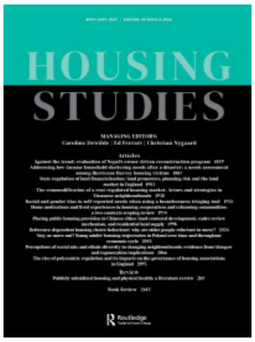

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The effect of dwelling-based and neighbourhood-based precariousness on mental wellbeing

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ABSTRACT
This study examines the impacts of dwelling-based and neighbourhood-based precariousness on mental wellbeing by applying panel data modelling approaches to the 2001–2020 Household, Income and Labour Dynamics in Australia (HILDA) survey. We find that living in unaffordable housing has the largest adverse effects on mental wellbeing among all forms of dwelling-based precariousness modelled in the study. Neighbourhood hostility and neighbourhood crime are key forms of neighbourhood-based precariousness that depress mental wellbeing. On the other hand, some forms of housing precariousness have insignificant impacts on wellbeing, in particular overcrowding and vandalism. Notwithstanding the importance of neighbourhood aspects, overall dwelling-based precariousness has a larger detrimental impact on mental wellbeing than neighbourhood-based precariousness. We test the robustness of linear models by implementing Tobit models that take into account the bounded nature of wellbeing measures that are ignored in linear models. We find that both models produce similar findings. The analysis in this study leads to important policy implications in a world that is increasingly exposed to public health crises. Importantly, the findings point to an urgency for policies and programs to be embedded within housing systems that ensure vulnerable population groups have long-term rather than temporary access to secure housing.

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Precarious housing; wellbeing; dwelling; neighbourhood; affordability

Introduction

The links between housing and wellbeing outcomes have been documented widely in the international literature. Housing is a fundamental contributor to individual wellbeing through the range of shelter and non-shelter benefits it provides. For instance, secure housing provides stability for employment, wealth creation, security, safety and a base from which to have a healthy and productive life. However, housing security is not the common experience across the population. Vast segments of

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populations worldwide experience housing precariousness, which occurs when people live in housing that is unsafe, unsuitable and insecure, which results in poor health and wellbeing (Clair *et al.*, 2019; Swope & Hernandez, 2019). Underscoring the importance of housing as a key contributor to wellbeing, the World Health Organization (WHO) in 2018 released a set of housing and health guidelines after conducting a rigorous review of the recent literature at the time, with the goal of informing housing policies on the impact of housing on health. They argue that the effect of housing on health and the prevalence of poor housing conditions globally justify the need for guidelines that ensure safe and healthy housing which provide protection from potential hazards.

While not explicitly stated in the literature, studies on the relationship between precarious housing and wellbeing have typically focused on either dwelling-based or neighbourhood-based dimensions. The general consensus in the literature is that both dwelling-based and neighbourhood-based precariousness have adverse impacts on wellbeing.

Dwelling-based precariousness broadly refers to aspects that are dwelling or household-specific, including tenure insecurity, unaffordability, and housing quality. Tenure insecurity is often proxied by renting in the private sector and the frequency of moves in the literature. Numerous studies have documented the negative links between private renting – a traditionally more insecure sector than either ownership or social housing – and wellbeing (McKee *et al.*, 2020; Dunn, 2002). The frequency of moves, and especially forced moves, are also found to have adverse impacts on wellbeing. For instance, Lim *et al.* (2022) link frequent moves after traumatic events to a higher risk of depression, Desmond and Kimbro (2015) document links between eviction and depression among mothers, and Ong ViforJ *et al.* (2022a) estimate that forced moves reduce average mental health scores and raise psychological distress scores by 2% and 3%, respectively. Unsurprisingly, studies have consistently found that housing unaffordability depresses wellbeing levels, using a range of measures such as housing cost to income ratios (Park & Seo, 2020; Baker *et al.*, 2020) and difficulty making housing payments on time (Curl & Kearns, 2015). That poor housing quality raises the odds of poor health is also a common finding. Examples include Boch *et al.* (2020) who discover that for each additional housing condition problem that is reported, there is a 1.2 times increased chance of poorer health, Navarro *et al.* (2010) who link a lack of heating or hot water to 1.2 times higher odds of poor health, and Pevalin *et al.* (2017) who show that persistent housing problems such as dampness and inadequate heating over a four-year period depresses mental health.

A parallel pool of literature exists, which investigates the effect of neighbourhood-based precariousness on wellbeing. This literature is broadly split into two strands of studies which focus separately on the neighbourhood's physical environment and the socioeconomic status (SES). Examples of studies making up the former strand are studies documenting links between neighbourhood crime and lower life satisfaction (Brenig & Proeger, 2018), dissatisfaction with neighbourhood aspects such as crime, building maintenance, friendliness and emotional distress (Wilson *et al.*, 2004) and perceived neighbourhood quality including vandalism, noise, untidy gardens and mental health (Bond *et al.*, 2012). Eibich *et al.* (2016) find that access to services leads to better mental health, while noise and pollution results in poorer mental health, whereas Astell-Burt and Feng (2019) conclude that greater exposure to green space is associated with lower psychological distress. Distance to amenities and urban facilities is found to be positively associated with life satisfaction (Arifwidodo & Perera, 2011), and the amount of green vegetation present in coastal areas is beneficial to life satisfaction (Kubiszewski *et al.*, 2019).

The literature has also found a consistently negative link between low neighbourhood SES and wellbeing. For instance, Jivraj *et al.* (2019) show a negative association between neighbourhood deprivation and mental health, where deprivation is commonly measured as a composite of common underlying SES measures, such as income, labour market participation, occupational status, welfare support and educational attainment. The World Health Organization (2018) argues that living in areas with higher neighbourhood-level poverty is linked with higher rates of hospitalization for childhood asthma. Bonomi Bezzo *et al.* (2021) find that during the COVID-19 lockdowns, residents of more deprived neighbourhoods experience a greater decline in hedonic wellbeing compared to those in better areas, and Godhwani *et al.* (2019) find that residents of more deprived areas are more likely to record poor general health than those in less deprived areas.

While most studies examine a single form of housing precariousness, a number investigate multiple forms at the same time. For example, Clair and Hughes (2019) and Baker and Lester (2017) explore a series of dwelling-based precarious aspects simultaneously in the form of tenure insecurity, unaffordability and housing quality. The former focuses on impacts on C-reactive protein, a biomarker associated with infection and stress, while the latter investigates psychological distress. Exceptions include studies such as Mallett *et al.* (2011), Jones-Rounds *et al.* (2014), Clair *et al.* (2019) and Ong ViforJ *et al.* (2022b) who investigate a mix of dwelling-based and neighbourhood-based precariousness.

Although the term 'housing precariousness' is traditionally used to solely refer to dwelling-based forms, it is clear from a review of the international literature that housing precariousness is a multi-dimensional experience which includes neighbourhood-based aspects. This is akin to conceptualization in an updated glossary on housing and health by Mansour *et al.* (2022, p834), who posit that 'healthy housing also extends beyond the four walls of the home. The surrounding environment, a sense of belonging to place and the community in which it is situated all play an important role'. They link healthy housing to neighbourhood aspects such as noise and pollutants. Similarly, the WHO (2018) associates the concept of healthy housing with aspects both inside and outside the home. We argue, therefore, that the converse must then be true, in that housing that is detrimental to health should also be conceptualized through the lens of both dwelling-based and neighbourhood-based forms. Furthermore, a European study by Clair *et al.* (2019) discusses access to services alongside dwelling-related aspects under the overall term of housing precariousness.

We illustrate our conceptualization of the links between precarious housing and wellbeing within Figure 1. We begin with Mansour *et al.*'s (2022) conceptual framing, which posits that healthy housing is a composite concept made up of the domains of security, affordability and suitability. Each of these three domains is in turn driven by distinct sets of housing-related aspects (see Figure 2 in Mansour *et al.*, 2022, p834). We enrich this framing by integrating the WHO's (2018) perspective on

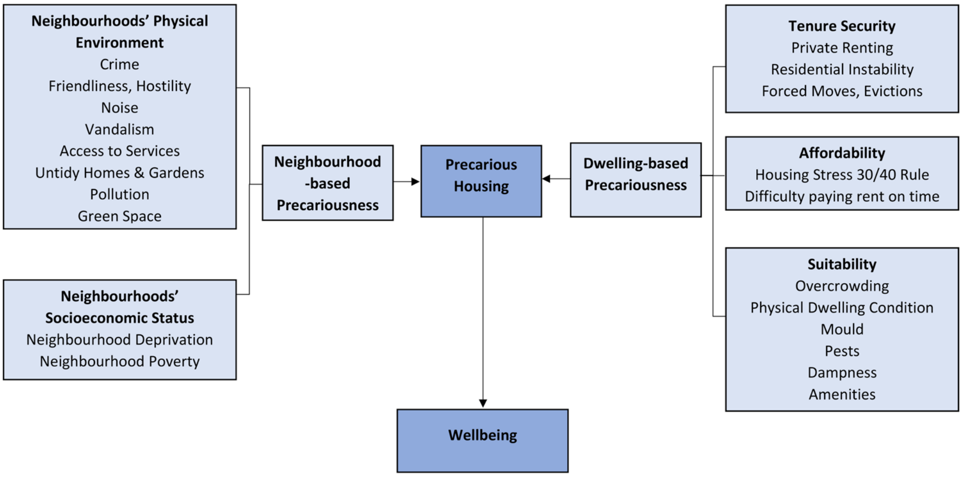

Figure 1. Conceptual framing of the links between precarious housing and wellbeing.
Source: Author's framing, adapted from Mansour *et al.* (2022), WHO (2018) and relevant literature.

healthy housing, which captures conditions both inside and outside the home and drawing on key dwelling-based and neighbourhood-based dimensions identified in the literature review. Hence, as shown in Figure 1, we posit that housing precariousness is a composite of dwelling-based and neighbourhood-based forms of precariousness. Each form of precariousness is in turn driven by distinct sets of dwelling-based and neighbourhood-based aspects, respectively.

While the evidence base linking housing precariousness to wellbeing is large, there remain some important limitations within this literature. There are at least four distinct gaps, which we address in our article.

First, we conceptualize housing precariousness as a multi-dimensional measure that manifests at both dwelling and neighbourhood levels. Existing studies have typically only focused on dwelling-based aspects when analysing precarious housing (e.g. Baker & Lester, 2017; Clair & Hughes, 2019). In this article, we broaden the conceptualization of housing precariousness to include both dwelling-based and neighbourhood-based aspects. We draw on Mansour *et al.* (2022), an epidemiology paper which proposes that the idea of healthy housing is not only influenced by dwelling-related aspects, but neighbourhood-related aspects as well. We argue that the converse must then apply. Thus, neighbourhood-based aspects are considered alongside dwelling-based aspects when discussing precarious housing in our study. We uncover specific precarious housing dimensions both dwelling and neighbourhood-based that are particularly important for wellbeing outcomes, thus providing a nuanced evidence base that can better support targeting of policy measures on the dwelling and neighbourhood dimensions which have the greatest impacts on population wellbeing.

The next three gaps relate to the methodological limitations of existing approaches to modelling the relationships between housing and wellbeing. If unaddressed, these existing approaches could result in erroneous findings which could lead to ineffective housing policy formulation. We therefore contribute three distinct methodological refinements, which could potentially enhance the accuracy of findings for informing housing policy development to promote wellbeing.

In relation to the first methodological refinement, we pay particular attention to the approaches in modelling the relationship. Most wellbeing measures are bounded between an upper and lower limit, such as the SF-36 Mental Component Summary (MCS) score which ranges from 0 to 100 or the Warwick-Edinburgh Mental Wellbeing Scale that ranges from 7 to 35. However, housing studies typically tend to analyse these bounded outcomes using traditional linear models (Baker *et al.*, 2013; Bentley *et al.*, 2016; Smith *et al.*, 2017; Ong ViforJ *et al.*, 2022a). We argue that the linear regression method is flawed because it assumes that reported wellbeing scores can take on any value from negative infinite to positive infinite (Brooks, 2014). We apply the Tobit model, which has been used outside the field of housing to model bounded wellbeing outcomes (Tran *et al.*, 2020). Conceptually, a Tobit model will present more accurate findings compared to linear models because our wellbeing scores are bounded. If linear models were applied, the models may be mis-specified and produce biased and inconsistent results (McDonald & Nguyen, 2015). By comparing results from the linear and Tobit models, we are able to shed light on whether a shift away from the simpler linear modelling towards more complex Tobit models is justified. If the two modelling approaches produce very different findings, then the shift in approach is justified despite the fact that linear models tend to be more easily interpretable.

The second methodological gap relates to the capture of the multidimensionality of housing precariousness within single indices rather than a range of separate discrete dwelling-based and neighbourhood-based variables. We construct indices that capture both sets of variables using Multiple Correspondence Analysis (MCA), which is a valuable methodological contribution to the wider housing literature. Most housing studies use composite measures to construct indices (Baker *et al.*, 2019; Boch *et al.*, 2020). All of the variables usually equally weighted in the index[1], therefore, not reflecting the relative importance of each variable or the correlation across variables. To overcome these shortcomings, a principal component analysis (PCA) is often used to construct indices by selecting a subset of components that aim to summarize the information contained in the data, thus allowing for factor reduction (Brooks, 2014). However, the PCA is suited to variables that are continuous[2] and also relies on the assumption of linearity. To overcome these limitations, we use MCA to create suitable indices from both the dwelling-based and neighbourhood-based variables. These aspects are non-continuous in nature (and may contain non-linear relationships) and this is exactly where MCA offers an advantage over PCA. In addition to this, MCA (similar to PCA) will select a subset of the most relevant factors. Our application of MCA represents a methodological improvement that is likely to produce more accurate findings on the links between overall housing precariousness and wellbeing for informing housing policy development than either the composite measures or PCA.

Our final contribution extends existing studies by analysing how *changes* in precarious housing conditions affect *changes* in wellbeing levels. A limitation of existing studies is that they typically analyse the relationship between housing and wellbeing using level models. However, the two types of models address different research questions. For instance, a level model may find that living in unaffordable housing is linked to a lower level of wellbeing than living in affordable housing. This does not explain whether falling into unaffordability (i.e. a change in affordability status) results in a change in wellbeing. This is important for determining which policy interventions may be the most effective in generating a change in wellbeing within a short timeframe.

Given this contextual background, we investigate how different dimensions of housing precariousness affect the wellbeing of Australian adults by addressing three research questions:

1. What are the multi-dimensional impacts of dwelling-based and neighbourhood-based precariousness on wellbeing?
2. Are estimates of the links between precarious housing and wellbeing sensitive to different model specifications?
3. What is the impact of a change in exposure to dwelling-based and neighbourhood-based precariousness on changes in wellbeing?

Methodology

Data and sample

This article draws on the Household, Income and Labour Dynamics Australia (HILDA) survey, a nationally representative longitudinal survey that tracks individuals and households over time. This survey has been collecting data annually since 2001. Data are obtained on a range of topics such as wellbeing, housing, employment and income. Information is gathered from respondents *via* face-to-face interviews and self-completed questionnaires (Melbourne Institute, n.d.).

The sample for this article is drawn from waves 1–20 of the HILDA survey, covering a timeframe spanning 2001–2020. We select individuals aged 15 years and over and who are independent adults in each wave. The observations from each wave are stacked into a person-period dataset, with each individual in the dataset possessing multiple records, one for each time period they are observed in. There are approximately 165,000 observations available for analysis pooled across all waves, ranging from 6,000 to 12,000 observations per wave. We apply a series of panel data regression models on this person-period dataset to estimates the links between precarious housing and wellbeing.

Key variables

We measure wellbeing using the SF-36 MCS score, which is derived from the SF-36 vitality, social functioning, mental health and role-emotional subscales. The MCS score is a continuous measure that is bounded between the values of 0 and 100, with a higher score representing better mental wellbeing. This summary score has been widely used as a measure for individual wellbeing in studies linking housing and wellbeing, such as Baker *et al.* (2020), Mallett *et al.* (2011) and Kavanagh *et al.* (2016).

The analysis draws on four dwelling-based and seven neighbourhood-based variables to explore the wide range of precarious housing dimensions affecting wellbeing, with the choice of variables influenced by the conceptualization of precarious housing by existing studies (Mallett *et al.*, 2011; Baker & Lester, 2017; Clair & Hughes, 2019; Mansour *et al.*, 2022). However, the variables that can be included in the analysis are limited to the information we can draw from the HILDA survey. Some of the key variables identified in the literature that are unavailable in the HILDA data include green space, distance to amenities and physical dwelling condition including mould and dampness. Nonetheless, the richness of the survey has enabled us to largely account for an extensive range of precarious housing dimensions that have been highlighted as important in the literature.

The dwelling-based precarious aspects employed in this analysis include forced moves, housing stress and overcrowding, representing the dimensions of tenure insecurity, unaffordability and housing quality respectively that have been identified in the literature as key aspects that affect wellbeing. Forced moves are defined as an address change since the last interview due to one of the following reasons – evicted, government housing and had no choice, or property is no longer available. Unaffordable housing is measured in two ways. First, we apply a widely used binary indicator of housing stress in Australia based on the 30/40 rule, which takes on a value of 1 if an individual's household spends more than 30% of their income on housing costs while being in the lowest 40% of the equivalised household income distribution (Baker *et al.*, 2020). Second, we apply an indicator for whether a person experienced difficulty making mortgage or rent payments due to a shortage of money in the last year, in addition to being in the lowest 40% of the equivalised household income distribution. Individuals are classified as living in overcrowded conditions if the number of bedrooms in their household is less than those specified under the Canadian National Occupancy Standard (CNOS)[3] (Mallett *et al.*, 2011).

The neighbourhood-based precarious aspects consist of six different variables that address the physical environment. They measure on a scale of 1–5 how frequently an individual experiences a particular issue in the neighbourhood, with 1 representing 'never happens' and 5 'very common'. These variables account for neighbourhood crime, hostility, homes and gardens in bad conditions, traffic noise, vandalism, and other noise from planes, trains, and industry. To allow for comparison to the dichotomous dwelling-based precarious aspects, each level of the scale for each of the neighbourhood indicators is converted to dummy variables. The socioeconomic environment is accounted for *via* a Socio-Economic Indexes for Areas (SEIFA) index of relative socioeconomic advantage/disadvantage to measure neighbourhood-based SES. This index is a continuum of disadvantage to advantage, taking into consideration elements such as those employed in a skilled occupation, tertiary education and proportion of families with high income (ABS, 2018). The SEIFA index is categorized into quintiles which are each entered into the models separately to allow comparison to the dwelling-based indicators. Moreover, the quintiles are reverse scored so that a higher quintile represents a more disadvantaged area.

MCA

MCA is applied to combine the four dwelling-based precarious housing factors into one index, and the seven neighbourhood-based precarious housing factors into another index. The two indices constructed are scaled to begin scoring at 0, with a higher score indicating greater levels of precariousness. The dwelling-based index scoring runs from 0 to 9.2, the neighbourhood-based index scoring runs from 0 to 12.4. Both indices are unequally weighted to highlight the importance of each factor within their respective index (Filali, 2012). Within the dwelling-based index, the first dimension accounts for 85.4% of the overall variance, with housing stress under the 30/40 rule and difficulty making housing payments on time providing the strongest contributions of 31.4% and 35.7% of the variance, respectively. Within the neighbourhood-based index, neighbourhood crime, hostility and vandalism have the strongest influences with each contributing to 21%–27% of the variance. A more detailed description of the index construction is presented in Section 1 of the online supplementary materials, which also describes how the index is weighted, illustrated using Table S1.

Modelling strategy

To address the first research question, we employ a Tobit regression, which is also known as a censored regression. It is a well-known technique used to deal with censored or bounded outcomes (Austin *et al.*, 2000; Smithson & Shou, 2021). Since the dependent variable employed in this analysis is bounded between 0 and 100[4], a standard OLS approach does not guarantee that the model predictions will be bounded. In fact, the OLS estimator is biased and inconsistent (McDonald & Nguyen, 2015). As such, an alternative framework is required which takes into account the boundness of the dependent variable. Moreover, only a random effects estimator is available for the Tobit model, as no appropriate fixed effects estimators are available (Greene, 2004)[5]. Thus, we employ a random effects Tobit model, which takes on the following form:

$$\mathrm{Well}_{i,t+1} = \beta_1 HH\mathrm{prec}_{i,t} + \beta_2 NHprec_{i,t} + \beta_3 X_{i,t} + \varepsilon_{i,t} \quad (1)$$

$$\mathrm{Well}_{i,t+1} = \mathrm{Well}^*_{i,t+1} \text{ if } 0 < \mathrm{Well}^*_{i,t+1} < 100$$

$$\mathrm{Well}_{i,t+1} = 0 \text{ if } 0 \leq \mathrm{Well}^*_{i,t+1}$$

$$\mathrm{Well}_{i,t+1} = 100 \text{ if } \mathrm{Well}^*_{i,t+1} \geq 100$$

where $\mathrm{Well}_{i,t+1}$[6] represents the observed MCS wellbeing score for individual i at time $t+1$. If the latent wellbeing score takes on a value less than or equal to 0, then wellbeing is bounded to a score of 0. Likewise, if the latent wellbeing score takes on a value greater than or equal to 100, then wellbeing is bounded to a score of 100. Unlike OLS models, this mechanism ensures that the Tobit model will not produce nonsensical values because it bounds these values which fall outside the lower or upper limit (in our case, 0 or 100, respectively). The variables $HHprec_{i,t}$ and $NHprec_{i,t}$ represent the indexed values of the dwelling-based and neighbourhood-based precarious variables for individual i at time t, respectively. The exception is the forced moves variable, which is measured as forced moves that occur between time t and $t+1$, so that it is an event occurring within the same year leading up to the wellbeing outcome of interest which is measured at $t+1$. The matrix of control variables, $\boldsymbol{X}$ includes gender, ancestry, housing tenure, socioeconomic characteristics, human capital characteristics, geography, and time fixed effects. The predictors including the controls are defined in detail in the online supplementary material Table S2.

The wellbeing outcome at time $t+1$ is matched with the dwelling-based and neighbourhood-based variables at time t. This approach attempts to minimize potential endogeneity by matching the predictor in one year with wellbeing outcomes a year later. The marginal effects are used to interpret the results/estimates of the model (Wooldridge, 2009).

Additional Tobit models are estimated which interchange the dwelling-based index and neighbourhood-based index into the model for the individual factors of the indices. This compares if overall, dwelling or neighbourhood-based precariousness has the greater impact on wellbeing.

To address the second research question, the random effects Tobit model estimates are compared with random effects linear models. This allows us to examine the full extent of misspecification produced by a linear model when analysing bounded wellbeing outcomes. Similar to Equation (1), additional linear models are deployed which substitute the two precarious housing indices for the individual precariousness factors.

To address the third research question, we estimate pooled Tobit change models. Change models account for unobserved heterogeneity such as ethnicity or sex that usually remain fixed across time periods (Andreß *et al.*, 2013; Wooldridge, 2009). The change model additionally eliminates measurement bias, which potentially arises with self-reported wellbeing responses in surveys (Liker *et al.*, 1985). The pooled Tobit change models take on the following form:

$$\Delta \text{Well}_{i,t\&t-1} = \beta_1 \Delta HH\text{prec}_{i,t\&t-1} + \beta_2 \Delta NH\text{prec}_{i,t\&t-1} + \beta_3 \Delta X_{i,t\&t-1} + \beta_4 Z_{i,t} + u_{i,t} \tag{2}$$

where $\Delta \text{Well}_{i,t\&t-1}$ denotes change in MCS score between waves t and t-1 for individual i, with the change model bounding the values between −100 and 100. The variables $\Delta HH\text{prec}_{i,t\&t-1}$ and $\Delta NH\text{prec}_{i,t\&t-1}$ represent the change in the dwelling-based and neighbourhood-based precariousness measures between adjacent waves for individual i, respectively.[7] The change in control variables is given by $\Delta\boldsymbol{X}$, while $\boldsymbol{Z}$ represents a selected group of time invariant control variables.[8]

In order to estimate the change model, variables which were originally binary indicators such as unaffordability and employment status were split into four categories. There is one category to indicate an 'improvement' between waves (i.e. gain employment), a 'decline' between waves (i.e. lose employment), 'remaining in the same positive state' between waves (i.e. remain employed) and 'remain in the same negative state' between waves (i.e. remain unemployed). Regarding the continuous and ordinal variables within the model, such as the wellbeing outcomes and neighbourhood scores, the first difference is taken to measure change. This is calculated by taking the value at time *t* and subtracting it from the value at *t - 1*. These changes can take on a positive or negative value depending on if there is an increase or decrease between time periods.

Similar to the previous modelling approach, an additional set of models is estimated which interchanges the change in separate precarious factors with the change in their respective indices. A likelihood-ratio test, comparing the panel Tobit model with the pooled version indicates that there are no panel effects detected within the change model and thus, a pooled specification is more suitable than a panel specification. This appears to be justified since the change specification essentially removes any fixed effects *via* differencing.

Results

Table 1 compares mean MCS scores across different forms of housing precariousness, with the full set of results reported in Table S3 in the online supplementary materials.

Table 1. Mean wellbeing score and characteristics of precarious housing groups, pooled observations from 2001 to 2020.

Variable at t	Number of observations	% of total observations	Mean SF-36 MCS score
All	164,698	100	51.8
Dwelling-based precariousness			
0 Forms of dwelling-based precariousness	147,654	89.7	52.4
1 Form of dwelling-based precariousness	14,451	8.8	47.7
2+ Forms of dwelling-based precariousness	2,593	1.5	42.0
Forced to move between t and t+1	2,373	1.4	47.9
In housing stress according to the 30/40 rule	9,121	5.5	46.7
Had difficulty paying rent or mortgage in the last 12 months	4,349	2.6	41.2
In overcrowded housing	3,986	2.4	48.8
Neighbourhood-based precariousness			
0 Forms of neighbourhood-based precariousness	51,179	31.1	54.6
1 Form of neighbourhood-based precariousness	57,219	34.7	52.4
2+ Forms of neighbourhood-based precariousness	56,300	34.2	48.8
Crime (burglary or theft) fairly or very common	20,432	12.4	47.6
People being hostile or aggressive fairly or very common	8,833	5.4	43.5
Homes and gardens in bad condition fairly or very common	18,639	11.3	47.3
Traffic noise fairly or very common	44,938	27.3	49.2
Vandalism fairly or very common	16,532	10	47.2
Noise from planes, trains, or industry fairly or very common	34,932	21.2	49.6
SEIFA (Lowest quintile)	30,592	18.6	48.7
Precarious housing indices			
High dwelling-based precarious index (above 90th percentile)	17,044	10.3	46.7
Low dwelling-based precarious index (below 90th percentile)	147,654	89.7	52.4
High neighbourhood-based precarious index (above 90th percentile)	16,313	9.9	49.3
Low neighbourhood-based precarious index (below 90th percentile)	148,385	90.1	52.1

Source: Authors' own calculations from the 2001–2020 HILDA Survey.
Full descriptive results are reported in Table S3 in the online supplementary materials.

We observe 33% experiencing one form of precariousness overall, with 18% and 20% observed for two and three plus forms of precariousness respectively. Highlighting how common precariousness is.

The incidence of dwelling-based precariousness ranges from 9% reporting one form and 2% two forms. Regarding the individual aspects, 1% report forced moves and 3% and 6% report unaffordability based on difficulty making housing payments on time and the 30/40 rule, respectively. Unaffordability appears to be the most common form of dwelling-based precariousness that households suffer from. We observe a much higher incidence of neighbourhood-based precariousness compared to dwelling-based precariousness. For instance, 34% experience two or more forms of neighbourhood-based precariousness. Specifically, 12% experience neighbourhood crime and 27% traffic noise fairly or very commonly, while neighbourhood hostility is the least frequent form of neighbourhood precariousness reported at 5%. These statistics highlight the prevalence of neighbourhood issues in everyday life, which have the potential to be detrimental to wellbeing, especially if they compound together with other forms of neighbourhood or dwelling-based precariousness.

The worst mean MCS scores (41 points) are detected among those who experience difficulty making housing payments on time and those who encounter neighbourhood hostility fairly or very commonly. The general trend evident in Table 1 is that there is a wellbeing penalty associated with the experience of precarious housing. In the absence of any form of precariousness, the mean MCS score is 52 points. When greater than 3 forms of precariousness exists, a MCS score penalty of 5 points is detected. At the top 10th percentile of the dwelling-based index, the average MCS score is 47, whereas those in the bottom to 90th percentile report an average MCS score of 52, a 5-point difference. There is a smaller difference of 3 points when considering the difference in average MCS score of those in the top 10th percentile and bottom to 90th percentile of the neighbourhood-based index distribution.

Additionally, we note that residing in the private rental sector, having a highest qualification equivalent to year 11 or below, and low incomes are all linked with lower-than-average MCS scores. On the other hand, homeownership, having a qualification of year 12 and above, employment and medium-to-high incomes are associated with a MCS score above the average. The lowest mean MCS scores are observed for public housing tenants and those with a long-term health condition, at 42 and 44 points, respectively.

Table 2[9] reports the random effects Tobit and linear model estimates expressed under Equations (1) and (2), where the wellbeing outcome is represented by the MCS score[10]. To address the first research question, we focus on the Tobit model estimates. Both dwelling and neighbourhood forms of precariousness are found to be detrimental to one's mental wellbeing after accounting for confounding influences in the regressions. Among the various forms of dwelling-based precariousness, the experience of difficulty making housing payments on time causes the largest decline in the MCS score by 1.5 points, or 3%.[11] Housing stress based on the 30/40 rule leads to the second largest drop in MCS score of 0.5 points or 1%. Among all forms of neighbourhood-based precariousness, neighbourhood hostility and a low neighbourhood SEIFA score have the biggest adverse impacts on the MCS score. Experiencing hostility in the neighbourhood very commonly causes a 1.7 point or

Table 2. Random effects Tobit and linear models of the link between dwelling-based and neighbourhood-based precariousness and wellbeing score, 2001–2020.

	Tobit marginal effects		Linear marginal effects	
Predictors	SF-36 MCS Score $t+1$	Std. Err.	SF-36 MCS Score $t+1$	Std. err.
Forced to move between *t* and *t*+1	−0.573**	0.226	−0.596***	0.231
Housing stress according to 30/40 rule	−0.508***	0.134	−0.538***	0.137
Difficulty paying rent or mortgage	−1.527***	0.180	−1.666***	0.183
Overcrowded	0.148	0.198	0.137	0.202
Experience neighbourhood crime – very rare	0.115	0.114	0.124	0.117
Experience neighbourhood crime – not common	−0.016	0.133	−0.013	0.136
Experience neighbourhood crime – fairly common	−0.259	0.167	−0.278	0.170
Experience neighbourhood crime – very common	−0.588**	0.269	−0.625**	0.275
Experience neighbourhood hostility – very rare	−0.269***	0.083	−0.300***	0.085
Experience neighbourhood hostility – not common	−0.695***	0.109	−0.761***	0.112
Experience neighbourhood hostility – fairly common	−1.108***	0.183	−1.242***	0.187
Experience neighbourhood hostility – very common	−1.657***	0.308	−1.810***	0.314
Experience neighbourhood homes and gardens in bad condition – very rare	−0.261**	0.125	−0.274**	0.128
Experience neighbourhood homes and gardens in bad condition – not common	−0.377***	0.132	−0.402***	0.135
Experience neighbourhood homes and gardens in bad condition – fairly common	−0.711***	0.162	−0.772***	0.165
Experience neighbourhood homes and gardens in bad condition – very common	−0.615**	0.242	−0.674***	0.248
Experience neighbourhood traffic noise – very rare	0.076	0.119	0.074	0.122
Experience neighbourhood traffic noise – not common	−0.130	0.129	−0.140	0.132
Experience neighbourhood traffic noise – fairly common	−0.417***	0.142	−0.446***	0.145
Experience neighbourhood traffic noise – very common	−0.665***	0.164	−0.717***	0.167
Experience neighbourhood vandalism – very rare	−0.082	0.101	−0.083	0.104
Experience neighbourhood vandalism – not common	0.024	0.129	0.019	0.132
Experience neighbourhood vandalism – fairly common	−0.159	0.170	−0.171	0.174
Experience neighbourhood vandalism – very common	0.020	0.282	0.026	0.288
Experience neighbourhood other noise (planes, trains, industry) – very rare	−0.074	0.084	−0.079	0.086
Experience neighbourhood other noise (planes, trains, industry) – not common	−0.171*	0.099	−0.189*	0.101
Experience neighbourhood other noise (planes, trains, industry) – fairly common	−0.109	0.116	−0.144	0.119
Experience neighbourhood other noise (planes, trains, industry) – very common	−0.181	0.152	−0.224	0.155
SEIFA index quintile 2, reverse scored	−0.195	0.138	−0.222	0.140
SEIFA index quintile 3, reverse scored	−0.252*	0.147	−0.308**	0.148
SEIFA index quintile 4, reverse scored	−0.593***	0.155	−0.659***	0.156
SEIFA index quintile 5, reverse scored	−1.101***	0.166	−1.197***	0.168
Constant			52.864***	0.394
Observations	164,698		164,698	
Number of groups	21,449		21,449	
Wald chi-squared (χ^2)	4,882.07***		5,393.62***	
Log-likelihood	−631,665.59			
Overall *R*-squared			0.113	

Source: Authors' own calculations from the 2001–2020 HILDA Survey.
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.
Standard errors are reported in parentheses. This table only reports key predictor estimates. Full regression model results including controls are reported in Table S4 in the online supplementary materials. The reference categories are: experience neighbourhood crime – not at all, experience neighbourhood hostility – not at all, experience neighbourhood homes and gardens in bad condition – not at all, experience neighbourhood traffic noise – not at all, experience neighbourhood vandalism – not at all, experience neighbourhood other noise – not at all, SEIFA index quintile 1, female, English ability – good, not Indigenous Australian, Country of birth – not Australia, Age 15–24, no dependent children, no long-term health condition, married, full-time employed, year 11 or below education, owner – outright, Sydney and wave 2.

3% fall in the MCS score compared to not experiencing hostility at all. Residing in an area in the lowest SEIFA quintile is associated with a 1.1 point or a 2% decrease in the MCS score compared to residence in the highest SEIFA quintile.

To address the second research question, we compare the random effects Tobit model estimates with the linear model estimates in Table 2. The marginal effect values for each predictor yielded from the linear model are only slightly higher compared to the Tobit model. Hence, the key findings remaining consistent between the two models. For instance, difficulty paying housing payments decreases the MCS score by 1.7 points in the linear model, compared to an estimated 1.5 point drop in the Tobit model. Very common hostility remains the neighbourhood-based variable that has the strongest impact on mental wellbeing across both models.

As a method of examining the sensitivity of the estimates to model specification, we have additionally estimated a fixed effects linear model, which is presented in Table S5 in the online supplementary materials, to compare the results with the random effects Tobit model. In general, the key findings remain consistent across the two models. Specifically, among dwelling-based precariousness predictors, forced moves, housing stress and difficulty paying rent are all statistically significant across both models, and overcrowding is insignificant across both. Regarding the neighbourhood-based precariousness aspects, the key findings are consistent across the two models, except for the neighbourhood crime and noise indicators. The very common indicator for crime and not common indicator for noise from planes, trains, or industry are significant in the Tobit model but not in the fixed effects linear model. Additionally, the fairly and very common traffic noise indicators possess stronger significance levels in the Tobit model. Furthermore, only one SEIFA quintile is statistically significant in the fixed effects model but in the random effects models, multiple quintiles are significant.

Table 3[12] presents the results from the levels model after combining the discrete dwelling-based and neighbourhood-based precarious variables into their respective indices. Examining the Tobit level model results initially, every unit increase in the

Table 3. Random effects Tobit and linear regression models of the link between overall dwelling-based and neighbourhood-based precariousness and wellbeing score, 2001–2020.

Predictors	Tobit marginal effects SF-36 MCS score $t+1$	Std. err.	Linear marginal effects SF-36 MCS score $t+1$	Std. err.
Dwelling-based Index	−0.328***	0.033	−0.353***	0.034
Neighbourhood-based Index	−0.085***	0.016	−0.093***	0.017
Constant	51.448***	0.389	51.763***	0.378
Observations	164,698		164,698	
Number of groups	21,449		21,449	
Wald chi-squared (χ^2)	4,444.01***		4,808.18***	
Log-likelihood	−631,873.80			
Overall R-Squared			0.094	

Source: Author's own calculations from the 2001-2020 HILDA Survey.
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.
Standard errors are reported in parentheses. This table only reports key predictor estimates. Full regression model results including controls are reported in Table S6 in the online supplementary materials. The reference categories are female, English ability – good, not Indigenous Australian, Country of birth – not Australia, age 15–24, no dependent children, no long-term health condition, married, full-time employed, year 11 or below education, owner – outright, Sydney and wave 2.

dwelling-based index is associated with a 0.3 point or 0.6% decrease in the MCS score, all else being equal. Every unit increase in the neighbourhood-based index results in a 0.1 point or 0.2% decline in the MCS score. Thus, as a whole, dwelling-based precariousness has the bigger influence on wellbeing. This could potentially be because the dwelling environment has a greater immediate impact on individuals' everyday life experiences than the neighbourhood environment. The former tends to be experienced daily; the latter might be encountered less frequently. A comparison of the effect of the dwelling-based and neighbourhood-based indices on the MCS score confirms very little difference across the Tobit and linear models. In both models, each additional unit rise in the dwelling-based (neighbourhood-based) precarious index causes a 0.4 (0.1) point fall in MCS.

Next, we address the third research question by analysing the change model estimates in Table 4.[13] Among dwelling-based change indicators, we find that exiting a period of difficulty paying rent or mortgage on time between *t*-1 and *t* results in

Table 4. Pooled Tobit change regression model of the link between change in dwelling-based and neighbourhood-based precariousness and change in wellbeing score, 2001–2020.

Predictors (change between *t* - 1 and *t*)	MCS score difference between *t* - 1 and *t*	Std. err.
Forced to move	−0.294	0.318
Fall into housing stress according to 30/40 rule	−0.066	0.223
Remain in housing stress according to 30/40 rule	−0.065	0.224
Escape from housing stress according to 30/40 rule	0.436**	0.213
Fall into difficulty making housing payments on time	−1.305***	0.284
Remain in difficulty making housing payments on time	−0.347	0.366
Escape from difficult making housing payments on time	0.936***	0.277
Fall into overcrowded housing	−0.265	0.365
Remain in overcrowded housing	0.269	0.293
Escape from overcrowded housing	−0.120	0.357
Increase in frequency of neighbourhood noise	−0.212*	0.111
Decrease in frequency of neighbourhood noise	0.265**	0.112
Increase in frequency of neighbourhood crime	−0.407***	0.125
Decrease in frequency of neighbourhood crime	0.059	0.122
Increase in frequency of neighbourhood hostility	−0.187	0.120
Decrease in frequency of neighbourhood hostility	0.383***	0.120
Increase in frequency of neighbourhood homes and gardens in bad condition	−0.300***	0.113
Decrease in frequency of neighbourhood homes and gardens in bad condition	0.242**	0.115
Increase in frequency of neighbourhood traffic noise	−0.095	0.112
Decrease in frequency of neighbourhood traffic noise	0.052	0.113
Increase in frequency of neighbourhood vandalism	0.016	0.127
Decrease in frequency of neighbourhood vandalism	0.095	0.125
Change in SEIFA index score, reverse scored	−0.001	0.001
Constant	−0.177	0.242
Observations	127,063	
Likelihood ratio chi-squared	1019.31***	
Pseudo R-squared	0.001	
Log likelihood	−492,476.98	

Source: Authors' own calculations from the 2001–2020 HILDA survey.
***$p<0.01$, **$p<0.05$, *$p<0.10$.
Standard errors are reported in parentheses. This table only reports key predictor estimates. Full regression model results including controls are reported in Table S7 in the online supplementary materials. Reference categories are not forced to move, remain out of housing stress according to 30/40 rule, remain out of overcrowding, remain out of difficulty paying rent or mortgage, neighbourhood score remains the same, number of dependents remains the same, remain without long-term health condition, remain partnered, remain employed, no change in education level, remain homeowner, remain in the city, age 15–24, and wave 2.

a wellbeing dividend. Conversely, entering a period of difficulty paying rent or mortgage on time results in a wellbeing penalty. However, while exiting housing stress as measured by the 30/40 rule augments the improvement in MCS score, entering housing stress as measured by the 30/40 rule has an insignificant impact on the change in MCS score. Furthermore, the impacts of changes in difficulty making housing payments are obviously larger than the impacts of movements into and out of housing stress according to the 30/40 rule.

Turning to neighbourhood-based change indicators, an increase in the frequency of neighbourhood crime has the largest adverse impact on a change in MCS score among all forms of neighbourhood-based precariousness.

Conclusion

This study has examined the impacts of dwelling-based and neighbourhood-based precariousness on mental wellbeing. Referring back to the different dimensions of housing precariousness set out in Figure 1 that we include in this analysis, we find the dwelling-based precariousness dimensions of forced moves, housing stress and difficulty paying housing costs have significant adverse impacts on wellbeing. In regard to neighbourhood-based precariousness dimensions, neighbourhood crime, hostility, homes and gardens in bad condition, traffic noise, other noise, and SES all have significant adverse effects on one's wellbeing. However, some housing precariousness aspects do not have a significant impact on wellbeing, namely overcrowding and neighbourhood vandalism.

All the models confirm that living in unaffordable housing is the form of dwelling-based precariousness that has the strongest adverse influence on an individual's mental wellbeing. This resonates with a common theme in the literature that has highlighted the wellbeing penalty associated with living in unaffordable housing (Park & Seo, 2020; Baker *et al.*, 2020; Curl & Kearns, 2015). Furthermore, all models suggest that difficulty making housing payments has a greater detrimental impact on mental wellbeing than a housing stress measure based on the 30/40 rule. This suggests the 30/40 rule may be less effective for reflecting the strain that individuals in unaffordable housing experience in comparison to a more subjective measure of difficulty making housing payments.

The level models show that experiencing hostility very commonly is the form of neighbourhood-based precariousness that has the largest adverse effect on the level of mental wellbeing. The change models highlight the additional penalty to mental wellbeing that is incurred by an increase in the frequency of neighbourhood crime and hostility. Wilson *et al.* (2004) and Ong ViforJ *et al.* (2022b) reached the same conclusions, both studies highlighting the adverse wellbeing effects of neighbourhood hostility and crime in the city of Hamilton in Canada and across Australia respectively. Few other studies have analysed the impact of both neighbourhood hostility and crime on mental wellbeing.

The findings re-emphasize a long-standing case for the implementation of housing affordability policies that assists those who are struggling to keep up with housing payments. The analyses also highlight the need for policy that focuses on reducing the incidence of hostility and crime within neighbourhoods through area-based policies that promote social cohesion and safety. Policy interventions focusing on housing affordability and neighbourhood crime are likely to be the most effective choices for eliciting a change in wellbeing within a short timeframe, based on the change model findings.

Notwithstanding the importance of neighbourhood hostility and crime, the indices analysis shows that overall dwelling-based precariousness has a larger detrimental impact on mental wellbeing than neighbourhood-based precariousness. This new insight is a key contribution of our study, given the lack of existing evidence that provides a comprehensive comparison of the wellbeing effects of dwelling-based *versus* neighbourhood-based precariousness. The findings suggest that policymakers should prioritize addressing dwelling-based rather than neighbourhood-based precariousness, though it is important to emphasize that both are important predictors of wellbeing. The urgency of addressing dwelling-based precariousness is intensified in a world that is now increasingly exposed to public health crises. The COVID-19 outbreak highlighted crucial health and wellbeing penalties experienced by those in precarious dwelling conditions, where homeless persons and individuals living in precarious dwellings were unable isolate safely (Parsell *et al*., 2020; Siu, 2020). In countries such as Australia and the USA, the government acknowledged this issue and provided funding to move homeless persons off the streets or out of congregate shelters into self-contained accommodation such as unused hotels or student housing (Colburn *et al*., 2022; Parsell *et al*., 2020). Various OECD countries also implemented eviction moratoriums in recognition of the heightened health and wellbeing risks that people in precarious dwelling circumstances are exposed to OECD (2021).

Overall, the findings lead to several important policy implications especially in light of likely future threats to public health. First, the findings re-emphasize a long-standing case for the implementation of housing affordability policies that assists those who are struggling to keep up with housing payments. Second, there is a need to prioritize resourcing towards policies that reduce the incidence of hostility and crime within neighbourhoods through area-based policies that promote social cohesion and safety. Third, given the rise in homelessness and continued threats of pandemics in Australia and other countries, the findings point to an urgency for policies and programs to be embedded within housing systems that ensure vulnerable population groups have long-term rather than temporary access to secure housing.

While the linear model specifically is technically flawed due to the bounded nature of mental wellbeing measures, the results generated from the linear and Tobit models remain very similar. This confirms that at least for our chosen wellbeing measure (the MCS) a linear regression methodology has been appropriate for estimating the relationship between housing and wellbeing. Despite our initial concerns, previous studies have not produced biased results from their use of linear regressions. However, we surmise that the similarities across the two models are due to the limited number of cases with wellbeing values close to the lower or upper limits of 0 and 100, respectively, in the MCS measure. Therefore, the results from the two models may diverge more if a wellbeing measure was chosen that has a greater number of cases with values close to the limits. In this case, the preferred model for informing policy development is still the Tobit, which is conceptually more appropriate for bounded measures.

The analysis conducted in this study gives rise to some important future research directions. First, future research could analyse the effects of persistent versus transient dwelling-based and neighbourhood-based precariousness on wellbeing. It is possible that adverse effects on wellbeing will only surface after several years of experiencing persistent precariousness. On the other hand, studies that have examined the concept of adaption suggest that individuals' wellbeing levels may shift as a result of a life shock, but return to their baseline levels over time (Diener *et al.*, 1999; Lucas *et al.*, 2003).

Second, different forms of housing precariousness often occur concurrently and wellbeing penalties can be amplified when multiple forms of precariousness co-exist. The epidemiology literature offers approaches to examining the additive and multiplicative risks of exposure to diseases (Lessler, 2008; VanderWeele & Knol, 2014), which can be drawn upon to measure the impacts of different mixes of housing precariousness forms on wellbeing. For instance, does a combination of unaffordability and overcrowding harm wellbeing more than a combination of unaffordability and neighbourhood crime?

Third, a random effects estimator was applied to the Tobit and linear regression models in this article. Future work could investigate the feasibility of implementing a fixed effects estimator that works asymptotically to a Tobit model, so that results can be compared across fixed effects Tobit and linear models.

Finally, our choice of precarious housing variables is limited by what is available within the HILDA survey. This limitation can be addressed in future research by employing data other than HILDA survey to draw out the influence of variables such as green space, access to amenities and dwelling condition.

Notes

1. Unequal weights may be assigned. However, these are often subjective (based on researcher's experience).
2. We acknowledge that there are certain non-standard adaptions of PCA which can be applied to categorical data. However, the interpretability of the results from these non-standard adaptions is challenging relative to MCA results.
3. The CNOS states that there should be no more than two persons per bedroom; children under 5 years old of different genders can share a bedroom; children 5 years and older of opposite genders should have separate bedrooms; children under 18 years of age and the same gender can share a bedroom; single adults 18 years and older, any coupled adults 18 years and older as well as parents should all have separate bedrooms.
4. Figure S1 in the online supplementary materials sets out the distribution of the MCS variable. There are around 170 observations with MCS scores at 0, which indicates the potential of a left-censoring issue.
5. Honore (1992) does propose an estimator, but can only demonstrate fixed effects working in a censored regression that has a small sample size and only two time periods of data.
6. $\mathrm{Well}^*_{i,t+1}$ is the latent variable.
7. The forced move variable is entered into the model without any adjustment into a change measure, as it already represents a transition or change in housing circumstance.
8. Because there is little movement between age brackets, a change version of this indicator is not constructed. The fixed calendar year variables control for seasonality and time effects, which would not be the case if they were modified into measuring change in year.

9. The full set of model results including the control variables are reported in Table S4 in the online supplementary materials.
10. As a robustness check, the Tobit and linear models are estimated using the SF-6D health state classification as the outcome variable. The findings are similar to the Tobit and linear models that employ the SF-36 MCS score.
11. The percentage change is calculated by taking the marginal effect, dividing it by the mean MCS score and then multiplying that number by 100.
12. The full set of model results are reported in Table S6 of the online supplementary materials.
13. The full set of model results are reported in Table S7 in the online supplementary materials.

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