the latter considers occurrence in periods that are more linked together, conditional on their frequency (Bossert et al., 2012; Clark et al., 2018). Using physical violence as an example, *chronicity* applies to a situation in which an individual experienced violent crime for a certain proportion of the time periods under consideration, without paying any attention to the durations of *unbroken* violent-crime spells. In contrast, *persistence* explicitly takes the continuity of physical-violence spells into account. We can illustrate *persistence* with a simple example. Assume that two individuals both experienced property crime this year, but the first also experienced this last year (but not the year before), while the second did not last year but did so in the year before that. These individuals' intertemporal victimisation profiles are different. Both experienced property crime twice in the three years considered, but the first did in two consecutive periods while the second did not.[3] We will here relate the *chronicity* and *persistence* indices of the history of crime victimisation to current sleep quality; this has not been considered in the existing literature.

Our empirical analysis will first consider the *chronicity* measure of Foster (2009), which is simply the average physical violence that an individual has experienced up to time t:

$$Foster_{it}^{PV} = \frac{1}{t}\sum_{\tau=1}^{t} PV_{i\tau} \tag{1}$$

where $PV_{i\tau}$ is the dummy for individual i having experienced violent crime in the period τ. The chronicity index for being a victim of property crime, $Foster_{it}^{PC}$, is defined analogously. The *chronicity* index measures the relative frequency of a crime from the first period observed to period t.

We pick up *persistence* in crime victimisation using the index proposed by Bossert et al. (2012), which weighs each spell by its length (denoted by l_τ). The BCD_{it}^{PV} index is the weighted average of

[3]The underlying idea of persistence is that individuals need time between negative events to recover, and that consecutive events impair this recovery.

physical violence from period 1 to period t, with the weight being given by the length of the spell to which the period belongs:

$$BCD_{it}^{PV} = \frac{1}{t}\sum_{\tau=1}^{t} l_\tau PV_{i\tau}. \tag{2}$$

The persistence index for experiencing property crimes, BCD_{it}^{PC}, is constructed in the same way.

We here provide a simple example to illustrate how these two indices are calculated. Take $PC_{i\tau}$, the dummy for being a victim of property crimes for individual i in period τ. Then the sequence (1, 1, 0, 1, 1) indicates that this individual experienced a property crime in periods 1, 2, 4 and 5, but not in period 3. The *chronicity* index is $Foster^{PC}$=$\frac{1}{5}$(1+1+0+1+1)=$\frac{4}{5}$=0.8, so that 80 percent of the five consecutive years in which individual i was surveyed were characterised by property crimes. The *persistence* index BCD^{PC}=$\frac{1}{5}$[2(1+1)+1(0)+2(1+1)]=$\frac{8}{5}$=1.6. The BCD^{PC} value here is larger than $Foster^{PC}$, as the PC_{it} value in each period is now weighted by the length of the continuous spell in which person reports the same value of the crime variable. On the contrary, the values of $Foster^{PC}$ and BCD^{PC} for someone with the contiguous sequence (1, 0, 1, 0, 1) are the same, as no crime spell is of length greater than one.

Sleep quality is measured only in wave 13 of HILDA. We consider the following five measures, which refer to the previous month: (i) reporting sleep quality to be very bad or fairly bad; (ii) cannot get to sleep within 30 minutes; (iii) waking up in mid-night or early morning; (iv) taking medicine to help sleep; and (v) hours of sleep per day in a typical week. The first four of these are dummy variables, while the fifth is continuous.

These answers about sleep quality are likely to be highly correlated with each other. For example, people who often report waking up in mid-night or early morning tend to report fewer hours of sleep per day. We address the possible correlation of these five items and construct a summary index that takes these correlations into account. We employ principal component analysis (PCA), a procedure that transforms possibly correlated variables into a smaller number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. We perform this analysis for the five sleep-quality measures.[4] The eigenvalues for the five transformed components are 2.00, 0.96, 0.89, 0.61 and 0.53 respectively. Applying the eigenvalue-one criterion (the Kaiser criterion) to solve the problem of number-of-components, we retain any component with an eigenvalue greater than 1. We therefore only keep the first of the five components, which explains about 40 percent of the variation in the outcomes. The principal component generated from the PCA has a mean of zero. We further standardise it so that its standard deviation equals one. In summary, the overall index of sleep quality we use is the standardised first principal component for the five sleep-quality measures, with a higher value of the index representing poorer sleep quality.[5]

In the following regression analysis, the Big Five personality traits (agreeableness, conscientiousness, emotional stability/neuroticism, extroversion, and openness to experience) will be used to control for (at least partially) selection into exposure to victimization. Information on these five traits was collected in Waves 2005, 2009 and 2013, and each trait is standardised to be between 1 and 7 in HILDA. As these psychological traits are also fairly stable over time (Cobb-Clark and Schurer, 2011), we follow Buddelmeyer and Powdthavee (2016) and calculate the mean of each personality trait in these three waves to minimise measurement error.

2.2 Descriptive statistics

As sleep-quality information is available only in HILDA Wave 13, we focus on individuals in that wave who are aged 16 or above. We drop observations with missing information on sleep quality, the victimisation profile and the other control variables in the estimations. Our final sample consists of 14,503 observations from 8,184 households.

The descriptive statistics of the estimation sample appear in Table 1. About 25 percent of the 14,503 individuals reported very or fairly bad sleep quality. Around 66 percent could not get to sleep within 30 minutes in the past month, 72 percent woke up in mid-night or early morning, and 14 percent took medicine to help sleep. The average daily hours of sleep of the Australians in our final

[4]The detailed PCA results appear in Appendix Tables A1 and A2.

[5]Appendix Table A2 shows that the index is positively correlated with the first four sleeping problems and negatively related to the number of hours of sleep per day.

sample is 7.2 in a typical week.

Regarding crime, in each year between 2002 and 2013 about 1.2 percent of individuals reported to have been a victim of physical violence, with the analogous figure for property crime being larger at 3.6 percent. Over the whole of the 2002–2013 period 7 percent of Australians reported experiencing at least one violent crime and 25.6 percent property crime. Last, for both types of crimes, the *persistence* index figure of Bossert et al. (2012) is only slightly above that of the *chronicity* index of Foster (2009). This is to be expected from Table 1, which indicates that both types of crime victimisation are only rare, so that there are relatively few cases of consecutive victimisation (which is what causes the *persistence* index to differ from the *chronicity* index: about 8.4 percent of violent-crime victims experience consecutive incidents; the analogous figure for property crime is 6 percent). Even so, our empirical results in Section 4 will show that we have enough cases to separately identify the effects of victimisation *chronicity* and *persistence* on sleep quality with a reasonable level of precision.

The average age of individuals in the final sample is around 45, about 47 percent are men, with an average of 12 years of education. Most observations come from the married (65 percent) or never married (22 percent). The income measure we use is real household disposable regular income in 2016 Australian dollars, which is around A$98,719. Last, around 64 percent of observations come from individuals who live in a major Australian city.

Table 2 shows the individual crime frequencies for victims over the 2002–2013 period. Among the 1,026 victims of physical violence in our final sample, 70 percent experienced violent crime once and 30 percent twice or more. For the 3,272 victims of property crime, 21 percent experienced property crime twice, and 8.5 percent three times or more. We below consider the effect of the past (*chronicity* and *persistence*) of victimisation on sleep quality.

3 Empirical approach

We assume that sleep quality is described by the following equation

$$SQ_{it} = CVP_{it}'\beta + X_{it}'\gamma + \epsilon_{it} \tag{3}$$

Table 1: Descriptive statistics

Variables	Mean	Standard deviation
Sleep quality		
Overall sleep quality in the past month (predicted from PCA)	0.000	1.000
Very bad or fairly bad sleep quality in the past month	0.247	0.431
Cannot get to sleep within 30 minutes in the past month	0.657	0.475
Wakes up in mid-night or early morning in the past month	0.717	0.450
Takes medicine to help sleep in the past month	0.138	0.344
Hours of sleep per day in a typical week	7.165	1.369
Past and present crime victimisation		
Victim of physical violence	0.012	0.110
Victim of property crime	0.036	0.185
Ever a victim of physical violence	0.071	0.256
Ever a victim of property crime	0.225	0.418
Foster index for physical violence	0.016	0.081
Foster index for property crime	0.045	0.116
BCD index for physical violence	0.018	0.102
BCD index for property crime	0.049	0.143
Socioeconomic characteristics		
Age	45.16	18.32
Male	0.466	0.499
Years of education	12.376	2.212
Married	0.654	0.476
Never married	0.218	0.413
Widowed	0.042	0.201
Divorced	0.060	0.238
Separated	0.025	0.157
Number of children in household	0.697	1.067
Household disposable regular income (A$000s, 2016)	98.719	72.816
Living in a major city	0.637	0.481
Big Five personality traits		
Agreeableness	5.179	1.087
Conscientiousness	5.446	0.911
Emotional stability (Neuroticism)	5.129	1.023
Extroversion	4.434	1.083
Openness to experience	4.254	1.060
Observations	14,503	

Table 2: Individual crime frequency among victims, 2002–2013

	Physical violence		Property crime	
	Individuals	%	Individuals	%
Once	723	70.47	2,288	69.93
Twice	190	18.52	702	21.45
Three times	70	6.82	189	5.78
Four times	19	1.85	55	1.68
Five times or more	24	2.34	38	1.16
Total	1,026	100.00	3,272	100.00

where SQ_{it} is a measure of sleep quality for individual i in period t (t=2013 here), CVP_{it} is a vector of individual-level crime-victimisation profile variables and X_{it} is a vector of explanatory variables, including age, age-squared, a gender dummy, years of education, marital status (married, single, divorced, widowed and separated), number of children in the household, the log of real household disposable regular income, a dummy for living in a major city, the Big-Five personality traits and postcode-level fixed effects.[6] ϵ_{it} is the error term. We estimate equation (3) with Ordinary Least Squares (OLS) regressions.[7]

As the sleep-quality variables only appear in HILDA wave 13, our past crime-victimisation profile variables are constructed using HILDA waves 2002–2012 and estimation is carried out via Ordinary Least Squares (OLS). We first consider the contemporaneous relationship between sleep quality and victimisation; we then explicitly introduce time, and ask whether past victimisation experience continues to affect current sleep quality. Last, we consider the role of *persistence*, whereby the order of spells matters: for a given number of years of crime victimisation, is sleep of worse quality when these years are joined together? Our three different sets of crime-victimisation profile variables are thus: (i) contemporaneous physical violence and property crime (PV_{it}, PC_{it}); (ii) contemporaneous victimisation (PV_{it}, PC_{it}) and past victimisation (ever happened from period 1 to period t–1)

[6]To facilitate interpretation, we normalised each of the psychological traits to have a mean of zero and a standard deviation of one before carrying out the estimations.

[7]Probit or logistic regressions can be used when the dependent variable is dichotomous. In this paper, we are interested in the marginal effects of explanatory variables on the explained variable. As explained in Chapter 3.4 of Angrist and Pischke (2008), "the upshot of this discussion is that while a nonlinear model may fit the conditional expectation function (CEF) for limited dependent variables (LDVs) more closely than a linear model, when it comes to marginal effects this probably matters little.". In general, probit regression, logistic regression and OLS (the linear-probability model) produce very similar covariate marginal effects.

($Past^{PV}_{it-1}$, $Past^{PC}_{it-1}$); and (iii) current victimisation (PV_{it}, PC_{it}), the lag of the Foster (2009) indices ($Foster^{PV}_{it-1}$, $Foster^{PC}_{it-1}$) and the lagged difference between the Bossert et al. (2012) and Foster (2009) indices of victimisation (BCD^{PV}_{it-1}–$Foster^{PV}_{it-1}$, BCD^{PC}_{it-1}–$Foster^{PC}_{it-1}$). The last two specifications allows us to investigate the impact of crime victimisation over time on sleep quality.

There are two potential concerns on the direction of causality if crime victimisation happens repeatedly to certain people. This could first reflect that the individual lives in a high-crime area, and we may wonder whether it is the crime victimisation *per se* or rather the area's other characteristics (crowding, noise, high rates of shift work etc.) that affect sleep. Second, repeated victimisation of certain individuals could reflect individual unobserved characteristics: for example, individuals who stay out late and drink a lot may be more likely to experience victimisation and also have poor sleep quality.

We address the first concern by including postcode-level fixed effects in equation (3), so that any characteristics of the residential area that may affect both crime victimisation and sleep quality are controlled for in our estimations. To address the second causal concern, we include the Big Five personality traits as controls. Whether individuals lead a lifestyle that makes them susceptible to victimisation is closely related to their psychological traits, in addition to the observed socioeconomic characteristics that we already control for. Last, the time dimensions of our variables also help reassure us as to the direction of causality in equation (3): respondents report their sleep quality *in the past month*, but whether crime victimisation occurred *over the past 12 months*. Moreover, we mainly focus on the impact of *past* profiles of crime victimisation (*chronicity* and *persistence*, measured up to time t–1) on *current* sleep quality (measured at time t). These victimisation variables may then be considered to largely pre-date the sleep measures.

4 Results

The estimation results appear in Table 3, with robust standard errors clustered at the household level in parentheses.[8] The dependent variable is the sleep-quality index predicted from the principal

[8]The estimated coefficients on the control variables appear in Appendix Table A3.

component analysis (PCA) of the five sleep-quality measures described in Section 2.1. This index has zero mean and unit variance, with a higher value indicating poorer quality of sleep.[9]

The OLS estimates from specification (1) in Table 3 show that contemporaneous physical violence and property crime are both associated with worse sleep quality: the index for overall poor quality of sleep is 0.422 standard deviations higher among those who were victims of physical violence over the past 12 months. The contemporaneous effects of physical violence are larger than those of property crime.

Table 3: Crime victimisation over time and poor sleep quality (OLS estimates)

	Overall index of poor sleep quality		
	(1)	(2)	(3)
PV_{it}	0.422***	0.309***	0.291***
	(0.083)	(0.089)	(0.090)
PC_{it}	0.219***	0.203***	0.194***
	(0.048)	(0.050)	(0.050)
$Past_{it-1}^{PV}$		0.194***	
		(0.036)	
$Past_{it-1}^{PC}$		0.055**	
		(0.022)	
$Foster_{it-1}^{PV}$			0.621***
			(0.120)
$Foster_{it-1}^{PC}$			0.212***
			(0.070)
BCD_{it-1}^{PV}–$Foster_{it-1}^{PV}$			0.597*
			(0.306)
BCD_{it-1}^{PC}–$Foster_{it-1}^{PC}$			0.139
			(0.189)
Observations	14,503	13,618	13,618
Adjusted R-Squared	0.097	0.097	0.097

Notes: *** p<0.01; ** p<0.05; * p<0.10. The dependent variable is the overall index of poor sleep quality predicted from PCA. Robust standard errors clustered at the household level are in parentheses.

We then introduce time, and ask whether past victimisation continues to diminish current sleep quality. We first add two dummies for the individual having experienced physical violence and/or

[9] We have checked whether survey non-response and attrition affect our estimation results. We follow Cai and Waddoups (2011) and Wilkins (2014) by using sample weights in our regressions to correct for possible attrition bias. The results reported in Appendix Table A4 are very similar to those in Table 3, confirming the findings of Watson and Wooden (2006, 2007) that there is a very large random component to non-response in HILDA and attrition bias appears to be only small.

property crime in the past (up to time t–1). The results in column (2) in Table 3 show that, conditional on current crime victimisation, past victimisation continues to reduce current sleep quality. The effect of past crime exposure is smaller than that of current crime exposure. The past victimisation variables are statistically significant: exposure to crime is not ephemeral and has sleep-quality effects that extend beyond its contemporaneous impact.

Instead of looking at the extensive margin of past crime in column (2), we can also consider the individual's entire cumulated experience of crime. We now introduce the past average percentage of years of in which crime was experienced (its *chronicity*: $Foster_{it-1}$ in equation (1])) and whether a given number of years of victimisation reduce sleep quality more if they are consecutive (picking up the *persistence* of crime victimisation: BCD_{it-1} in equation (2])), both calculated for all of the past years excluding the current year. As can be seen from equation (2), the BCD *persistence* index mechanically includes *chronicity*. In order to disentangle the two, we introduce both the lagged $Foster$ index ($Foster_{it-1}$) and the difference between the two terms (BCD_{it-1}–$Foster_{it-1}$) in the regressions. This second term then picks up *persistence* conditional on the *chronicity* of crime victimisation. We expect past crime *persistence* (BCD^{PV}_{it-1}–$Foster^{PV}_{it-1}$, BCD^{PC}_{it-1}–$Foster^{PC}_{it-1}$) to be associated with worse current sleep quality.

The results in column (3) in Table 3 clearly show that the *chronicity* of crime reduces sleep quality, with the effects being much larger for physical violence than for property crime. It is thus not only contemporaneous crime victimisation that matters, but also the degree to which crime has been experienced in the past. The results with respect to the *persistence* of crime victimisation are much more mixed. *Persistence* in physical violence (BCD^{PV}_{it-1}–$Foster^{PV}_{it-1}$) is positive and statistically significant at the 10% level. However, there is no evidence that the *persistence* of property crimes leads to a lower quality of sleep. This weaker set of results for *persistence*, conditional on *chronicity*, may well reflect the lack of conditional variation in *persistence* that was suggested by the mean figures in Table 1.

While we have found significant negative effects of both contemporaneous and past experiences of physical violence and property crimes on the overall measure of poor sleep quality, it is worth going further and investigating each component which make up this multifaceted indicator. It is not clear

Table 4: Crime victimisation over time and specific sleep quality (OLS estimates)

		Sleep quality				
		(i)	(ii)	(iii)	(iv)	(v)
Panel A	PV_{it}	0.163***	0.080**	0.104***	0.146***	–0.258*
		(0.038)	(0.033)	(0.031)	(0.037)	(0.134)
	PC_{it}	0.068***	0.069***	0.074***	0.023	–0.198***
		(0.022)	(0.022)	(0.019)	(0.018)	(0.070)
	Observations	14,503	14,503	14,503	14,503	14,503
	Adjusted R-Squared	0.072	0.052	0.061	0.049	0.057
Panel B	PV_{it}	0.110***	0.053	0.083**	0.143***	–0.096
		(0.042)	(0.036)	(0.034)	(0.041)	(0.143)
	PC_{it}	0.060**	0.070***	0.075***	0.029	–0.124*
		(0.024)	(0.023)	(0.020)	(0.019)	(0.072)
	$Past_{it-1}^{PV}$	0.092***	0.039**	0.049***	0.045***	–0.109**
		(0.017)	(0.017)	(0.015)	(0.014)	(0.055)
	$Past_{it-1}^{PC}$	0.017*	0.024**	0.013	0.008	–0.037
		(0.010)	(0.011)	(0.010)	(0.008)	(0.031)
	Observations	13,618	13,618	13,618	13,618	13,618
	Adjusted R-Squared	.074	0.052	0.059	0.048	0.051
Panel C	PV_{it}	0.105**	0.051	0.074**	0.139***	–0.080
		(0.043)	(0.037)	(0.035)	(0.041)	(0.145)
	PC_{it}	0.058**	0.065***	0.072***	0.029	–0.109
		(0.024)	(0.023)	(0.020)	(0.019)	(0.072)
	$Foster_{it-1}^{PV}$	0.270***	0.122**	0.187***	0.134***	–0.378*
		(0.057)	(0.051)	(0.047)	(0.047)	(0.209)
	$Foster_{it-1}^{PC}$	0.058*	0.109***	0.064*	0.006	–0.149
		(0.034)	(0.033)	(0.033)	(0.027)	(0.109)
	BCD_{it-1}^{PV}–$Foster_{it-1}^{PV}$	0.230	0.224*	–0.199	0.025	0.352
		(0.145)	(0.126)	(0.134)	(0.123)	(0.536)
	BCD_{it-1}^{PC}–$Foster_{it-1}^{PC}$	0.036	0.024	0.009	–0.006	–0.458
		(0.088)	(0.080)	(0.084)	(0.084)	(0.287)
	Observations	13,618	13,618	13,618	13,618	13,618
	Adjusted R-Squared	0.073	0.052	0.060	0.047	0.051

Notes: *** p<0.01; ** p<0.05; * p<0.10. (i) Very or fairly bad sleep quality in the past month; (ii) cannot get to sleep within 30 minutes in the past month; (iii) wakes up mid-night or early morning in the past month; (iv) takes medicine to help sleep in the past month; and (v) hours of sleep per day in a typical week. Robust standard errors clustered at the household level are in parentheses.

whether the five specific sleep problems will be affected by crime victimization in the same fashion. Moreover, as mentioned in Section 2.1, the overall index predicted from the PCA only explains about 40 percent of the variation in these five measures of sleep problems. We therefore below estimate the effects of crime victimisation over time separately for the five sleep problems, using the same specifications as in Table 3.

The simplest estimates in Panel A of Table 4 show that physical violence has a significant contemporaneous relationship with all the five sleep-quality measures. For example, those who were victims of physical violence over the past 12 months have a 16.3 percentage-point higher probability of very or fairly bad sleep quality, and daily duration of sleep in a typical week that is 0.258 hours (15 minutes) lower. The contemporaneous effects of property crime are smaller. While there is no evidence that current experience of a property crime increases the probability of taking medicine to help sleep, its effects on the other four sleep-quality measures are all statistically significant and of the expected sign.

Panel B of Table 4 then shows that, after controlling for current crime victimisation, past victimisation has a scarring effect on current sleep quality, particularly for physical violence. In addition, the results in Panel C suggest that the *chronicity* of crime reduces sleep quality, with the effects being larger for physical violence than for property crime. Furthermore, the *persistence* of physical violence is positive and statistically significant at the 10% level for having difficulty in getting to sleep within 30 minutes, but not for the other four sleep measures. In contrast, for property crime, we find no evidence that *persistence* is related to the five specific sleep problems. In general, the results in Table 4 are consistent with those in Table 3.

5 Conclusion

We here used data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey to investigate the link between crime victimisation over time and sleep quality. We first highlight that both contemporaneous physical violence and property crime are associated with worse sleep quality, with the former having a much larger impact than the latter. Second, any past crime exposure continues to impair current sleep, with a negative effect that is somewhat smaller than that of contemporaneous victimisation. Third, the intensive margin of past crime exposure, *chronicity*, also reduces current sleep quality. Last, there is weaker evidence that the *persistence* of crime victimisation also matters, although we do not have much variation to play with here. Consecutive years of physical violence are associated with more difficulty in getting off to sleep, while sleep duration is shorter with consecutive years of property crime.

Overall then, crime has long-lasting impacts on one of the most important health inputs, sleep. We thus provide new information on the non-pecuniary costs of crime, explicitly taking the past into account: the comparison of the figures in Table 3 suggest that taking the past into account produces a sleep cost of crime that is often between one quarter to one half larger than that implied by the contemporaneous correlation. We also help to bridge the gap between theoretical and empirical research, by showing that the *chronicity* and *persistence* indices recently developed in the theoretical literature can be applied to the question of how crime affects the quality of sleep. In terms of crime prevention or medical or psychological help for crime victims, the most vulnerable groups are not only the current victims but also those who have been more heavily exposed in the past. For many of our estimates in Tables 3 and 4, the poorer-sleep consequences of someone who is a victim today but has not been so in the past are smaller than those of someone who is not a victim today but has past crime exposure of around 50 percent. Public policy in this context needs to take the whole history of crime exposure into account.

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Table A1: Principal component analysis of sleep problems

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.001	1.036	0.400	0.400
Comp2	0.965	0.073	0.193	0.593
Comp3	0.892	0.278	0.178	0.771
Comp4	0.613	0.084	0.123	0.894
Comp5	0.530	.	0.106	1.000

Table A2: Contribution of variables to the components in PCA

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Unexplained
Very or fairly bad sleep quality	0.496	–0.341	0.141	0.784	0.062	0.000
Cannot get to sleep within 30 minutes	0.509	0.367	–0.294	–0.052	–0.720	0.000
Wakes up mid-night or early morning	0.501	0.324	–0.382	–0.162	0.687	0.000
Takes medicine to help sleep	0.327	0.297	0.865	–0.237	0.046	0.000
Hours of sleep per day	–0.371	0.746	0.031	0.548	0.065	0.000

Table A3: Estimated coefficients on the control variables in Table 3 (OLS estimates)

	Overall index of poor sleep quality		
	(1)	(2)	(3)
Age	0.030***	0.027***	0.029***
	(0.003)	(0.003)	(0.003))
Age-squared/100	–0.026***	–0.023***	–0.025***
	(0.003)	(0.003)	(0.003)
Male	–0.188***	–0.194***	–0.193***
	(0.017)	(0.018)	(0.018)
Years of education	–0.029***	–0.028***	–0.028****
	(0.005)	(0.005)	(0.005)
Married (Reference: Never married)	0.008	0.017	0.012
	(0.027)	(0.029)	(0.029)
Widowed	0.114**	0.113*	0.109*
	(0.057)	(0.058)	(0.058)
Divorced	0.160***	0.164***	0.163***
	(0.046)	(0.047)	(0.048)
Separated	0.199***	0.186***	0.185***
	(0.061)	(0.062)	(0.062)
Number of children in household	0.002	0.004	0.004
	(0.010)	(0.010)	(0.010)
Log of real household disposable regular income	–0.018	–0.014	–0.015
	(0.011)	(0.011)	(0.011)
Living in a major city	0.013	–0.026	–0.026
	(0.099)	(0.098)	(0.098)
Agreeableness	–0.034***	–0.033***	–0.033***
	(0.010)	(0.011)	(0.011)
Conscientiousness	–0.028***	–0.026***	–0.026***
	(0.010)	(0.010)	(0.010)
Emotional stability (Neuroticism)	–0.177***	–0.178***	–0.178***
	(0.010)	(0.010)	(0.010)
Extroversion	–0.046***	–0.049***	–0.050***
	(0.009)	(0.009)	(0.009)
Openness to experience	0.033***	0.032***	0.032***
	(0.010)	(0.010)	(0.010)
Constant	0.143	0.147	0.119
	(0.318)	(0.318)	(0.319)
Observations	14,503	13,618	13,618
Adjusted R-Squared	0.097	0.097	0.097

Notes: *** p<0.01; ** p<0.05; * p<0.10. The dependent variable is the overall index of poor sleep quality predicted from the PCA. Postcode-level fixed effects are included in the estimations. Robust standard errors clustered at the household level are in parentheses.

Table A4: OLS estimates after correcting for survey non-response

	Overall index of poor sleep quality		
	(1)	(2)	(3)
PV_{it}	0.493***	0.344***	0.346***
	(0.099)	(0.105)	(0.105)
PC_{it}	0.215***	0.197***	0.191***
	(0.063)	(0.067)	(0.068)
$Past^{PV}_{it-1}$		0.224***	
		(0.040)	
$Past^{PC}_{it-1}$		0.043*	
		(0.025)	
$Foster^{PV}_{it-1}$			0.609***
			(0.138)
$Foster^{PC}_{it-1}$			0.163***
			(0.077)
BCD^{PV}_{it-1}–$Foster^{PV}_{it-1}$			0.737**
			(0.352)
BCD^{PC}_{it-1}–$Foster^{PC}_{it-1}$			0.160
			(0.193)
Observations	14,503	13,618	13,618
Adjusted R-Squared	0.121	0.123	0.121

Notes: *** p<0.01; ** p<0.05; * p<0.10. The dependent variable is the overall index of poor sleep quality predicted from the PCA. Robust standard errors clustered at the household level are in parentheses. Survey non-response is corrected using sample weights.