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New evidence on mental health and housing affordability in cities: A quantile regression approach

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Abstract

Unaffordable housing costs are one of the most pressing issues facing our cities, affecting people's health in difficult to measure ways. People's health varies over time and dynamically interacts with experiences of housing. Longitudinal analyses rarely explicitly model these variations. Quantile regression is an underutilised tool for testing associations across the distribution of an outcome. In this paper we apply panel quantile regression to test whether cumulative exposure to unaffordable housing over time has differential impact on mental health, dependent on initial health status. Using an annual longitudinal sample of 20906 urban Australians (2001-2016), we model mental health outcomes using quantile regression (accounting for being in 10th, 50th, 90th mental health percentile initially). Although traditional fixed-effects models find weak evidence of cumulative effect, quantile regression reveals that individuals with low-median initial mental health were more affected by unaffordable housing, and individuals with high initial mental health appeared to be protected. Our findings suggest that it is important to look beyond the average effects revealed by undifferentiated traditional regression models. Initial mental health appears to modify the later mental health effects from exposure to unaffordable housing. Quantile regression is a promising method for understanding complex human effects of urban problems.

Key words

Longitudinal; Mental Health; Quantile regression; Housing; Urban

Highlights

- Quantile regression is a promising new method that reveals the extent of variation in the impact of urban problems on wellbeing.
- Having unaffordable housing has a negative mental health effect on residents of cities.
- Individuals with low and median initial mental health were more affected by unaffordable housing, and individuals with high initial mental health appeared to be somewhat protected.

1. Introduction

Understanding the role of housing in generating health outcomes has been a topic of research interest in our cities for almost 200 years. Since at least the early work of John Snow in London (Snow, 1855) we have known that housing and health are associated. Initial work following Snow focussed largely on developing an evidence base on the influence of physical characteristics of housing – such as mould and damp – on occupant health. With physical problems better understood, research momentum has evolved toward a focus on the influences and mechanisms by which housing affordability impacts on health and wellbeing. Housing affordability is increasingly seen as a dominant driver of housing-related health outcomes (for example Bentley et al, 2019; Krieger and Higgins, 2002) because it can dictate the physical characteristics of dwellings that people are able to secure, as well as accessibility, quality, and tenure. Housing affordability also has broader implications for economic security, with the cost of housing determining what remains in household budgets for food, education, health care and other costs that affect lifestyle and quality of life.

Across almost all post-Industrial cities, housing affordability has become one of the most pressing social and policy issues (Desmond, 2018; Wetzstein, 2017). Australia especially, has some of the most unaffordable cities, and a well-documented 'affordability crisis' (Jacobs, 2015). Similar to other nations, Australia's housing unaffordability phenomenon grows each year, and is now estimated to affect around 11 per cent (Daniel et al, 2018) of all households. For individuals and their families, the growth of the housing affordability crisis over time means that more people will experience unaffordable housing, and importantly *experience it for longer*. In this context, there is a need to understand housing problems and document their effects - over time. In this study, we investigate the distributional effect of housing affordability and how cumulative exposure can affect the mental health of urban residents. Using a quantile regression approach introduced by Powell (2016) and population representative longitudinal data from Australia between 2001 and 2016, we will evaluate the effect on mental health of experiencing housing affordability stress over time relative to for city residents. Our findings will provide empirical evidence for policy makers who wish to address unexpected mental health consequences of housing affordability in high-income countries (for example see Bentley et al, 2016; Kavanagh et al, 2016; Singh et al., 2019).

A growing body of studies have considered the relationship between unaffordable housing (often referred to as Housing Affordability Stress, HAS, the measure that we also adopt and is described in more detail below) and health. A number of studies find associational evidence of a relationship between unaffordable housing and declining or poor health (for example Baker et al, 2014 ; Baker et al, 2017). Clair et al (2016), in their longitudinal multi-country analysis of self-reported health status and housing payment problems during the Global Financial Crisis, found that when people experienced housing payment problems there was an overall deterioration of their self-reported health. The magnitude of effect was regarded in this study as being greater than the impact of job loss. Similarly, a cross-sectional United States (US) study (Pollack et al, 2010) found that housing unaffordability was related to increased odds of poor self-rated health, as well as increased odds of experiencing a number of related health outcomes, such as hypertension. Also in the US, a longitudinal study of homeowners (Yilmazer et al, 2015) found that respondents reporting difficulties in mortgage repayments experienced increased psychological distress. Another large cross-sectional sample, focussed on New York renters (Meltzer and Schwartz, 2016), observed poorer health outcomes (self-rated health and postponement of healthcare services) with increased rental-cost burdens. Rowley and Ong (2012) also reported highly significant associations between unaffordable housing costs and self-reported health in a cross-sectional Australian sample. A recent and novel quasi-natural experiment (Reeves et al, 2016), examined the mental health of private sector rental tenants in the United Kingdom (UK) between 2011 and 2013 during which government housing benefits were reduced. The authors reported an increase (1.8 per cent) in the prevalence of self-reported depressive symptoms amongst a large cohort receiving Housing Benefits compared a cohort of those not receiving the support. Finally, Pierse et al (2016) found no evidence of any effect of housing affordability on psychological distress in a longitudinal sample of New Zealand households. They did however suggest that individual deprivation was related to increased psychological distress, and arguably, indicators of individual deprivation may be associated with limited financial resources due to high housing costs.

Reflecting the relatively recent growth in the availability of high quality, large longitudinal datasets, and the parallel development of methods to understand longitudinal patterns of exposure, relatively few studies report on the cumulative effects (often referred to as ‘dose-response effects’ in health literature) of exposure to housing affordability problems. Among the few studies that have explored cumulative exposure using longitudinal methods, Bentley et al (2018) used marginal structural models and machine learning to examine the mental health effect of periods of continuous exposure to social or public housing. In a parallel literature, Kravitz-Wirtz (2016) investigated the consequences of prolonged exposure to neighbourhood disadvantage, finding that the ‘dose’ of exposure to neighbourhood disadvantage was associated with an increase in the odds of reporting poorer health. One of the few studies directly exploring cumulative exposure to unaffordable housing to date, examined the influence of cumulative time spent with housing affordability problems on the mental health of Australian men and women using a nationally representative panel dataset (Bentley et al, 2012). This analysis found that, during the 2001–2009 period, there was no evidence of a dose-response health effect of cumulative exposure for individuals.

Reflecting on this earlier study, we hypothesise that within these results, some people are more vulnerable to the effects of unaffordable housing. We suspect that people with poor mental health are likely to be especially vulnerable to a further worsening of their mental health from exposure to unaffordable housing. An evolving methodological toolkit now allows us to conceptualise and measure cumulative effects (Binder and Coad, 2011). Quantile regression, an approach increasingly used in econometrics but rarely used in urban social research provides a potentially powerful means to explore these, and similar questions. This paper therefore tests a quantile regression approach to understand if exposure to unaffordable housing costs has a differential impact on people dependent on their initial mental health status. It offers a departure from the existing literature described above, in that it seeks to look, not just at average effects, but effects by prior health distribution. This new approach has not been applied to urban research. Our findings are not only related to Australian population from which our data originates, but also other high-income countries such as the UK or US. Previous studies have documented the comparable effects of unaffordable housing costs on mental health across post-industrialised countries including the UK and Australia (e.g. Bentley et al., 2016).

The heterogeneity of the effect of unaffordable housing across the mental health distribution is captured by using a quantile regression method. Specifically, we employ the longitudinal data and panel dimension of the Powell (2016) quantile panel method to understand cumulative and dynamic effects. A critical early contribution is the recent quantile analysis (Binder and Coad, 2015), using British longitudinal data to show that higher existing levels of wellbeing are protective when individuals face unemployment. The approach has also been applied by Contoyannis and Li (2017) in their analysis of the dynamics of youth depression. Another recent study focussed on health effects of job loss using quantile regression (Schiele and Schmitz, 2016), finding that health outcomes were highly conditional, and that people with low to moderate initial physical health were most affected by job loss, while the most initially healthy 20 per cent of the distribution were virtually unaffected. In their recent systematic review, Singh et al. (2019) confirm that exposure to housing disadvantage such as housing affordability stress may result in long-term mental health outcomes in high-income countries. However, all studies include in Singh et al.'s (2019) systematic review focus on the average effect of housing affordability related issues on mental health (i.e. by using fixed-effects regression methods for example).

In order to explore the cumulative health effects of unaffordable housing in our cities using a quantile regression approach, this paper asks:

1. *Is there a relationship between cumulative exposure to unaffordable housing and mental health?*
2. *If so, does this vary by people's initial mental health?*

2. Data and methods

In order to investigate distributional (rather than average) effects of changes to mental health in response to the cumulative time spent in unaffordable housing, we use the quantile treatment effect approach for panel data with fixed-effects by Powell (2016). Powell's (2016) approach stands on the shoulders of earlier quantile methods, such as Koenker's (2004) penalized quantile regression approach, that enabled the vector of individual effects to be shrunk toward a common value. This was critiqued by Lamarche (2010) who highlighted the difficulty of finding a precise value of the regularization parameter. Kato et al (2012) later proposed to include individual dummy variables in the quantile panel fixed effect regression.

Powell's quantile regression approach is essentially a three-step process, it initially eliminates fixed effects, then uses information from the entire distribution to rank a mental health score structure, conditioning on explanatory variables, the method then acknowledges surrounding mental health scores to derive coefficients. This means that the estimates of the coefficients are robust even if density of exposure is sparse at either end of the mental health distribution and standard errors may be wide. The likelihood that people's initial good mental health provides them with a certain degree of protection against any negative impacts of their housing situation suggests that we need to examine the relationship between unaffordable housing and mental health as a heterogeneous effect across the mental health distribution. We use the Markov Chain Monte Carlo algorithm (MCMC) and adjust for clustering at the individual level, using the most highly regarded method to eliminate fixed effects across quantiles, addressing the methodological challenge of generating different effects estimates across quantiles (as systematically detailed in Powell, 2016).

Data: The relationship between housing affordability and mental health has become an emerging issue in high-income countries. In building the evidence base required to understand this relationship, data from multiple countries will eventually be needed. This study utilises Australian panel data from the Household, Income and Labour Dynamics in Australia (HILDA) survey (2001 and 2016).

The HILDA longitudinal study has followed Australian households and individuals across annual survey waves from 2001.The dataset is based on a nation-wide probability sample of individuals aged 15+years, and is focussed on income, employment, health and well-being, with data collected using face-to-face interviews and self-completion questionnaires (Summerfield et al, 2017). We focus on Australians resident in cities and major regional towns across 16 annual waves of the survey (2001-2016). In a highly urbanised national like Australia, where almost 90 per cent of the population live in cities and major regional towns (ABS, 2018), this cohort also accounts for almost 90 per cent of the HILDA sample. The analysis therefore includes 139,344 responses from 20,906 participants with available data for housing status, physical health, mental health, and other required covariates.

Outcome variable: The analysis aims to test the dose-response effect of unaffordable housing on self-assessed mental health using the Mental Component Summary (MCS), an internationally standardised measure (Hemmingway et al, 1997) contained in the Short Form 36. This is one of the most widely used self-completion measures of health (Coons et al, 2000), and has been validated for the Australian population (Butterworth and Crosier, 2004). The items consist of questions on mental health, vitality, physical functioning, bodily pain, general health perceptions, and physical, social and emotional role functioning. A low MCS score indicates frequent psychological distress, social and role disability due to emotional problems, and poor self-rated health. The MCS is a standardized score that has a mean of 50 and standard deviation of 10. The potential range of scores is from 0 to 100.

Predictor variables: Unaffordable housing is defined as occurring when a household is in the lowest 40 per cent of the equivalised disposable income distribution and paying more than 30 per cent of gross household income in rent or mortgage costs. This definition is widely used in Australia and internationally (for example Yates and Milligan, 2007; AIHW, 2008; Milligan et al, 2016), and is often referred to as a measure of Housing Affordability Stress (HAS). In order to measure the dose-response effect, exposure to unaffordable housing was classified cumulatively. Cumulative time spent in unaffordable housing was classified on the number of consecutive annual waves an individual was in a household with unaffordable housing. In order to more precisely capture the years of cumulative exposure, each period of exposure must have been preceded by an immediate annual wave with no exposure (i.e. in affordable housing). Our analytical sample, therefore, include people who change their HAS status at least once in the time frame under consideration, with a reference group of individuals who do not change their HAS status over the study duration. This means that people who, perhaps due to poor health, are continuously exposed to HAS, are excluded from our analyses. Though this restriction reduces the size of the analytical sample (139,344 responses from 20,906 participants), it substantially increases the robustness of the findings. Cumulative exposure was compared for people who spent 1, 2, 3, 4, and 5 or more consecutive years in unaffordable housing. The reference category was affordable housing for at least 2 consecutive years. We note that some people's exposure pattern (e.g. included in the dataset for one wave of affordable housing only) precluded them from the analysis.

Confounders: Potential confounders were identified from existing literature and consideration of the likely relationship between cumulative exposure to unaffordable housing and change in mental health. All models were controlled for age, the square root of age, household income, marital status, tertiary education status, home ownership, states, major cities, disability, health status, smoking, drinking, and occupation.

Modelling approach: The classical panel fixed effects model that relates mental health scores to cumulative exposure to housing unaffordable housing (HAS) is:

$$MCS_{it} = \sum_{j=1}^{5+} \beta_j * cumulative\ HAS_{j,it} + z_{it}'\gamma + \alpha_i + \mu_t + e_{it} \qquad (1)$$

where MCS_{it} is mental health for individual i at time t; $cumulative\ HAS_{j,it}$ is an indicator variable of whether individual i spent j years (e.g. 1, 2 or 5 plus years) in HAS at time t; z_{it} is a vector of control variables such as age, the square root of age, household income, marital status, tertiary education status, home ownership, states, major cities, disability, health status, smoking, drinking, and occupation. α_i and μ_t are unobservable individual and year fixed-effects, respectively, that address any potential endogeneity in the variables of interest, $cumulative\ HAS_{j,it}$. e_{it} is the unobservable error term.

Panel regression models with individual and year fixed-effects estimators, and robust clustered standard errors were run in Stata MP 15.0. Clustered standard errors at the individual level were used to enable statistical inferences at the population level (Adabie et al. 2017). The inclusion of individual fixed-effects estimators enabled adjustment for time-invariant characteristics. This inclusion is to capture systematic differences in self-reported mental health. For example, because each person has their own perception in accessing their health, self-reported mental health can be correlated with personality type (Bagod'Uva et al, 2008). Personality type is also correlated to whether individuals are cumulatively exposed to unaffordable housing, and how their mental health scores respond. For instance, males have been previously found to have a stronger dose-response than females (Bentley et al, 2012). Therefore, personality type is correlated to the main explanatory variables and the model outcome in our model. The inclusion of fixed-effects will enable us to detect changes in mental health self-reporting and account for this form of time invariant confounding.

As comparisons were made for the same individual at different time points, only factors that varied over time were considered for confounder adjustment. As such, the coefficients obtained from the models reflected only the differences within people who changed their unaffordable housing status across the survey. Furthermore, we included year fixed-effects in our longitudinal regressions. The year fixed-effects capture economic and political changes that are different year by year but affect individuals each year in the same way. These year fixed-effects have the potential to influence earnings, and lift individuals in and out of unaffordable housing, affecting the identification of the exposure cohort.

The quantile fixed-effects approach of Equation (1) is:

$$MCS_{it} = \sum_{j=1}^{5+} \beta_j(U_{it}) * cumulative\ HAS_{j,it} + z_{it}'\gamma(U_{it}) + \mu_t(U_{it}) \qquad (2)$$

and

$$U_{it} = f(\alpha_i, v_{it}) \qquad (3)$$

for all quantiles $\tau \in (0,1)$ of the mental health score MCS_{it}.The effect of cumulative HAS on at the $\tau - quantile$ of the mental health score of individual i in year t is capture by the coefficient $\beta_j(U_{it})$ is our coefficient of interest which measures the effect of cumulative HAS on individual mental health; is a vector of control variables; $\gamma(U_{it})$ measures the effect of a change in the control variables at the $\tau - quantile$ of MCS; and μ_t is the year effect. The term U_{it} in Equation (3) is a function of individual time-invariant fixed effect α_i and time variant idiosyncratic error v_{it}. The function of U_{it} indicates that the variation in the coefficients $\beta_j(U_{it})$ of interest at the $\tau - quantile$ of MCS.

3. Results

Descriptive results: Table 1 reports descriptive statistics (i.e. number of observations, mean and standard deviation) and mean MCS across the main explanatory variables. Across the analytic dataset, MCS a mean of 48.9 and a standard deviation of 10.2. Overall, males had slightly higher mean mental health than women. As found in a number of previous studies, mean mental health is higher for older, compared to younger age cohorts, and the difference between mean mental health for the 15-19 year and 75+ years cohort was a notable 3.5 percentage points. Perhaps unsurprisingly, people who were employed had the highest mean mental health (49.4), followed by people who were not in the labour force (this can be defined in the Australian context as people who are not employed, but not looking for work, and is therefore likely to largely composed of people in retirement or receiving a non-unemployment related pensions). Considering tenure, homeowners (including home purchasers) had the highest mean mental health (49.7), followed by private renters (47.0) and social renters had the lowest mean mental health of any population group examined (44.3). Interestingly, there appears to be no appreciable pattern when mean mental health is examined across the income spectrum. The lowest income cohort had a mean mental health score (48.0) only slightly lower than the highest income cohort (49.9). When health status is considered, the mean mental health score of the cohort with a long term disability or health condition was low (45.9), especially when compared to the cohort who assessed their general health (physical and mental) as 'excellent' or 'very good'. The cohort living in couple households had the highest mean mental health score (50.2). This mean score was substantially higher than for single parents (45.8). Finally, comparing the mean mental health scores of the housing affordability exposure cohorts (no exposure and 1,2,3,4,5+ years of exposure), the cohort with no exposure to unaffordable housing had the highest mean mental health score (49.2). Interestingly, although the cohorts who had any exposure to unaffordable housing had substantially lower mean mental health, there were only minor differences between the five exposure cohorts (highest= 45.5 compared to lowest= 44.5).

Table 1. Summary statistics and Mean mental health scores by selected descriptive characteristics, 2001-2016 Variable	Observations (n)	Mean	SD	Mean mental health score
Mental Health Score (MCS)	139,344	48.966	10.229	
Gender				
Male	65,468	0.470	0.499	49.697
Female	73,876	0.530	0.499	48.318
Age				
15-19	9,724	0.070	0.255	47.639
20-29	22,039	0.158	0.365	47.294
30-49	51,398	0.369	0.482	48.141
50-59	23,715	0.170	0.376	49.579
60-75	24,630	0.177	0.381	51.444
75+	7,838	0.056	0.230	51.083

Labour market status				
Employed	92,533	0.664	0.472	49.376
Unemployed	4,072	0.029	0.168	44.886
Not in labour force	42,739	0.307	0.461	48.466
Tenure				
Homeowner/purchaser	105,764	0.759	0.428	49.708
Social Renter	4,950	0.036	0.185	44.287
Private Renter	27,854	0.200	0.400	47.014
Income quintile				
1st	25,292	0.182	0.385	48.017
2nd	25,403	0.182	0.386	48.567
3rd	26,479	0.190	0.392	48.849
4th	29,524	0.212	0.409	49.249
5th	32,646	0.234	0.424	49.850
Long-term health condition	36,359	0.261	0.439	45.888
Excellent or good health	66,832	0.480	0.500	52.181
Household structure				
Couple with children	50,858	0.365	0.481	48.826
Couple no children	51,502	0.370	0.483	50.213
Lone parent	11,590	0.083	0.276	45.764
Lone person	19,900	0.143	0.350	48.413
Other	5,494	0.039	0.195	47.325
Years of continuous exposure to unaffordable housing				
0 year	131,675	0.945	0.228	49.186
1 year	5,009	0.036	0.186	45.392
2 years	1,397	0.010	0.100	44.488
3 years	601	0.004	0.066	45.230
4 years	280	0.002	0.045	44.511
5+ years	382	0.003	0.052	45.519

Table 2 reports average transition probabilities between quantiles of mental health score and the share of individuals exposed to HAS between 2001 and 2016. The average transition probabilities capture the persistence in the mental health score without taking into account influences of any explanatory variables (i.e. the unconditional persistence). Specifically, between rows 1-5 and columns 2-6 entries in the main diagonal of Table 2 represent the average probability of staying within the same quintile of MCS; and entries off the diagonal are the average probability of changing across the quintiles between years t and $t-1$. We notice that the likelihood to stay within the same quintile of MCS next year is highest for individuals who are in the lowest and in the highest quintile in previous year (i.e. a chance of 56%). The staying probabilities in the middle of the MCS distribution (i.e. the 2nd to 4th quintiles) are almost 10% to 15% lower. We also observe that it is a very rare phenomenon that individuals switch between the extreme ends of the MCS distribution (about 3% to 3.5% individuals switched). On average, about 27% individuals were exposed to HAS in any given year and these individuals are concentrated in the lowest quintile of MCS (about 9%).

Table 2: Average transition probabilities between quintiles of mental health score and the share of individuals exposed to HAS, 2001-2016

Quintile	t-1					
	1	2	3	4	5	%
1	56.36	24.39	10.78	5.34	3.12	100
2	23.58	35.07	23.16	11.88	6.31	100
3	10.55	22.67	31.07	24.20	11.50	100
4	5.47	11.58	23.45	35.16	24.34	100
5	3.49	5.97	11.04	23.93	55.57	100
Share of HAS	9.03	6.04	4.74	4.04	3.67	27.52

Note: Average transition probabilities between quintiles of five-item mental health score calculated across 2001–2016. Share of HAS is the share of individuals exposed to unaffordable housing across all waves.

Analytical results: Table 3 summarises results for the fixed-effects regression (column 1), and the quantile treatment effect regression results (columns 2–4). Notable across the fixed-effects regression model results are almost uniformly small effect sizes, and confidence intervals suggest statistical significance only for one and two years of exposure. The quantile treatment effect models, however, provide markedly different results. By framing these models to separate effects based on relative initial mental health, rather than average effects regardless of initial mental health, we find that there are strong, often graded negative effects of cumulative exposure to unaffordable housing for some groups. These larger effects are concentrated among individuals with low (represented in the 0.1 quantile) and moderate (represented in the 0.5 quantile) initial mental health.

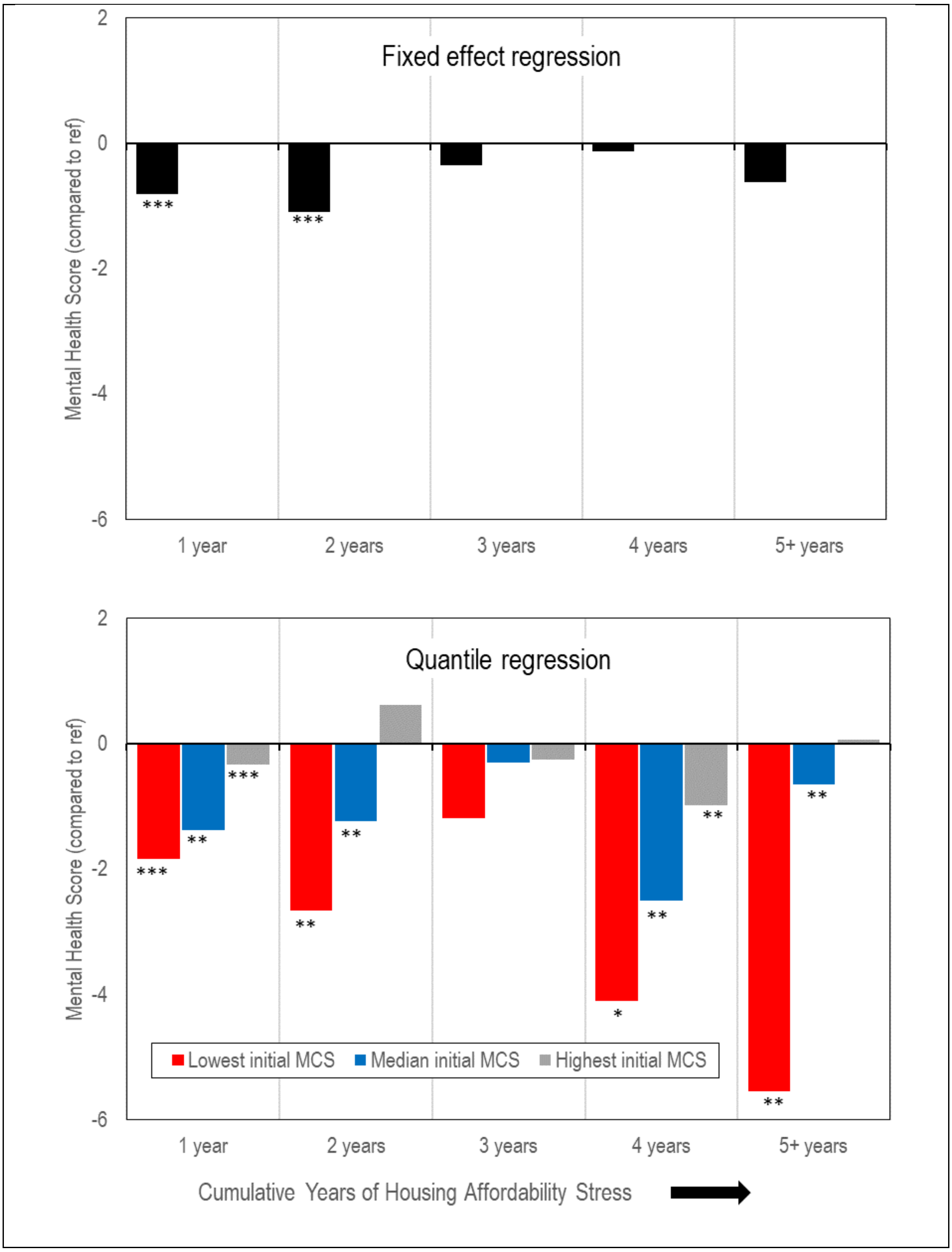
Table 3. Estimates of the effect of cumulative exposure to unaffordable housing on Mental Health Score, 2001-2016

Year of cumulative exposure	Fixed-effects	Quantile Treatment Effect		
		0.1 quantile	0.5 quantile	0.9 quantile
1	-0.809***	-1.839***	-1.370***	-0.334***
	[-1.089; -0.528]	[-2.809; -0.870]	[-1.475; -1.264]	[-0.370; -0.298]
2	-1.084***	-2.656***	-1.240**	0.617
	[-1.569; -0.598]	[-3.452; -1.859]	[-2.255; -0.225]	[-0.158; 1.392]
3	-0.345	-1.185	-0.297	-0.258
	[-1.104; 0.414]	[-3.363; 0.993]	[-1.519; 0.926]	[-0.913; 0.397]
4	-0.131	-4.108*	-2.503***	-0.984**
	[-1.207; 0.946]	[-8.550; 0.333]	[-2.793; -2.212]	[-1.785; -0.184]
5 or more	-0.611	-5.538**	-0.651**	0.059
	[-1.848; 0.626]	[-10.019; -1.056]	[-1.176; -0.127]	[-0.105; 0.223]

*Note: * P < 0.1, ** P < 0.05, *** P < 0.01. 95% confidence intervals are reported in the brackets; standard errors are clustered at individual level. The sample contains 20,906 individuals (139,344 observations) from HILDA in 2001–2016. All regressions control for household income, household size, age, age squared, marital status, tertiary education, occupation, health conditions, daily drinking and smoking, state/territories, major city, individual and year fixed-effects. The low, moderate and high initial mental health scores are represented in the 0.1, 0.5 and 0.9 quantiles respectively.*

Comparing these results graphically in Figure 1 highlights the importance of capturing initial differences – such as mental health – between people within a study population. The estimated effect of exposure to unaffordable housing for people with the lowest initial mental health (10^{th} MCS quantile) appears to broadly increase with exposure (with the exception of a non-significant effect for people with 3 years of exposure). The scale of effect for this group is stark, rising from almost 2 percentage points with one year of exposure, to more than 5.5 percentage points for people exposed to 5 or more years of unaffordable housing. To place the scale of this into the context of other similar, causally focussed analyses using the SF36 MCS scale, the earlier study by Bentley et al (2012) found a MCS effect size over two years, of -1.19 percentage points (95% confidence -1.97 to -0.41) for low income people entering unaffordable housing. The recent study by Kavanagh et al (2016) estimated the MCS effect of disability acquisition (also using fixed effect regression), finding a decrease in MCS of -1.6 (95% confidence -2.1 to -1.1) percentage points for homeowners and -4.2 (95% confidence -5.2 to -1.4) for people in unaffordable housing following disability acquisition. Although the scale of the findings for the cohort with low initial mental health is important, findings for the middle (50%) quantile cohort are also noteworthy. For this group, the effect size appears to peak at 4 years exposure at -2.5 percentage points (95% confidence -2.8 to -2.2). The high initial mental health cohort (90^{th} MCS quantile) are shown to have negligible effect sizes (<1 percentage points) at every exposure level, and these results are only significant at 1 year of exposure.

Figure 1. Comparison of Fixed and Quantile regression effect estimates.



Note: Statistical significance, *=0.1, **= 0.05, ***=0.01

4. Discussion

This is the first paper to apply quantile regression to an analysis of housing's health effects. It highlights the benefit of looking *within* average effects, and reveals a substantial differentiation of outcomes. Overall, this paper gives us valuable insight into the dynamics of mental health in our cities, it shows that people with low initial mental health are particularly vulnerable to the negative mental health effects of unaffordable housing.

Estimates of the association from standard fixed effects regression models are shown to be relatively small. In comparison, the quantile regression estimates of association are substantially larger, suggesting a greater impact of cumulative housing stress dependent on initial mental health status. By statistically stratifying the regression to account for initial mental health, rather than simply averaging it (as in traditional fixed effects regression approaches), this study provides more nuanced evidence of relatively large mental health effects of cumulative time spent in unaffordable housing not previously documented. This suggests that the most compelling finding of this analysis is the additional insight provided by the quantile regression method. Quantile regression reveals significant and sizeable effects among people with low and moderate initial mental health, and that people with high initial mental health appear to be protected. A further finding of this paper relates to scale. By statistically acknowledging differences in initial mental health, the quantile regression analysis demonstrates that, for people with low and moderate mental health at least, mental health effects are large, and increase with cumulative exposure time (max >5 percentage points).

What does this analysis mean for policy and potential interventions in our cities? From a policy perspective, these findings show housing affordability to be a substantial potential driver of people's poor mental health, especially people who have low mental health to start with. Even though housing overall is considered to be a key social determinant of health (WHO, 2018), physical housing characteristics, including structural conditions, smoke ventilation or warmth (things that have measureable physical outcomes such as respiratory disease) tend to be prioritised in policy as health drivers. Affordability is a less obvious and harder to measure housing characteristic than physical attributes of dwelling. Further, it affects mental rather than physical health, and as this analysis has shown, these effects can be difficult to measure. The findings of this paper may be helpful to policy response, in not only documenting a potentially substantial mental health effect of exposure, but also the existence of a dose-response gradient. This means that interventions to make people's housing more affordable will provide both current and future mental health improvements for some people. The finding of a stronger effect among people with lower initial mental health suggests that if government assistance resources were limited, the best overall improvements in mental health outcomes would come from a targeting of people with existing low mental health. Looking to the descriptive results, lone parents, the unemployed, renters, and people with long-term disabilities and health conditions are population groups with notably low mental health who may benefit from targeted assistance. This is both because their existing mental health appears to make them especially vulnerable to the further mental health effects of unaffordable housing costs, but also because any worsening of their mental health would take them further from population averages.

We acknowledge both the strengths and weaknesses of this study. We used a large nationally representative longitudinal dataset to examine the relationship between housing affordability and mental health. Our regression approach allowed us to control for both time invariant confounding and generate causally robust estimates that focus on change, which few studies have done to date. Looking to potential weaknesses, our findings might not adequately capture macro events such as the Global Financial Crisis of 2007-2009. We pooled the pre- and post-2009 data in our analysis. By doing so, we underscored the structural break that might have occurred within the Australian economy. As pointed out by Eslake (2009), the Australian policy response to the GFC largely protected Australians from many of the negative effects. We expect therefore that the GFC's effect on our estimates of the relationship between cumulative HAS and mental health would be minor.

We acknowledge that exposure to HAS and people's mental health status prior to the 5-year window of time used in our analyses is not accounted for and remains as a potential source of confounding in our models. This is somewhat ameliorated by using quantile regression models that take baseline mental health into account i.e. assume an interaction between baseline mental health and the relationship between cumulative exposure and mental health. Our models only include people who change their HAS status at least once in the time frame under consideration. This means that people who, perhaps due to poor health, are continuously exposed to HAS, are excluded from our analyses. Our results, therefore, are only generalisable to a population of people who change HAS status over time. In addition, one may concern that, within each year, there is likely a bi-directional relationship between changes in mental health and HAS. Cumulative HAS negatively affects individuals' mental health, whereas individuals with low mental health scores are likely to encounter financial difficulties that are associated with higher chances to expose to housing unaffordability for a longer time. However, the stronger direction of effect is likely to be from HAS to mental health rather than the reverse. If this assumption is true, then reverse causality is minimised in our fixed effects models. Finally, our analysis of cumulative periods spent in unaffordable housing is classified across five exposure groups. The final group is a category of 5+ years, which we acknowledge to be a less well-specified group than the other exposure groups because it includes a very small number of people who may have had much longer exposure to HAS (in rare cases up to 14 years following a period of affordable housing costs) .

We end this paper with a challenge for future work to re-examine the evidence base and broaden our understanding of the escalating urban problems of housing disadvantage including affordability by acknowledging the dynamic nature of mental health. Our study underlines the importance of taking mental health differences into account using new methods to the field, such as quantile regression.

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Online Appendix

Table A1: **(Full table)** Estimates of the effect of cumulative exposure to unaffordable housing on Mental Health Score, 2001-2016

Variable	Fixed-effects	Quantile Treatment Effect		
		0.1 quantile	0.5 quantile	0.9 quantile
Year of cumulative exposure				
1	-0.809***	-1.839***	-1.370***	-0.334***
	[-1.089; -0.528]	[-2.809; -0.870]	[-1.475; -1.264]	[-0.370; -0.298]
2	-1.084***	-2.656***	-1.240**	0.617
	[-1.569; -0.598]	[-3.452; -1.859]	[-2.255; -0.225]	[-0.158; 1.392]
3	-0.345	-1.185	-0.297	-0.258
	[-1.104; 0.414]	[-3.363; 0.993]	[-1.519; 0.926]	[-0.913; 0.397]
4	-0.131	-4.108*	-2.503***	-0.984**
	[-1.207; 0.946]	[-8.550; 0.333]	[-2.793; -2.212]	[-1.785; -0.184]
5 or more	-0.611	-5.538**	-0.651**	0.059
	[-1.848; 0.626]	[-10.019; -1.056]	[-1.176; -0.127]	[-0.105; 0.223]
Control variables				
married	0.552***	2.388***	0.880***	0.257***
	[0.307; 0.796]	[1.883; 2.894]	[0.770; 0.991]	[0.079; 0.436]
household income	0.001***	0.004***	0.001***	0.001***
	[0.000; 0.002]	[0.002; 0.006]	[0.000; 0.002]	[0.000; 0.001]
age	-0.068***	-0.011	-0.058***	-0.113***
	[-0.118; -0.019]	[-0.087; 0.065]	[-0.062; -0.054]	[-0.168; -0.058]
age^2	0.001***	0.002***	0.002***	0.002***
	[0.000; 0.001]	[0.002; 0.003]	[0.002; 0.002]	[0.002; 0.003]
household size	-0.115***	0.161	-0.140***	-0.030***
	[-0.185; -0.045]	[-0.204; 0.527]	[-0.168; -0.113]	[-0.032; -0.027]
occupation (manager)	0.413***	3.674***	0.962***	0.072**
	[0.156; 0.671]	[3.098; 4.251]	[0.728; 1.195]	[0.011; 0.133]
occupation (professional)	0.471***	2.673***	0.680***	-0.148*
	[0.232; 0.710]	[1.977; 3.369]	[0.580; 0.779]	[-0.313; 0.017]

occupation (blue collar)	1.051***	4.653***	1.854***	0.348***
	[0.811; 1.291]	[4.395; 4.911]	[1.752; 1.957]	[0.227; 0.469]
occupation (sales/admin)	0.616***	2.715***	1.174***	0.004
	[0.415; 0.816]	[2.638; 2.792]	[1.122; 1.225]	[-0.005; 0.013]
tertiary	0.309	-1.193***	-0.013	-0.647***
	[-0.154; 0.773]	[-2.088; -0.298]	[-0.635; 0.610]	[-0.839; -0.455]
home owner	0.175	0.875***	0.733***	0.420**
	[-0.034; 0.384]	[0.647; 1.104]	[0.697; 0.769]	[0.070; 0.769]
health condition	3.251***	10.290***	5.168***	1.889***
	[3.115; 3.387]	[9.467; 11.113]	[4.754; 5.583]	[1.521; 2.257]
self-assessed health	-1.300***	-5.544***	-3.090***	0.084
	[-1.459; -1.140]	[-6.618; -4.470]	[-3.265; -2.914]	[-0.058; 0.225]
daily alcohol consumption	-0.468***	-1.205**	0.373	-0.255**
	[-0.701; -0.234]	[-2.385; -0.025]	[-0.176; 0.922]	[-0.473; -0.037]
daily smoking	-0.571***	-1.092***	-0.870***	-0.261***
	[-0.839; -0.302]	[-1.460; -0.724]	[-0.880; -0.861]	[-0.400; -0.123]

Note: * $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$. 95% confidence intervals are reported in the brackets; standard errors are clustered at individual level. The sample contains 20,906 individuals (139,344 observations) from HILDA in 2001–2016. These individuals are living in cities and major regional towns. All estimates control for state/territories, major city, individual and year fixed effects.