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How do housing and labour markets affect individual homelessness?

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ABSTRACT

We examine the impact of housing and labour market conditions on individual risks of homelessness. Our innovation is a focus on homelessness entries, although findings from jointly estimated homelessness entry and exit probit equations are reported. Risky behaviours and life experiences such as regular use of drugs, the experience of violence and biographies of acute disadvantage lead to a higher risk of becoming homeless. Public housing is a strong protective factor. We find clear evidence that for certain subgroups it is being the 'wrong person in the wrong place' that matters most when considering risks of entering homelessness. Indigenous Australians, for example, are no more likely to become homeless than other vulnerable groups holding housing and labour market conditions constant. However, tighter housing markets and weaker labour markets expose Indigenous Australians to significantly higher risks of entering homelessness.

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Homelessness; housing markets; labour markets; dynamics; longitudinal

1. Introduction

Effective policies to reduce homelessness require an understanding of what causes people to enter homelessness, as well as what prevents them exiting homelessness. Of particular importance is to identify the relative significance of area level structural factors from individual level risk factors: if it is a lack of jobs and affordable housing that precipitate homelessness among vulnerable individuals, then employment and housing policy strategies could prove effective. However, if personal characteristics such as drug misuse or relationship breakdown are overriding determinants of homelessness regardless of the state of housing and labour markets, support services targeting these behaviours are more likely to be successful.

Research in this area has been hampered by a lack of longitudinal data allowing the separate analysis of flows into and out of homelessness. Longitudinal data on a geographic scale permitting analysis of housing and labour market conditions is also

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uncommon. We address this gap by combining a unique micro-level panel survey of 1682 insecurely housed Australian welfare recipients, with area-level measures of housing and labour market conditions to examine how housing and labour markets affect individual risks of homelessness. Our focus is on the factors shaping pathways into homelessness as identified within a model that jointly estimates the likelihood of entering into and exiting out of homelessness. An additional innovation of our study is that we model heterogeneous housing and labour market effects across individuals with different risk factors to offer new insights into how being the 'wrong person in the wrong place' can cause homelessness.

Economic theory provides the conceptual foundation for empirically testing housing and labour market impacts on homelessness. Constraints on housing supply, such as minimum housing standards or topological characteristics, can reduce the supply of low cost, albeit unsatisfactory, housing, with homelessness a possible consequence (Early, 1999; Glomm & John, 2002; O'Flaherty, 1996, 2012). Local labour market conditions may affect individual risks of homelessness, as those located in weak labour markets are more susceptible to negative income shocks.

Empirical studies examining the effect of housing and labour markets typically employ city-level data to explain differences in point prevalence measures of homelessness (see Honig & Filer, 1993; Quigley & Raphael, 2001). These studies, predominantly from the US, indicate that structural factors are the main contributors to homelessness, but find little evidence that individual risk factors matter (Appelbaum *et al.*, 1991; Burt, 1992; Elliott & Krivo, 1991; Florida *et al.*, 2012; Honig & Filer, 1993; Lee *et al.*, 2003; Quigley, 1990; Quigley & Raphael, 2001; Quigley *et al.*, 2001).

Less common are inquiries using micro-level data to analyse individual risks of homelessness across different areas, typically cities. Studies such as Early (1998, 1999, 2004, 2005) and Early & Olsen (1998, 2002) estimate the probability of homelessness as a function of personal and city characteristics using cross-sectional data. Housing and labour market conditions are rarely significant but individual characteristics such as race, gender, age, mental illness, and poverty are invariably important predictors of homelessness. Cobb-Clark *et al.* (2016) utilises longitudinal data to isolate significant but small effects of housing and labour market conditions on exits from homelessness, but entries are not examined.

As O'Flaherty (2004) points out area level studies tend to overstate the role of structural factors. On the other hand the micro-level studies examined use samples drawn from all persons living in selected regions, a sampling approach that will understate structural factors such as housing market impacts because 'the housing market has no effect on people who are not at risk; they are never homeless'. It is the conjunction of being the 'wrong person in the wrong place' that exposes people to homelessness. To our knowledge this theory has only ever been empirically examined in Curtis *et al.* (2013), but only in a static model of homelessness, never on flows into (or out of) homelessness.

We follow O'Flaherty (2004) and Curtis *et al.* (2013) and model the intersection of individual risk and area-level factors on risks of homelessness entry, thus allowing scrutiny of the notion that at least some homelessness results from being the 'wrong person in the wrong place'. By analysing entries into homelessness, rather than static experiences of homelessness, we fill another important void in the literature. Finally, in addition to examining the effect of private housing market conditions on entries into homelessness we also examine the role that social housing tenure has in protecting people from homelessness entry. Here, we distinguish residence in public housing from residence in community housing, which has a particular resonance given a major Australian policy shift that is growing the community housing sector relative to public housing by transferring public housing stock, as well as developing tools that provide community housing agencies with the financial capacity to grow their stock. In community housing, security of tenure is typically weaker. There is also a relevance to other advanced countries whose public housing stocks have also been squeezed.

The limited geographic coverage in much of the previous research in this area is overcome by utilising a national dataset, thus providing ample variation in housing and labour market conditions. Its sample design also helps to address attenuation bias by only selecting those that are homeless, or vulnerable to homelessness. The data are longitudinal, with detailed current and retrospective information about a rich array of individuals' characteristics, allowing for joint estimation of their differential effects on flows into and out of homelessness. The longitudinal data permit use of a random effects estimator that at least partly accounts for unobserved heterogeneity.

Next, we describe how researchers have approached empirical studies of homelessness, and explain how economic theory has influenced our research questions and methodology. Section 3 follows with a data description. Our estimation method is explained in Section 4 and the main set of results in Section 5. Section 6 examines whether there is heterogeneity in housing and labour market effects across different population groups. Section 7 concludes.

2. Background

In the literature on homelessness two theoretical perspectives on the causes of homelessness have consistently featured, one emphasising the role of structural explanations, the other stressing the part played by certain personal characteristics (Elliott & Krivo, 1991; Johnson & Jacobs, 2014; Main, 1998). The second of these two perspectives draws on a substantial body of empirical evidence showing that a lack of social capital, adverse childhood experiences, severe disadvantage and/or behavioural problems, such as mental health and substance misuse, can precipitate homelessness (Bantchevska *et al.*, 2008; Bassuk *et al.*, 1984; Johnson *et al.*, 2018; Penzerro, 2003; Shlay & Rossi, 1992).

Structural accounts explain homelessness as a result of factors largely beyond an individual's control such as the condition of housing and labour markets (see Early, 1999; Honig & Filer, 1993; Quigley & Raphael, 2001). However, researchers are beginning to accept the argument that theoretical explanations and empirical inquiry are most incisive when they incorporate the interaction of structural factors with individual characteristics (Florida *et al.*, 2012; Main, 1998; O'Flaherty, 2004).

The basic premise of this 'interactional' approach is that structural factors expose subgroups vulnerable to homelessness to different levels of risk. It acknowledges the possibility that structural or individual characteristics can on their own cause homelessness, but also recognises how the process of becoming homeless (or avoiding homelessness) is mediated through the interaction of individual characteristics and social and economic structures. Sociological studies that have tried to explain how social structures affect homelessness through personal characteristics such as human capital, and individual behaviour, have been 'pragmatic rather than theoretically robust' (Fitzpatrick, 2005, p. 3). Further, much of the empirical work has been descriptive and failed to support a cogent explanation of the mechanisms through which structure and individual characteristics interact (Clapham, 2002, 2003).

While there a range of factors that could be considered 'structural', here, we focus on housing and labour market effects.[1] Economic theory's housing demand and supply under constraints perspective is capable of generating hypotheses that are easily testable empirically, provided one has the appropriate data on homelessness dynamics. Following O'Flaherty (1996), Early (1999), and Glomm & John (2002) we therefore describe homelessness as one consequence of utility maximising choices between housing and non-housing consumption under extreme income constraints, and at a single point in time and place.[2] Assuming that individuals are price-takers they can, in principle, trade-off consumption of one good for another in order to reach different feasible bundles of housing and other consumption. However, when income is very low the affordable options shrink to those allowing consumption of very low quality housing that nevertheless absorb a large portion of income; or if regulation prevents supply of low quality housing, a corner solution involving increased consumption of other necessities but accompanied by homelessness.

This conceptual framework yields a number of important hypotheses. First, among the income poor an adverse employment shock leaves fewer resources for consumption and therefore increases the risk of homelessness. Local labour market conditions affect individual risks of homelessness, as negative shocks are more likely in weak labour markets. Income shocks that arise due to biographical disruption (relationship breakdown, bereavement), and happenstance (victims of crime, natural disaster) will similarly affect the acutely income constrained. Second, at very low income levels, individuals with an urgent need for other goods will have little income left over for housing consumption. For example, people with high health expenditures are at greater risk of homelessness. Third, since housing consumption and income are correlated, the less housing an income poor person is currently consuming the sooner he/she is likely to become homeless (O'Flaherty, 2012). This makes the choice of spatial unit particularly important as within cities homelessness is likely to be concentrated in areas with the cheapest housing stock.

Quigley & Raphael (2001) and Quigley *et al.* (2001) invoke constrained utility maximisation models to explain how housing market conditions affect individual homelessness. Rising house prices and rents tighten the already severe income constraints of vulnerable groups, making corner solutions more likely. Rents and prices also vary across regions, with differentials reflecting regional demand and housing supply constraints. Supply constraints arise due to topographical features (e.g. areas with steep inclines are more costly to develop, Saiz, 2010), rent controls (Quigley, 1990), regulation of land and buildings (Hilber & Vermeulen, 2014) and building construction industry bottlenecks (eg skill shortages). Minimum building standard and lot size requirements can be especially important because they prevent low quality housing, and reduce affordable housing opportunities (see Raphael, 2010). The risk of experiencing homelessness could then be higher in areas with tight building and land use controls.

Importantly however, O'Flaherty (2004) posits that it is not just being in the 'wrong place' that directly leads to homelessness but rather the conjunction of being the 'wrong person' in the 'wrong place' that matters; it is only those individuals with personal characteristics that make them vulnerable to homelessness that are at risk of becoming homeless due to adverse housing market conditions. Subgroups among the vulnerable could also become more susceptible in weak labour markets. Those employers inclined to discriminate on the basis of observable risk factors are more likely to do so in slack labour markets, leaving stigmatised groups more prone to homelessness in tight local labour markets. We therefore account for interactions between individual and area-level characteristics in our estimation.

3. Data and definitions

3.1. Journeys home (JH)

Our primary data source is the JH Limited Release file (see Scutella *et al.*, 2017; Wooden *et al.*, 2012). JH is an interviewer-administered survey that followed a sample of Australian welfare recipients exposed to homelessness or housing insecurity. The administrative data held by Australia's social assistance agency (Centrelink) provides the sampling frame for JH. With virtually all individuals vulnerable to homelessness, or currently homeless and eligible to receive social assistance the JH sampling frame results in a broader representation of the population with a non-trivial probability of homelessness than do previous longitudinal homeless studies (see Allgood *et al.*, 1997; Culhane & Kuhn, 1998; Shinn *et al.*, 1998). It is also able to explore factors precipitating entry into homelessness, as well as those lifting people out of homelessness.

Since 2010, Centrelink staff have employed a set of protocols to flag clients assessed to be either 'homeless', or 'at risk of homelessness'. These protocols were designed to target service delivery rather than enumerate the homeless population, thus non-flagged clients will likely include some homeless persons (Scutella *et al.*, 2017; Wooden *et al.*, 2012). A third group was therefore identified using the predicted probability of being flagged as 'homeless' or 'at risk' of homelessness.[3] By design this group have characteristics similar to those identified by Centrelink as 'homeless' or 'at risk', thus constituting a group that is in a statistical sense, vulnerable to homelessness. A total of 139 801 individuals, or 2.9 per cent of all Centrelink welfare enrolments, were flagged as either homeless, at risk of homelessness or have a high predicted probability of becoming homeless.

A stratified random sample from this population was selected for interviews, with wide geographic coverage across major cities, regional and some remote areas. Almost 62 per cent of those sampled ($n = 1682$) agreed to wave 1 interviews conducted in 2011, which was followed by five 6-monthly interviews. Respondents were interviewed in person, with telephone interviews conducted when face-to-face interviews were not feasible. Fully 91 per cent (wave 2), 88 per cent (wave 3), 86 per cent (wave 4), 85 per cent (wave 5), and 83 per cent (wave 6) of wave 1 respondents were re-interviewed. These initial response and re-interview rates are extremely high given this population's relatively high rates of mobility, mortality, and imprisonment. Although attrition is not random it is unlikely to be a major concern (Melbourne Institute, 2014).

Unsurprisingly, the profile of JH respondents is very different to that of the general population (Scutella *et al.*, 2017). Respondents are on average younger, more likely to be male, single, an Indigenous Australian, an ex-offender, and to have experienced mental illness.

3.2. The spatial unit

Structural variables used in estimation are defined at the Statistical Area Level 4 (SA4) of the Australian Statistical Geography Standard (ASGS). There are 87 SA4 regions across Australia, with an average 2011 census population size of 246 617, ranging from 35 797 to 658 016; 36 regions were originally sampled, but all 87 regions are represented in JH because of inter-regional moves over the JH study timeframe.

Although SA4s provide the best sub-state socio-economic breakdown in the ASGS (ABS, 2010), it is questionable whether they are appropriate to represent housing and labour markets. People move within capital cities sorting across areas such that the poor and most vulnerable move to areas with the cheapest housing stock within cities, which is a potential source of endogeneity (Cheshire, 2007; Culhane *et al.*, 1996; O'Flaherty, 2012). Metropolitan wide commuting patterns also suggest that local labour markets are larger than SA4s. We therefore follow the rationale applied by Dustman & Preston (2001) and merge the SA4 spatial units within capital cities to form greater capital city regions, while continuing to use SA4s outside capital cities. Fewer moves across these redefined boundaries will help address endogeneity issues, though there will be less variation in the structural variables. Sensitivity analysis is conducted to detect the impact of different spatial unit definitions.

3.3. Housing and labour market variables

Our main housing market variable measures rental housing costs in the more affordable market segments of each spatial unit. We obtained monthly data by taking the median of the weekly asking rents of houses and units at the postcode level from SQM research,[4] and then chose the 20th percentile from the postcode distribution of median rents in each spatial unit.[5] The 20th percentile measure better reflects housing costs in the more affordable segments of the rental housing market than the median, although the sensitivity of model estimates to a median measure is tested. Volatility of the monthly measure is smoothed using a 3-month moving average. Finally, nominal data were converted to real values using the national Consumer Price Index (ABS, 2016, Tables 1 and 2).

Local labour market conditions are captured by monthly area unemployment rates (ABS, 2014). The series are quite volatile due to small samples in many regional areas. A 12-month moving average unemployment rate measure is therefore employed.

3.4. Defining entries into and exits from homelessness

We adopt the cultural definition of homelessness (Chamberlain & MacKenzie, 1992) widely accepted by Australian policy-makers and researchers. It is a broader definition than the literal homelessness measure commonly employed in the USA. The cultural definition classifies a person as homeless if (s)he has no accommodation, is residing in emergency accommodation or accommodation that does not meet the minimum community standard.[6]

Homeless entry and exit measures are constructed as binary variables representing the transition between a respondent's current homeless status and that at their next interview (time t and $t+1$), roughly a 6 month interval. Homeless entry measures are defined for those housed at time t, and take a value of 1 if the person becomes homeless at time $t+1$, zero otherwise. Homeless exit measures are defined for those homeless at time t, and take a value of 1 if the person is formally housed at time $t+1$, zero otherwise. The estimation sample of 5503 person-periods contains 4391 housed and 1112 homeless observations across waves 1 to 6. Of the 4391 observations housed in t, 350 (8 per cent) transition into homelessness in $t+1$; likewise, from 1112 homeless observations in t, 440 (39.6 per cent) make transitions into formal housing in $t+1$.

3.5. Aggregate homeless entry and exit rates by 20th percentile rents and unemployment rate

Figures 1 and 2 illustrate the relationship between homelessness entry and exit rates and spatial rent and unemployment rate variables. Rents are grouped into A$10 ranges and unemployment rates into 0.1 percentage point ranges. Figure 1a suggests no real relationship between aggregate homeless entry rates and rents at the 20th percentile. Figure 1b shows a stronger relationship between exit rates and rents with exit rates seemingly lower in tighter housing markets. Figure 2a indicates a weak positive relationship between unemployment rates and transition rates into homelessness, but the slope of the fitted line is slight. Figure 2b shows an unexpected positive relationship between exit rates and unemployment rates. However, these aggregate figures could be masking many of the factors contributing to individuals' risks of homelessness.

4. Estimation methods

The prevalence of homelessness at any point in time is determined by the flows into and out of homelessness at that time, as well as the numbers with an enduring homeless status. We model flows in both directions, and allow risk factors to have different effects on entries and exits. However, since there may be unobserved factors affecting

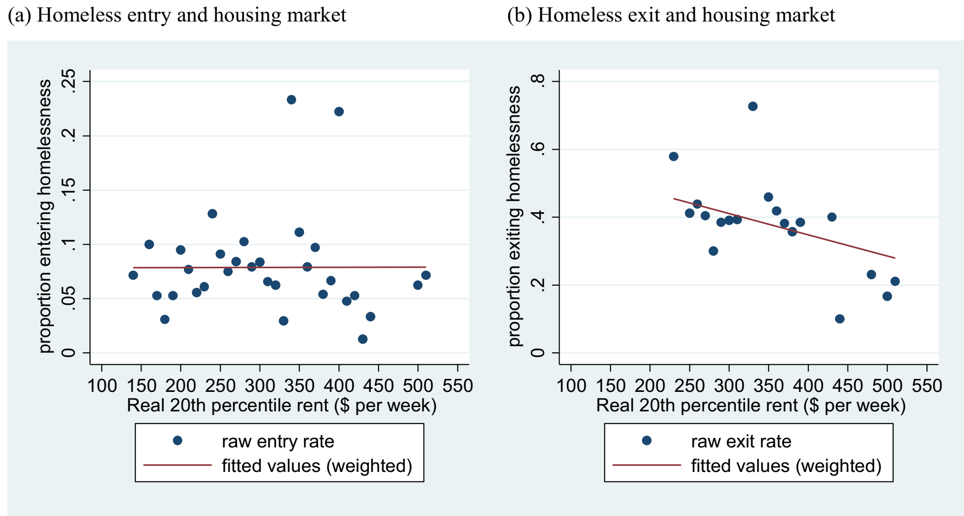

Figure 1. Homelessness entry and exit rates by real 20th percentile rent of area. (a) Homeless entry and housing market. (b) Homeless exit and housing market.

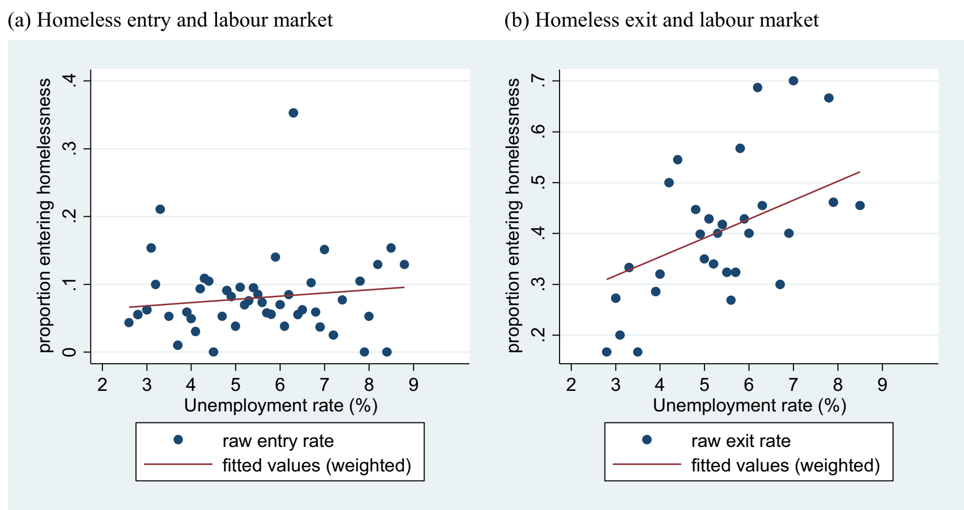

Figure 2. Homelessness entry and exit rates by unemployment rate of area. (a) Homeless entry and labour market. (b) Homeless exit and labour market.

both homeless entry and exit, we jointly estimate the two transitions allowing time-invariant unobserved heterogeneity to be correlated between the two equations. More specifically, we estimate a joint random effect probit specification of individual i's transition into homelessness between time t and $t+1$ (equation 1 below) and individual i's transition out of homelessness (equation 2 below):

$$H_{it}^{*} = X_{it}\beta_H + Z_{it}\gamma_H + \mu_i + e_{it} \tag{1}$$

$$H_{it} = 1 \ \ if \ \ H_{it}^{*} > 0, \ \ \text{zero otherwise}.$$

$$L_{it}^{*} = X_{it}\beta_L + Z_{it}\gamma_L + \nu_i + \varepsilon_{it} \tag{2}$$

$$L_{it} = 1 \ \ if \ \ L_{it}^{*} > 0, \ \ \text{zero otherwise.}$$

Where H_{it}^{*} represents an unobserved latent variable relating to homeless entries for individual i at time t, and H_{it} is individual i's observed binary outcome of homeless entry at time t. Similarly, L_{it}^{*} and L_{it} represent an unobserved latent variable and the observed binary outcome reflecting homeless exit for individual i at time t. The error terms contain permanent components (μ_i and ν_i) and transitory components (e_{it} and ε_{it}). The transitory components are assumed to be normally distributed with means of zero, variances of 1 and independent of the time invariant components. The permanent components (time-invariant individual heterogeneity) are assumed to be normally distributed with means of zero, variances σ_{H}^2 and σ_{L}^2 and may be correlated with a correlation coefficient ρ_{HL}.

The explanatory variables include both individual characteristics X_{it}, and area level characteristics Z_{it}. Individual characteristics include the demographic controls age, gender, marital status, presence of children, country of birth and whether people identify as an Aboriginal or Torres Strait Islander. Gross household incomes measure the financial resources of each individual. Human capital variables include highest level of education, current labour force status, employment history and health measures. Persons growing up in particularly adverse circumstances are captured by an indicator of whether individuals were ever present in the child protection system. An index of current levels of social support is also included together with measures of experiences of violence or incarceration, and engagement in risky behaviours such as substance use and excessive alcohol consumption. We also include indicators of public and community housing residence[7] as well as a marker signalling whether individuals had ever slept rough. Variable definitions and summary statistics are presented in Appendix Table A1.

To allow the effects of housing and labour market conditions to differ by subpopulation Z_{it} is interacted with individual characteristics. We do not add all interaction terms simultaneously because the reduced degrees of freedom will result in imprecise estimates. The addition of interactions is instead conducted individually for each characteristic one at a time so that separate probit regressions are estimated for each characteristic in question.

As the coefficients from probit models are difficult to interpret we present average marginal effect estimates of each of the independent variables. For dichotomous variables marginal effects are calculated over discrete changes of the variable; instantaneous changes are estimated for continuous variables.

5. Results

5.1. Homeless entries

Table 1 presents estimates of the average marginal effects from our entry and exit model specifications. Consider the entry model estimates. Males are 2.1 percentage points less likely to sustain secure housing than females, while couples are no more

Table 1. Probability of homeless entry and exit: mean marginal effects from probit with random effects.

	Entry	Exits
Male	0.021**	−0.080
	(0.009)	(0.056)
Age group (reference = 15–21 years)		
21–44 years	−0.003	−0.213***
	(0.011)	(0.069)
45+ years	0.019	−0.320***
	(0.017)	(0.083)
ATSI	0.017	0.018
	(0.013)	(0.060)
Country of birth (reference = Australia)		
Born in English speaking country	−0.014	−0.025
	(0.015)	(0.088)
Born in non-English speaking country	0.005	−0.032
	(0.020)	(0.092)
Married/defacto	−0.011	−0.060
	(0.010)	(0.069)
Have resident children	−0.020**	0.229***
	(0.010)	(0.076)
Educational (reference = post school qualification)		
Year 12 or eq	0.005	0.047
	(0.013)	(0.080)
Year 10 or 11	0.013	0.038
	(0.010)	(0.053)
Year 9 or below	0.023*	0.046
	(0.013)	(0.064)
Labour force status (reference = employed)		
Unemployed	0.002	−0.068
	(0.015)	(0.089)
Not in the labour force	0.010	−0.122
	(0.014)	(0.083)
Work history		
Never employed	0.040*	0.102
	(0.022)	(0.094)
Lost job in the last 2 years	0.014	0.069
	(0.011)	(0.053)
Time employed since left FT education (per cent)	−0.000	0.001
	(0.000)	(0.001)
Family history		
Ever in State care	0.024*	−0.012
	(0.012)	(0.057)
No principle caregiver at age 14	−0.006	0.136
	(0.016)	(0.086)
Exposure to violence (reference = did not experience)		
Experienced violence	0.020*	0.031
	(0.012)	(0.051)
Did not respond to violence questions	0.013	−0.073
	(0.022)	(0.101)
Incarceration (reference = never incarcerated)		
Ever (but not recently) incarcerated	−0.002	−0.043
	(0.010)	(0.050)
Incarcerated in the last 6 months	0.024	−0.090
	(0.029)	(0.091)
Alcohol consumption per day	0.002*	−0.005
	(0.001)	(0.004)
Illicit drug use (reference = did not use illicit drugs in the last 6 months)		
Used drugs less than once a week	0.016	0.016
	(0.012)	(0.061)
Used drugs once a week or more	0.028**	−0.050
	(0.012)	(0.051)

(*Continued*)

Table 1. Continued.

	Entry	Exits
Health		
Activity limiting long term health condition	0.005	0.028
	(0.009)	(0.046)
Ever diagnosed with mental illness	−0.026**	0.048
	(0.011)	(0.049)
Social support score	−0.018***	0.007
	(0.005)	(0.026)
Homeless history and housing status		
Ever slept rough	0.037***	0.019
	(0.009)	(0.051)
Public housing resident	−0.060***	
	(0.007)	
Community housing resident	−0.010	
	(0.012)	
Equivalised income (A$100/per week)	−0.001	0.003
	(0.002)	(0.011)
Area characteristics (reference = major urban)		
Other urban	0.030**	−0.032
	(0.015)	(0.064)
Non-urban	0.005	0.058
	(0.019)	(0.095)
Housing and labour market characteristics		
Rent at 20th percentile	0.029***	−0.046
	(0.009)	(0.043)
Unemployment rate	0.009**	−0.008
	(0.004)	(0.023)
Number of observations	4391	1108

Standard errors in parentheses.
$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$.

prone to tumble out of secure housing than singles. However, the presence of children lowers the probability of becoming homeless by 2 percentage points, regardless of relationship status. The sample mean probability of entry into homelessness is 8 per cent, so the effect of resident children and gender is large. Age, indigeneity and country of birth are statistically insignificant.

Now consider the vector of human capital characteristics. Those with less than 10 years of schooling are more prone to exit formal housing, but only marginally so (statistically significant at 10 per cent). There is tentative evidence that employment history matters; those with no record of employment are more liable to become homeless, with a high 4.0 percentage point marginal effect estimate, but again significance is at only 10 per cent. Income proves to be statistically insignificant.

Turning to family history and markers of severe disadvantage, we discover that a recent experience of violence and a past custodian of state care stand out with marginal effects of 2.0 and 2.4 percentage points, respectively. However, these variables are again only marginally significant. Incarceration variables are unexpectedly insignificant. Only 2.2 per cent of the entry sample has been incarcerated in the last 6 months. A larger 28 per cent have a past record of incarceration, but this indicator variable is again insignificant.

A minority of those vulnerable to homelessness engage in risky behaviours (drinking, drug use) or suffer ill health (long-term health condition and bipolar or schizophrenia diagnosis). Nevertheless, there are statistically significant effects; regular illicit drug use and higher alcohol consumption precipitate entries into homelessness.[8]

However, the health variables yield unexpected findings. Those with long term health conditions (43 per cent of the entry sample) are no more likely to become homeless; moreover individuals with diagnosed mental health conditions have a statistically significant 2.6 percentage point lower probability of becoming homeless. Diagnosis may signal medical treatment and targeting of support services that helps secure their housing status. On the other hand those with undiagnosed mental health problems and other risk factors may be more precariously positioned in relation to homelessness.

Social support, past experience of homelessness, and current housing circumstances are very important. Social support helps cement residency in secure housing; if there has been a prior episode of primary homelessness, housed but vulnerable individuals are more liable to slip back into homelessness. Whether this is due to a scarring effect (past experience has a debilitating effect that undermines resilience), or learning effect (previous experience facilitates adaptation to homelessness), is uncertain. Regardless, its influence lifts the chances of losing secure housing by 3.7 percentage points, a large impact. Public housing offers very effective protection against homelessness by lowering the probability of becoming homeless by 6 percentage points. This is comfortably the most important indicator variable in the entry model, though only 17 per cent of the entry sample is resident in public housing.

Area level variables reveal that housing and labour market conditions are statistically significant.[9] A one unit ($100) increase in an area's 20th percentile weekly market rent lifts the risk of entry by roughly 2.9 percentage points.[10] Likewise, we estimate that a 1 percentage point increase in a region's unemployment rate increases the likelihood of entry by roughly 0.9 percentage points. The point elasticity with respect to the 20th percentile market rent is 1.65 and that with respect to the unemployment rate is 0.86. However, we are unable to reject the null hypothesis of equal proportional effects of housing and labour markets on risk of entry into homelessness.[11] These housing and labour market effects remain statistically significant and important at these levels, even after including controls that distinguish urban from non-urban regions. Those housed but vulnerable individuals that are located in what the Australian Standard Geographical Classification refers to as other urban regions, that is, outside the major urban localities, have a marginal effect estimate of 3 percentage points.

Table 1 reported the average marginal effects at one point in the distribution, but in Figure 3 we present estimated predicted probabilities of entering homelessness across the distribution of 20th percentile rents (in panel a) and unemployment rates (in panel b). These predicted probability plots differ from the aggregate rates of entry into homelessness presented earlier in Figures 1a and 2a. The comparison underlines the importance of accounting for differences in observable and unobservable individual characteristics.

Figure 3a shows the predicted probability of entering homelessness ranging from 0.024 in areas with plentiful affordable housing, to 0.17 in areas where rents are very high (A$550 a week). The slope of this curve increases at higher levels of the rent variable, thus marginal rent increases in expensive markets have relatively large impacts on the risk of homelessness. Likewise, Figure 3b establishes a stronger

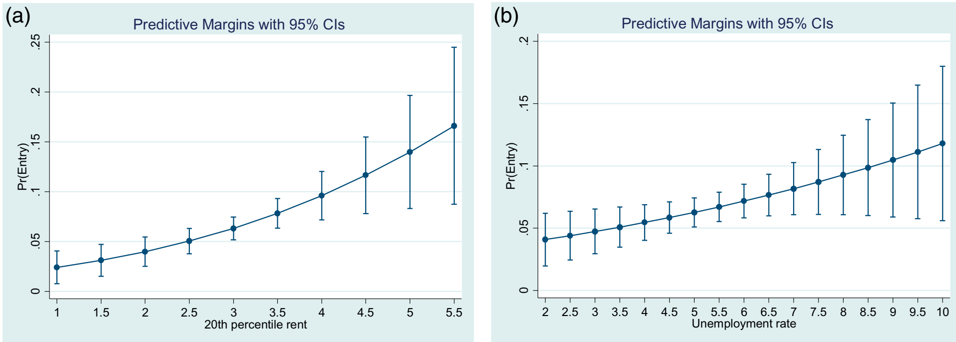

Figure 3. Predicted probabilities of homeless entry by area level rent and unemployment rate, with 95 per cent confidence intervals. (a) 20th percentile rent. (b) Unemployment rate.

positive relationship between local unemployment rates and the probability of entering homelessness as compared to that in Figure 2a.

Housing and labour market impacts could be muted because those public housing tenants present in estimation samples pay rents that cannot exceed 25 per cent of assessable household income, and they have security of tenure. On omitting them from the sample our 20th percentile rent variable does become stronger; a 3.3 percentage point marginal effect estimate instead of 2.9 percentage points. However, the unemployment rate effect is now weaker, and loses significance (see Appendix Table A2).[12]

Further sensitivity analysis highlights the importance of the spatial unit's definition. A finer spatial unit dampens the impact of rents on entries into homelessness, while the unemployment rate variable becomes statistically insignificant, perhaps reflecting misrepresentation of local labour markets and endogenous sorting within capital cities as discussed in section 3.2.

5.2. Homeless exits

Table 1 also lists marginal effect estimates from an exit model with the same vector of explanatory variables. The sample size is smaller because most of the JH sample is housed in any given wave and so the standard errors are generally larger. There are also noteworthy differences in sample composition. Mature age respondents (45 years and over) are much more common in the exit sample at one third, compared to just under one fifth of the entry sample. Married's share of the entry sample (20 per cent) is nearly twice their share of the exit sample (11 per cent) and the incidence of resident children in the entry sample is nearly three times that in the exit sample. The proportion employed is much lower in the exit sample, while risky behaviours (illicit drugs, alcohol and cigarette consumption) are more common, as is recent incarceration and past episodes of primary homelessness. In short, the exit sample has a stronger representation of older single males with risky behaviours and episodic homelessness profiles.

These differences in the sample's size and composition mirror differences between the processes driving exits from homelessness and those tipping previously housed individuals into homelessness. Most conspicuous is the exit model's lack of statistically significant variables, a finding that is consistent with Cobb-Clark *et al.* (2016), Culhane & Kuhn (1998), and the Markovian processes proposed in O'Flaherty (2012).

Indeed the only significant variables are age and the presence of children. While all age groups appear equally likely to tumble into homelessness (see also Allgood & Warren, 2003; Cobb-Clark *et al.*, 2016), escape from homelessness is much less probable at older ages. The 21–44 year group are 21.3 percentage points less likely to escape than the reference age group (15–20 years), and individuals 45 years and older are 32 percentage points less likely to exit. Past episodes of homelessness are frequent among homeless individuals, so scarring or experience effects could be relevant, but these are controlled for in the model.[13] The age effects are a notable finding and we return to their interpretation and wider significance in the concluding section.

Strongly significant and large marginal effects (22.9 percentage points) in the anticipated direction are detected with respect to resident children. While this appears to contradict O'Flaherty's (2012) theory that exiting homelessness is delayed for those paying more for housing, it could reflect the targeting of services to homeless families.

On the face of it, the insignificance of area-level housing and labour market conditions in the exit model departs from the findings of Cobb-Clark *et al.* (2016). They discover small but statistically significant effects on the duration of homeless spells, but use the JH housing calendar data to examine homeless to housed transitions over 10 day periods, rather than transitions between adjacent survey waves that are typically 6 months apart. The small impacts detected when measuring the duration of spells using ten day intervals become insignificant on modelling transitions out of homelessness over 6 month intervals.[14]

5.3. Heterogeneity in housing and labour market effects

We now scrutinise the notion that a conjunction of being the 'wrong person in the wrong place' is what matters most. We therefore examine whether housing and labour market conditions impact the chances of entry into homelessness among certain types of people that a priori are considered at risk of homelessness. The dichotomous variables listed in Table 1 identify such subgroups. Sample sizes are too small for the analysis of subgroup exits from homelessness, so we only undertake analysis for entries into homelessness. Table 2 presents, for individuals in each subgroup, the average marginal effect of a change in the 20th percentile rent (column 1) and unemployment rate (column 2) on their probability of entering homelessness.

Two sets of statistical significance tests have been conducted. We first test whether we can reject the hypothesis of a mean marginal effect that is not significantly different from zero. We also conduct a Wald test to determine whether we can reject the hypothesis of equal mean marginal effects across subgroups. Table 2 only reports those marginal effects where we reject the null hypothesis of equal marginal effect estimates across subgroups.

Table 2. Mean marginal effects of median rent and unemployment rate from probit with random effects where differences between groups are statistically significant.

	20th percentile rents (1)	Unemployment rates (2)
Aboriginal or Torres Strait Islander	0.085***	0.034***
	(0.023)	(0.012)
Not Aboriginal or Torres Strait Islander	0.018**	0.004
	(0.009)	(0.005)
Ever incarcerated	0.051**	
	(0.017)	
Never incarcerated	0.020**	
	(0.009)	
Opted out of violence questions	0.108**	
	(0.044)	
Experienced violence in last 6 months	0.035	
	(0.023)	
Did not experience violence in last 6 months	0.023**	
	(0.009)	
Ever diagnosed with mental illness	0.017*	0.004
	(0.010)	(0.005)
Never diagnosed with mental illness	0.057***	0.019**
	(0.016)	(0.008)
Currently uses drugs	0.010	
	(0.016)	
Does not use drugs	0.038***	
	(0.009)	
Numbers of observation	4391	4391

Standard errors in parentheses.
$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

Consider first the results on differential effects with respect to housing market conditions (column 1 of Table 2). Aboriginal or Torres Strait Islanders, the ever incarcerated, and those opting out of questions on violence are particularly sensitive to housing market conditions. In addition, survey participants never before diagnosed with mental illness, or not currently using drugs, have predicted probabilities of becoming homeless that are raised (lowered) when rents increase (decrease). Differential effects of local labour market conditions are more limited. Aboriginal or Torres Strait Islanders, those ever incarcerated or never diagnosed with mental illness are significantly more sensitive to local labour market conditions. It seems that some subgroups that are no more prone to enter homelessness than the average survey participant are nevertheless more likely to become homeless when there is an increase in local rents, or local unemployment rates. A case in point is Aboriginal or Torres Strait Islanders. Overall, this group is not at a significantly higher risk of entering homelessness than other similarly vulnerable persons in the presence of controls for socioeconomic characteristics and housing and labour market conditions (see Table 1). However, on adding interaction terms we find that tighter housing markets and/or weaker labour markets expose Aboriginal or Torres Strait Islanders to a higher risk of entering homelessness (see Table 2).

This is illustrated in Figure 4 where we plot Aboriginal or Torres Strait Islanders' predicted probabilities of entering homelessness against those of all other individuals. In areas with abundant affordable housing, the likelihood of entering homelessness is quite low for both groups (Figure 4a). However, once 20th percentile rents reach $300 a week or more, Aboriginal or Torres Strait Islanders become substantially more liable to enter homelessness. What's more, the marginal effect continues to rise (as

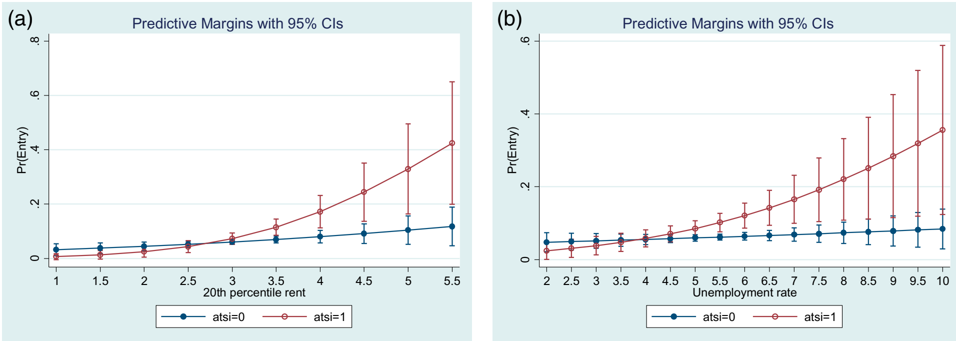

Figure 4. Predicted probabilities of homeless entry by area level rent and unemployment rate (Aboriginal or Torres Strait Islanders versus non-ATSI). (a) Rent. (b) Unemployment rate.

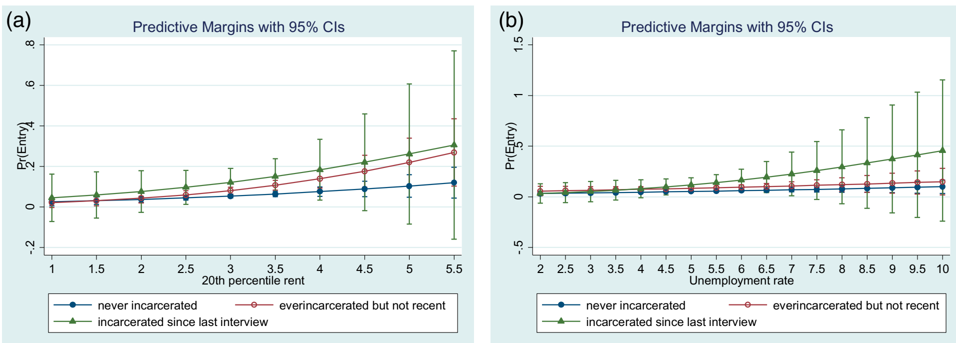

Figure 5. Predicted probabilities of homeless entry by area level rent and unemployment rate (by incarceration history). (a) Rent. (b) Unemployment rate.

represented by the slope of the curve) the tighter the housing market. A similar pattern is apparent in relation to labour market effects (see Figure 4b). A heterogeneous housing market effect is also evident among ex-offenders (see Figure 5a) as well as for those opting out of questions on violence (see Figure 6a).

These findings offer some support for the 'wrong person in the wrong place' hypothesis put forward in O'Flaherty (2004); some subgroups in the vulnerable to homelessness population—the indigenous, ex-offenders and those opting out of questions on violence—are only at higher risk of becoming homeless if living in areas lacking affordable housing and/or employment opportunities. Discrimination in housing and labour markets could be a source of heterogeneous effects as it is more likely to be exercised in tighter housing markets and/or weaker labour markets, and groups such as ex-offenders and Indigenous Australians are especially prone to discrimination.

However, there is an apparently puzzling finding. We find that those diagnosed with mental illness, another group typically considered to be at-risk of homelessness,

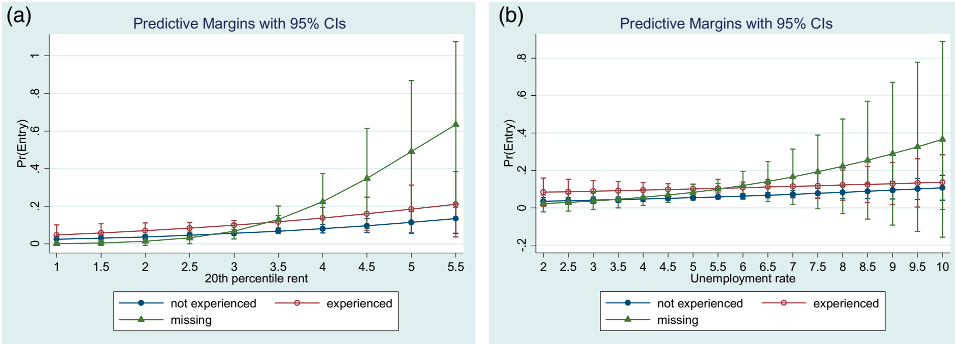

Figure 6. Predicted probabilities of homeless entry by area level rent and unemployment rate (by experiences of violence). (a) Rent. (b) Unemployment rate.

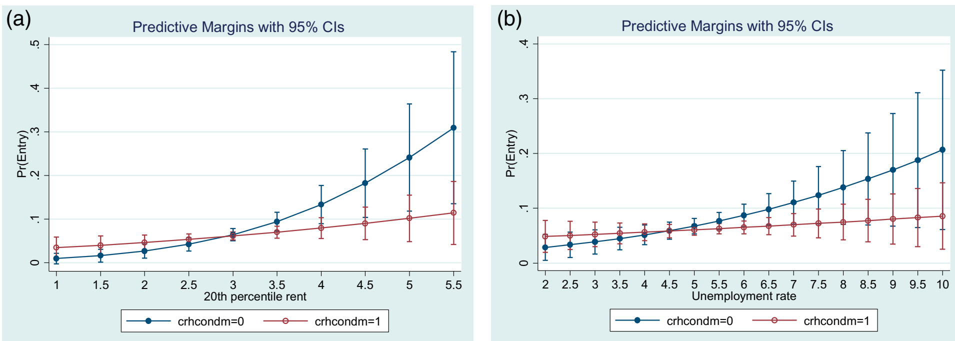

Figure 7. Predicted probabilities of homeless entry by area level rent and unemployment rate (by mental health diagnosis). (a) Rent. (b) Unemployment rate.

are less prone to homelessness overall and their risk of becoming homeless is only marginally affected by rising rents and unaffected by rising unemployment rates (see the predicted probability plots in Figure 7). Here, we suspect that housing and labour market effects are neutralised because those diagnosed with mental ill-health are more likely to receive a range of support services, including housing.

Finally, there is one risk factor—drug use—that elevates the probability of entering homelessness but equally so regardless of where you live. As shown in Figure 8 the predicted probability of entering homelessness hovers around 0.1 regardless of the value of the 20th percentile rent (panel a), or the unemployment rate (panel b).

6. Conclusion and policy implications

This paper examined whether housing and labour market conditions affect individuals' transitions into and out of homelessness. Consistent with previous individual level studies we find that individuals with particular risk factors are, on average, more

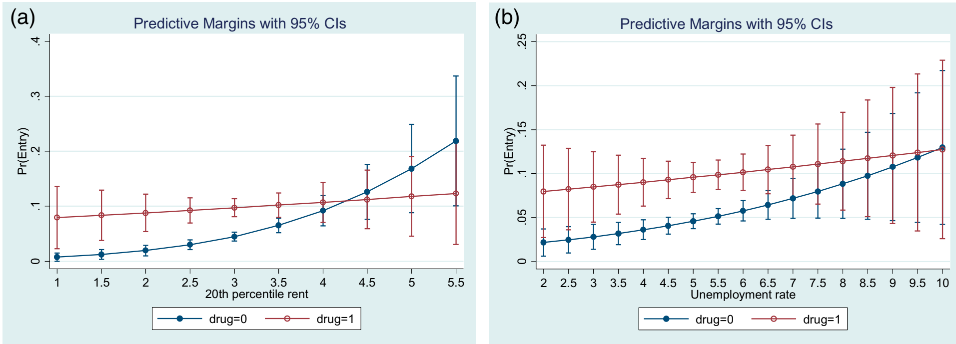

Figure 8. Predicted probabilities of homeless entry by area level rent and unemployment rate (Drug users vs non-drug users). (a) Rent. (b) Unemployment rate.

likely to become homeless. Risky behaviours and adverse life experiences, such as regular use of drugs, heavy drinking and the experience of violence expose people to higher risks of becoming homeless. Vulnerable people with biographies marked by acute disadvantage (eg <10 years of schooling, no previous record of employment, growing up in State care, past episodes of homelessness) are also more likely to slip into homelessness. There is a strong gender dimension to homelessness; previously housed but vulnerable males are much more likely to enter homelessness. However, the presence of children lowers the chances of becoming homeless, regardless of relationship status; as does strong social support. However, unexpectedly, those diagnosed with mental health conditions are less likely to transition into homelessness. We suspect that it is the protective effect of universal health and other support services for the mentally ill that might account for this finding.

Importantly, we found public housing to be a very strong protective factor reducing risks of homelessness. Public housing is particularly effective because it is affordable. It has also traditionally offered a long-term, secure housing option for those at the bottom of the housing market. This is because public housing leases provide the benefits of security of tenure commonly associated with home ownership. Community housing on the other hand appears to not offer the same level of protection. These findings emerge despite community housing being affordable, however security of tenure is weaker possibly because providers are more dependent on rent revenue and therefore less tolerant of rental arrears. Despite such evidence, the stock of public housing continues to decline in Australia with State government-initiated transfers of stock to the community housing sector accelerating this trend. This finding is also of relevance to other developed countries whose public housing stocks have been squeezed.

Interestingly, and in contrast to many other individual level studies of factors relating to homelessness, we find that area level housing and labour markets are strongly related to homelessness entry. Further, we find supporting evidence for O'Flaherty's theory that homelessness is a result of being the 'wrong person in the wrong place' for certain at-risk subgroups. While these subgroups are no more prone to enter homelessness overall than the average survey participant, they are significantly more likely to become homeless when they live in tight housing markets, or slack labour markets. Aboriginal or Torres Strait Islanders and ex-offenders are typically considered to be at particular risk of homelessness in Australia. Overall, these groups are not at a significantly higher risk of entering homelessness when controls for socioeconomic characteristics and housing and labour market conditions are present in model specifications. However, on allowing for heterogeneous effects tighter housing markets are found to expose Aboriginal or Torres Strait Islanders and ex-offenders to significantly higher risks of becoming homeless. Aboriginal or Torres Strait Islanders are also more sensitive to local labour market conditions.

However, we discover that those diagnosed with mental illness, another commonly stigmatised group, are less vulnerable to homelessness and their risk of becoming homeless seems unaffected by rising rents, and/or rising unemployment rates. This is not what we expected given a literature that consistently identifies people with serious mental health problems as over-represented in the homeless population as compared to the general population. We speculate that those diagnosed are more likely to be receiving treatment, housing support and care (even institutionalised care), thereby lowering the chances of experiencing homelessness as compared to those with other risk factors. These services also protect people with a mental illness against the effects of worsening housing and labour conditions. Moreover, this argument implies that those with undiagnosed conditions but not receiving treatment and support, are more likely to become and remain homeless. If this is indeed the case, it emphasises the crucial role that Australia's universal health services play in the prevention of homelessness.

There does appear to be one risk factor that makes individual's equally likely to enter homelessness regardless of where they live, and that is drug use. The significant and positive predicted probability of entering homelessness for drug users hovers at around the same higher level than non-drug users across the distribution of 20th percentile rents and unemployment rates. Thus, drug users are just as likely to become homeless in areas with abundant affordable housing as they are in areas with little affordable housing.

Our model estimates can be used to identify the most effective (but not necessarily the most efficient) ways of reducing homelessness. Public housing's strong protective effect is confirmed by model simulations suggesting that approximately 73 per cent of cases flowing into homelessness could be avoided if the vulnerable were placed in public housing.[15] Likewise around a quarter (26 per cent) could avoid homelessness if affordable housing (at the 20th percentile) were capped at A$250 a week in all areas; and if this cap was reduced to A$200 almost 40 per cent could avoid homelessness.[16] Targeting drug use however is a less effective strategy with only 14 per cent predicted to avoid homelessness if all drug users were successfully treated.[17]

It is important to mention that processes shaping pathways out of homelessness appear to be very different from those shaping entries into homelessness, so it is important to separately analyse transitions into and out of homelessness. Indeed our results are in keeping with O'Flaherty's (2012) hypothesis that the process driving exits from homelessness is Markovian; that is, once a person becomes homeless the personal characteristics and structural factors explaining how they got there typically have no effect on their likelihood of exiting. Age and the presence of children are the only exceptions to this proposition. Older homeless people are much less likely to escape their predicament, perhaps because older individuals become disconnected from housing and labour markets as well as homelessness services. Age could also be a key influence because young people are more adaptable as well as more mobile, and hence access a wider range of housing and labour market opportunities. The presence of children probably also reflects the targeting of service support.

In concluding, we must acknowledge that there are inevitable caveats to our analysis because researchers can never rule out there being unobserved area-level characteristics that have not been accounted for in estimation. Furthermore, these could be correlated with area-level covariates included in our model specifications.

However the estimation approach represents a significant innovation on previous research into the drivers of homelessness. Firstly, we exploit the panel data by measuring personal and area characteristics in the time period preceding entry or exit. This addresses endogeneity concerns arising from reverse causation. Secondly, we take unobserved heterogeneity at least partially into account by adopting a random effects estimator. Thirdly, joint estimation of entry and exit models of homelessness uses information on the correlation between error terms to improve the efficiency of estimates. Fourthly, we have a rich set of control variables representing the influence of observable factors commonly associated with the risk of homelessness. Finally, we have followed the methodology set out in Dustman & Preston (2001) to address selection bias by defining our area boundaries such that endogenous moves are minimised. Therefore, although caveats remain in our identification strategy, our findings provide policy makers with quite a firm indication of the importance of housing and labour markets, and of their interactions with individual level characteristics, when framing policy responses to homelessness.

Notes

1. These are not to be confused with broader neighbourhood effects (crime, quality of schools and so on) such as described by Galster (2012), and the focus of Chetty & Hendren (2018a, 2018b).
2. There are therefore no moves and location is not an attribute over which preferences are defined.
3. A logistic regression of the probability of being flagged as 'homeless' or 'at risk of homelessness' was estimated; those non-flagged individuals with predicted probabilities that place them in the highest 2% of all Centrelink clients were added to the vulnerable to homelessness group.
4. SQM Research conducts on-going monitoring of a number of real estate listings websites. SQM Research believes it captures over 97% of all real estate listings. See http://www.sqmresearch.com.au/about-us.php.
5. The spatial units have a median 41 postal codes.
6. See Chamberlain (1999) and Chamberlain & MacKenzie (2003, 2008) for details; because of different JH data items, our cultural homelessness measure is slightly different from theirs. This wider conception of homelessness has become the widely accepted benchmark used by Australian policy makers and researchers to frame analysis and policy initiatives.

7. Public housing is managed by State Housing Authorities; community housing is managed by not-for-profit organisations.
8. Roughly 20% use illicit drugs at least weekly over the last 6 months. However, the average daily consumption of alcohol is only 1.5 units per day.
9. These variables remain significant even after using bootstrapping techniques to estimate standard errors taking into account the clustering of areas. Thus, we can be confident that it is not the reduced variability of our area-level covariates that is driving this result.
10. These variables remain significant even after using bootstrapping techniques to estimate standard errors taking into account the clustering of areas. Thus, we can be confident that it is not the reduced variability of our area-level covariates that is driving this result.
11. Sensitivity tests with respect to alternative rent measures that include a median market rent from the SQM data as well as the median market rent from the 2011 Australian Census are presented in Appendix Table A2. In both entry and exit models these alternative measures generate similar qualitative results for housing and labour market effects, with a slightly smaller marginal effect estimated in response to a change in median rents.
12. Other coefficient estimates are stable with no changes in their significance.
13. Very nearly three quarters of the exit sample have had a prior episode of homelessness. The lack of sample variation in this variable might be responsible for its statistical insignificance in the exit model.
14. The housing calendar data was unsuitable for our analysis as we wanted to include time-varying versions of housing, labour market and individual characteristics variables, which cannot be identified over 10 day intervals.
15. With a base level predicted probability of homeless entry of .0657336 and a predicted probability of entry if everyone was placed into public housing of .017903.
16. With a base level predicted probability of homeless entry of .0657336; a predicted probability of entry if everyone was in areas where the 20th percentile rent was capped at $250 of .0488221; and a predicted probability of entry if everyone was in areas where the 20th percentile rent was capped at $200 of .0395731.
17. With a base level predicted probability of homeless entry of .0657336 and a predicted probability of entry if everyone avoided drug use of .0563981.

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Appendix

Table A1. Variable definitions and summary statistics.

		Housed at interview		Homeless at interview	
		Mean	STD	Mean	STD
Entered homelessness	For those housed at current interview: equals 1 if became homeless in the next interview, and zero otherwise.	0.080	0.271		
Exited homelessness	For those homeless at current interview: equals 1 if became housed in the next interview, and zero otherwise.			0.397	0.490
Male	Equals 1 if male, and 0 if female	0.490	0.500	0.690	0.463
Age group	Age determined from date of birth				
15–20 years	Equals 1 if aged 15–21 years, and 0 otherwise	0.237	0.425	0.151	0.358
21–44 years	Equals 1 if aged 21–44 years, and 0 otherwise	0.573	0.495	0.514	0.500
45+ years	Equals 1 if aged 45 years plus, and 0 otherwise	0.190	0.392	0.336	0.472
ATSI	Equals 1 if identifies as Aboriginal or Torres Strait Islander; and 0 otherwise. Options are as provided in the ABS Census.	0.161	0.368	0.187	0.390
Country of birth					
Born in Australia	Equals 1 if born in Australia, and 0 otherwise.	0.875	0.331	0.866	0.340
Born in English speaking country	Equals 1 if born in main English speaking country, and 0 otherwise.	0.065	0.246	0.069	0.253
Born in non-English speaking country	Equals 1 if born in non-main English speaking country, and 0 otherwise.	0.060	0.238	0.065	0.247
Married/defacto	Equals 1 if married/defacto, and 0 otherwise.	0.204	0.403	0.106	0.307
Have resident children	Equals 1 if have dependent children living who are living with them, and 0 otherwise.	0.289	0.453	0.106	0.309
Education					
Post school qualification	Equals 1 if has at least a Certificate Level 3 qualification or higher recognised by the Australian Qualifications Framework (AQF); and 0 otherwise	0.333	0.471	0.315	0.465
Year 12 or eq	Equals 1 if completed high school and does not have a post-school qualification (Certificate Level 3 or higher) or has completed a Certificate Level I or II qualification with at least Year 10 schooling completed; and 0 otherwise.	0.119	0.324	0.091	0.288
Year 10 or 11	Equals 1 if has completed at least Year 10 at school and does not have a post-school qualification (Certificate Level 3 or higher) or has less schooling but has completed a Certificate Level I or II qualification; and 0 otherwise.	0.392	0.488	0.387	0.487

(*Continued*)

Table A1. Continued.

		Housed at interview		Homeless at interview	
		Mean	STD	Mean	STD
Year 9 or below	Equals 1 if has not completed Year 10 at school and has not completed any other AQF recognised qualifications; and 0 otherwise.	0.156	0.362	0.207	0.405
Labour force status	Determined by a series of questions from the ABS Monthly Population Survey, with the concept of "last week" replaced by "the last 7 days", which follow international standards on labour statistics as set out by the International Labour Organisation.				
Employed	Equals 1 if employed, and 0 otherwise	0.256	0.437	0.156	0.363
Unemployed	Equals 1 if unemployed, and 0 otherwise	0.258	0.437	0.272	0.445
Not in the labour force	Equals 1 if not in the labour force, and 0 otherwise	0.486	0.500	0.572	0.495
Work history					
Never employed	Equals 1 if has spent no time since first left full-time education in paid work; and 0 otherwise.	0.079	0.271	0.061	0.240
Time employed since left FT education (per cent)	Per cent of time employed since first leaving full-time education (with values >0 and <100).	40.687	30.806	42.879	30.552
Lost job in the last 2 years	Equals 1 if reported not employed and last paid job was within last 2 years; 0 otherwise	0.302	0.459	0.332	0.471
Ever in state care	Equals 1 if reported being placed in either foster care or residential care before the age of 18, and 0 otherwise	0.165	0.371	0.181	0.385
No principle caregiver at age 14	Equals 1 if had no principle caregiver at age 14, and 0 otherwise	0.053	0.225	0.070	0.256
Recent violence					
Did not experience	Equals 1 if reported not having experienced physical violence or force or sexual violence against them in the last 6 months; and 0 otherwise.	0.800	0.400	0.723	0.448
Experienced violence	Equals 1 if anyone has used physical violence or force or sexual violence against them in the last 6 months; and 0 otherwise.	0.162	0.368	0.237	0.426
Did not respond to questions	Equals 1 if did not respond to questions on violence; and 0 otherwise.	0.039	0.193	0.040	0.195
Incarceration					
Never incarcerated	Equals 1 if never been in juvenile detention, adult prison or remand in last 6 months; and 0 otherwise.	0.699	0.459	0.567	0.496

(*Continued*)

Table A1. Continued.

		Housed at interview		Homeless at interview	
		Mean	STD	Mean	STD
History of incarceration (but not in the last 6 months)	Equals 1 if ever been in juvenile detention, adult prison or remand but not in the last 6 months; and 0 otherwise.	0.279	0.448	0.379	0.485
Incarcerated in the last 6 months	Equals 1 if in juvenile detention, adult prison or remand in last 6 months; and 0 otherwise.	0.022	0.148	0.054	0.226
Alcohol consumption	Average number of standard drinks consumed per day.	1.484	3.582	2.648	5.800
Illicit drug use					
Did not use illicit drugs	Equals 1 if did not use any type of illicit drug (including cannabis) in the last six months; and 0 otherwise	0.660	0.474	0.519	0.500
Used drugs less than once a week	Equals 1 if used any type of illicit drug irregularly (ie less than weekly) in the last six months; and 0 otherwise.	0.144	0.351	0.170	0.376
Used drugs once a week or more	Equals 1 if used any type of illicit drug at least weekly in the last six months; and 0 otherwise.	0.196	0.397	0.311	0.463
Activity limiting long-term health condition	Equals 1 if reports a long-term health condition, impairment or disability causing restrictions in everyday activities, and has lasted or is likely to last, for 6 months or more; and 0 otherwise.	0.438	0.496	0.523	0.500
Ever diagnosed with mental illness	Equals 1 if ever diagnosed with Bipolar affective disorder (manic depression), Schizophrenia, Depression, Post-traumatic stress disorder, or Anxiety disorder; and 0 otherwise.	0.680	0.467	0.653	0.476
Social support score	An index averaging across the following 4 items, with each rated on a scale ranging from 1 "Strongly agree" to 5 "Strongly disagree": i. You often need help from other people but can't get it? ii. You have someone you can lean on in times of trouble? (reversed) iii. There is someone who can always cheer you up when you are down? (reversed) iv. iv) You often feel very lonely?	3.566	0.808	3.256	0.853
Ever slept rough	Equals 1 if have ever experienced primary homelessness; and 0 otherwise.	0.530	0.499	0.741	0.438
In public housing	Equals 1 if living in public housing; and 0 otherwise	0.171	0.377		
In community housing	Equals 1 if living in community housing; and 0 otherwise	0.085	0.280		

(*Continued*)

Table A1. Continued.

		Housed at interview		Homeless at interview	
		Mean	STD	Mean	STD
Major urban	Equals 1 if living in a major urban area as defined by the ABS Section of State in the ASGS; and 0 otherwise	0.784	0.411	0.795	0.404
Other urban	Equals 1 if living in an other urban area as defined by the ABS Section of State in the ASGS; and 0 otherwise	0.167	0.373	0.149	0.356
Non-urban	Equals 1 if living in a rural area or bounded locality as defined by the ABS Section of State in the ASGS; and 0 otherwise	0.049	0.216	0.056	0.230
Real Equivalised family income ($100 per week)	Family Income/square root (family size) deflated by CPI	4.176	2.924	3.813	2.345
Real 20th percentile rent ($100 per week)	[Weekly 20th percentile rent of greater capital city area or SA4 for regions outside of capital cities] divided by 100; 3 month centred moving average; deflated by CPI	3.140	0.641	3.254	0.659
Unemployment rate (per cent)	Unemployment rate of greater capital city area or SA4 for regions outside of capital cities; 12 month centred moving average	5.338	1.063	5.301	1.134
Number of observations		4391		1108	

Table A2. Sensitivity to alternative area level measures (average marginal effects of Probit estimation[a,b]).

	Broader spatial unit (main results)		Broader spatial unit		Finer SA4 spatial unit		Exclude public housing residents		Broader spatial unit - Census	
Variables	Entries	Exits	Entries	Exits	Entries	Exits	Entries	Exits	Entries	Exits
20th percentile rent	0.029***	−0.046			0.021***	−0.033	0.033***	−0.045		
	(0.009)	(0.043)			(0.006)	(0.031)	(0.010)	(0.043)		
Median rent			0.021***	−0.012					0.029***	0.006
			(0.007)	(0.034)					(0.008)	(0.051)
Unemployment rate	0.009**	−0.008	0.009**	0.001	0.005	0.015	0.007	−0.006	0.010**	0.015
	(0.004)	(0.023)	(0.004)	(0.023)	(0.003)	(0.019)	(0.005)	(0.023)	(0.005)	(0.027)
Observations	4391	1108	4391	1108	4391	1108	3640	1108	4391	1108

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.
[a]All other controls listed in Table 1 are also included in joint estimation.
[b]Standard errors in parentheses.