

How Do Housing and Labour Markets Affect Homeless Entry and Exits?*

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Abstract

In this paper we combine micro-level longitudinal data obtained from 1682 Australian income support recipients, with area-level observations of housing and labour market conditions to explore the relationship between structural conditions, individual characteristics and transitions into and out of homelessness. Findings from jointly estimated entry and exit probit equations are reported. We discover that risky behaviours and life experiences such as regular use of drugs and the experience of violence as well as people with biographies marked by acute disadvantage, are at a higher risk of becoming homeless. The estimates also suggest that the risk of becoming homeless is greater in regions with higher median rents and slack labour markets; residence in public housing has a strong protective effect. Transitions out of homelessness appear to be largely unrelated to risky behaviours and signals of marked disadvantage. The results emphasise the importance of modelling both entries into and exits from homelessness as behavioural traits and structural housing and labour market conditions can have different impacts on transitions into and out of homelessness. Finally, we find that there is heterogeneity in the effects of housing and labour markets. Individuals vulnerable to homelessness but not engaging in risky behaviours (e.g. regular drug users), or possessing particular risk characteristics (e.g. long term health condition), are more likely to be tipped into homelessness when housing market conditions tighten and labour market conditions weaken. Persons with particular risk factors however have similar chances of entering homelessness regardless of housing and labour market conditions. Ex-offenders however appear to particularly sensitive to private rental housing markets.

1. Introduction

Homelessness continues to be a feature of wealthy nations, which is of particular concern as it can have serious negative consequences on those affected. In order to develop effective policies to prevent or alleviate homelessness it's important to understand what causes people to enter homelessness and then prevents them from finding adequate housing.

In this paper we explore the relationship between area-level structural conditions, individual characteristics and transitions into and out of homelessness. We combine micro-level longitudinal data obtained from 1682 Australian income support recipients facing housing insecurity, with area-level observations of housing and labour market conditions and jointly estimate the likelihood of entering into and exiting out of homelessness using a random effects logistic estimator. In addition to examining the overall impact of housing and labour markets on individual risks of homelessness, we examine whether there is a heterogeneous impact across individuals with different characteristics. That is do housing and labour market conditions affect those with particular risk factors such as mental illness, physical illness, substance misuse, and/or histories of incarceration more than others.

Why might we expect housing and labour markets to affect homelessness? Housing supply constraints mean that there is a non-convexity in the housing technology such that housing is not available below minimum housing standards (O'Flaherty 1996 & 2012, Early 1999 and Glomm and John 2001). Supply constraints can arise due to topographical features (e.g. areas with steep inclines or flood plains are more costly to develop), regulation of land and buildings and bottlenecks within the building construction industry (e.g. skill shortages), and planning system. These supply constraints prevent the expansion of low-cost rental to accommodate those displaced, and homelessness results. We can also expect local labour market conditions to affect individual risks of homelessness, as those in areas with weak labour markets are more likely to experience negative income shocks associated with unemployment.

Empirical studies examining the effect of housing and labour markets however have been dominated by macroeconomic analysis at the city-level. Most area-level studies use cross-sectional data to explain the inter-city variations in homelessness (for an early example see

Honig and Finer, 1993)¹. In a small number of studies, characteristics of areas at multiple time points (panel studies) allow the dynamics of geographical variation in homelessness to be examined (Quigley and Raphael, 2001).

Studies that use area-level observations indicate that structural factors are the main contributors to homelessness and find little evidence that individual risk factors matter. In the US, these studies find that housing markets seem to matter the most, with little evidence that local labour markets or concentrations of poverty matter (Appelbaum *et al.* 1991; Elliott and Krivo 1991; Burt 1992; Honig and Filer 1993; Quigley and Raphael 2000; Quigley *et al.* 2001; Lee *et al.* 2003; Florida *et al.* 2012). In Australia, however, the situation seems reversed. These studies find that local labour markets matter a lot, and housing markets don't appear to matter much (Batterham 2012; Wood *et al.* 2014). However, both US and Australian area-level studies are similar in their finding that individual characteristics do not appear to matter a great deal.

In contrast are studies that have used micro-level (or individual) data to examine variations in individual risks of homelessness across different areas, but these are far less common (Early 1998; Early and Olsen 1998; Early 1999; Early and Olsen 2002; Early 2004; 2005). The approach used in each of these studies is quite similar. They match cross-sectional observations on a sample of the homeless to a low-income but housed population. Although the estimation methods differ, each estimates the probability of individuals being homeless as a function of household characteristics and the characteristics of the city in which the household resides. The estimation method adjusts for the oversampling of the homeless in the data. The results of these studies are consistent – area level conditions rarely matter but individual characteristics such as race, gender, age, mental illness and poverty are almost always important predictors of homelessness in individual level studies.

Why do these individual-level studies get systematically different findings from area-level studies - namely, that individual characteristics matter but structural conditions do not? As O'Flaherty (2004) shows it is because both sets of models are actually misspecified: it's the conjunction of being the wrong person in the wrong place that matters. To understand the

¹ These cross section studies tend to use point prevalence measures of homelessness – a count of the number of homeless at a point in time. Because there is considerable turnover in the homeless population, point in time measures disproportionately reflect the characteristics of individuals suffering long spells (Quigley and Raphael, 2001)

way area-level structural factors impact on homelessness it is therefore crucial to explicitly account for their possible interaction with individual-level factors. This can only really be done at the microeconomic level by examining the effect of area-level factors on individual risks of homelessness, as the Early studies have done. However, there are some important limitations to the Early studies.

Firstly, there is little variation in the metropolitan area variables examined (only 22 metropolitan areas are covered). Thus the coefficients of area level variables cannot be estimated as precisely as individual variables. Secondly, and more fundamentally, the effect of the housing market will be attenuated ‘as the housing market has no effect on people who are not at risk; they are never homeless. Thus pooling the at-risk population with the population not at risk reduces the average effect of the housing market’ (O’Flaherty, 2004, p11). Although the above studies do focus on a population of individuals/households on low incomes, rather than the entire population, there may still be attenuation bias as described in O’Flaherty (2014) as many of those on low-incomes aren’t at real risk of homelessness. Thirdly, the data on the homeless are from different sources to those on the housed. There may therefore be inconsistencies in the measurement of variables across the two surveys and in the timing of each survey. And finally, the data used in each of these studies is cross-sectional. They can’t therefore look at differences in the effects of housing and labour markets on entries and exits nor can they account for unobserved heterogeneity.

Our study does not suffer these limitations. The data that we use, from the Journeys Home survey, have a wide nationally representative geographic coverage including major cities in Australia, regional and some remote areas thus providing more variation in housing and labour market characteristics than that previously studied. It also has a sample design that only selects those with a high propensity of being or entering homelessness, and so does not pool the at-risk population with the population not at risk. Thus our estimates on the effects of housing markets are less likely to suffer from the attenuation bias described in O’Flaherty (2014) that the Early studies are more likely to suffer from. The data are also longitudinal, and include high levels of detail about individuals’ attributes and behaviour, both current and historical, thereby allowing us estimate the differential effects of a rich array of individual characteristics on flows into and out of homelessness, which are jointly critical to the determination of homelessness. Longitudinal data also enables us to at least partly account for unobserved heterogeneity playing a part in entries into and exits out of homelessness, which we control for using a random effects estimator. An added innovation is that in jointly

estimating entry and exit probit equations we allow for unobserved heterogeneity for entries and exits to be correlated.

Finally, we examine whether there is heterogeneity in the impact of housing and labour market conditions on individuals with different characteristics. This further ensures that we are actually looking at the intersection of individual risk factors and area-level factors on risks of homelessness.

We discover that risky behaviours and life experiences such as regular use of drugs and the experience of violence as well as people with biographies marked by acute disadvantage are at a higher risk of becoming homeless. Also the risk of becoming homeless is greater in regions with higher median rents and slack labour markets; residence in public housing has a strong protective effect. The results emphasise the importance of modelling both entries into and exits from homelessness as, unlike entries, transitions out of homelessness appear to be largely unrelated to behavioural traits and structural housing and labour market conditions. We also find that there is heterogeneity in the effects of housing and labour markets. Individuals otherwise vulnerable to homelessness but not engaging in risky behaviours (e.g. regular drug users), nor possessing particular risk characteristics (e.g. long-term health condition), are more likely to be tipped into homelessness when housing market conditions tighten and labour market conditions weaken. On the other hand persons with particular risk factors have similar chances of entering homelessness regardless of housing and labour market conditions. Ex-offenders however appear to particularly sensitive to private rental housing markets.

Next we provide a discussion of the data used in the analysis. Section 3 then follows with our estimation strategy, which includes a discussion of the conceptual framework underlying the analysis and the econometric models that we estimate to address our research questions. Our main set of results is presented in Section 4 with sensitivity and robustness checks discussed in Section 5. Section 6 then examines whether there is heterogeneity in the effects of housing and labour markets across different population groups. Section 7 concludes.

2. Data and definitions

2.1. *Journeys Home*

The primary data source used in this analysis is the *Journeys Home* (JH) Limited Release file. JH is an interviewer-administered survey that has followed a sample of Australian income support recipients exposed to homelessness or housing insecurity over time. Crucially, unlike prior longitudinal studies of the homeless such as Allgood et al. (1997), Shinn et al. (1998) and Culhane and Kuhn (1998), the JH sample is representative of a broader population of people experiencing housing insecurity, and not restricted to a population of those who are currently homeless. It is therefore able to explore the factors precipitating entry into homelessness, as well as those helping to lift people out of homelessness.

In Australia, all social assistance benefits are administered at the national level through one central agency known as Centrelink. The administrative data held by Centrelink provide the sampling frame for Journey's Home. As virtually all at-risk individuals across the range of precarious housing situations, e.g. couch surfing, public housing, shelters, boarding houses, living on the streets, etc., are eligible to receive some form of social assistance the Journey's Home sampling frame results in a much broader representation of the homeless population than do previous studies.

Since 2010, Centrelink staff has been using a set of protocols to identify—and flag—customers that they assess to be either 'homeless' or 'at risk of homelessness'. When combined, the Centrelink staff's definitions of 'homeless' and 'at risk' roughly accord with the cultural definition of homelessness put forward by Chamberlain and MacKenzie (1992). These protocols were designed to target service delivery rather than identify the homeless population. As such, a third group was identified using the propensity of being flagged as homeless or 'at risk' of homelessness (see Wooden et al. 2012 for further details on the population and sampling methodology). Although not flagged by Centrelink staff as currently 'homeless' or 'at risk' of homelessness, this group nevertheless have characteristics similar to those flagged by Centrelink as 'homeless' or 'at risk' thus constituting a group that is, at least in a statistical sense, vulnerable to homelessness. In total 139,801 individuals were identified as either homeless, at risk of homelessness or have high a propensity of becoming homeless, which account for approximately 2.9% of all Centrelink income support payment recipients over the reference period.

A stratified random sample from this population were then selected for interviews. Almost 62 per cent of this group (n=1682) agreed to participate in a wave 1 interview, which was conducted between September and November 2011. This response rate is much higher than in other Australian studies that sample from seriously disadvantaged populations (Johnson et al. 2008; RPR Consulting 2003; Thomson Goodall and Associates 2001), and is in line with the Household Income and Labour Dynamics in Australia survey of the general population, which had a wave 1 response rate of 66 per cent (Watson & Wooden 2010).

Five additional follow-up interviews at six-monthly intervals have been undertaken. Respondents are interviewed in person whenever possible, with telephone interviews conducted in situations where face-to-face interviews were not feasible. Fully 91 per cent (wave 2), 88 per cent (wave3), 86 per cent (wave 4), 85 per cent (wave 5) and 83 per cent (wave 6) of wave 1 respondents were re-interviewed. These re-interview rates are extremely high, especially when account is taken of the relatively high rates of mobility, mortality and imprisonment in this population. Although attrition is not random it is unlikely to be a major concern for our estimation (Melbourne Institute 2014).

JH collects a wide range of information, both current and historical, with surveys capturing information on participants' social and demographic characteristics, employment and voluntary work, service use and social networks, health and wellbeing, contact with the justice system, exposure to violence as well as measures of income and financial stress. JH is thus ideal for the kind of analysis proposed here as it not only includes detailed information about individuals' characteristics but also has wide geographic coverage will allow us to examine variation in housing outcomes across a range of geographical level factors, hitherto not appropriately examined.

2.2. Housing and labour market measures

Our main housing market measure is the median rental price of an area, which typically reflects the level of housing demand relative to its supply in an area, and is commonly used as an indicator of the tightness of housing markets. To construct our measure of the median rental price of areas monthly data on median asking rents at the postcode level was obtained from SQM research. These nominal data were converted to real values by dividing by the CPI. Postcode level median rents were then aggregated to the spatial unit used in the analysis, which we describe in further detail below, using total numbers of vacant properties as weights. While data for some postcodes was not provided by SQM this was mainly for small

postcodes, so the missing data is unlikely to generate large bias when considering the median of a larger area. Resulting geographic coverage across Australia is thus quite high.

The local unemployment rate is used as an indicator of the strength of local labour markets. Data to construct this measure is sourced from the ABS monthly *Regional Labour Force Statistics* (ABS 2014). To reduce noise in our monthly measures we take a three-month centred moving average for both our median rent and unemployment rate measures.

An alternative data source to capture the median rental price of areas is the 2011 Australian Census (ABS 2011). However the Census data has a number of limitations. Perhaps the most important limitation is it does not capture time series variations in local housing markets as it measures the characteristics of areas at one point in time, Census night in 2011. Also, the Census only provides information on the rental costs of occupied dwellings, but not vacant properties. Therefore, we can only use occupied rental properties as a proxy to measure the market rent of rental properties. Finally, it only provides rent paid in ranges therefore to use this data one must take the mid-point of the rent range when constructing the median, thus removing actual variation in the state of the housing market. Due to these limitations we use median rent data from SQM for our main analysis and undertake sensitivity analysis to the use of data from the Census data.

2.3. *The spatial unit*

Our spatial unit is defined using Statistical Area Level 4 (SA4) which is based on the Australian Statistical Geography Standard (ASGS). There are 87 SA4 regions across mainland Australia and Tasmania, with an average population size of 246 617 at the 2011 Census. The least populated SA4 had a population of 35 797 and the most populated a population of 658 016. All 87 of these regions are represented in JH. However, in those areas that do not include any of the 36 original sampling clusters, the numbers of observations are small, as they only include sample members who moved across regions over the course of the JH study.

Although SA4s provide the best sub-state socio-economic breakdown in the ASGS (ABS 2010), it is questionable whether they are the appropriate classification to use when representing the housing and labour markets that capital city residents are exposed to. People can, and do, move around within capital cities sorting into areas where they can afford housing (i.e. the poor and most vulnerable tend to move to the cheapest areas within cities) (Culhane et al. 1996; Wong & Hillier 2001; Cheshire 2007). Likewise local labour markets

are clearly not confined to SA4s within capital cities. We therefore collapse the spatial unit for SA4s within capital cities to the greater capital city area. This has the added benefit that our analysis is using a spatial unit of observation that is more consistent with US studies that use the city as the unit of observation. Therefore, in our preferred specification, we use these as our spatial unit for SA4s within greater capital city regions, and continue to use the straight SA4 for areas outside of capital cities. The number of moves will be fewer, and there will be less variation in the structural variables, than if the finer SA4 classification were used.

2.4. *Definition of entries into and exits from homelessness*

Where to draw the line between the housed and the homeless is controversial and so the idea of homelessness remains a contested concept in many parts of the world. In Australia, the situation is slightly different. The cultural definition put forward by Chamberlain and MacKenzie (1992) is widely accepted by policy-makers and researchers. The core idea underpinning the cultural definition is that there are shared community standards about the minimum accommodation that people can expect to achieve in contemporary society. The minimum for a single person (or couple) is a small rental flat with a bedroom, living room, kitchen and bathroom and an element of security of tenure provided by a lease.

The cultural definition is an ‘objective’ accommodation-based approach, and is therefore relatively straightforward to operationalise. However, due to the different data items that are available to us, the approach we use to operationalise the cultural definition is slightly different from the method used by Chamberlain and Mackenzie in their ‘Counting the Homeless’ program of research (Chamberlain 1999; Chamberlain & MacKenzie 2003, 2008).

To operationalise the cultural definition of homelessness we take each respondent’s housing situation at each interview based on the quite detailed information they provide about their current accommodation. If a person has no accommodation, is residing in emergency or crisis accommodation or accommodation that does not meet the minimum community standard, such as caravans, boarding houses, hotels or motels, they are classified as homeless².

² Obviously the quality of caravans and hotels or motels can vary considerably and when examining residents across the general population, as the Census does many caravans and hotels or motels will meet the minimum community standard of a small self-contained flat. However, as the *Journeys Home* sample is such a disadvantaged population group, we consider residents of caravan parks and hotels/motels as similar to residents of boarding houses. Therefore, anyone living or staying in these types of accommodation are considered homeless.

Respondents who are residing with family or friends in a house or unit are classified as homeless if the arrangement is a short-term, temporary one. A short-term or temporary arrangement is operationally defined as being in the current accommodation for three months or less and not being able to, or not knowing whether they can stay there for the next three months. If, however, the arrangement appears to be long-term and the respondent was sleeping in a bedroom, they are classified as housed.

Homeless entry and exit variables are binary variables reflecting the transition between a respondents' current homeless status and that at their next interview (time t and $t+1$), which roughly covers a 6 month period. Homeless entries, which are only defined for those who are housed at time t , takes a value of 1 if the person makes the transition between being housed at time t and being homeless at time $t+1$ and zero otherwise. Whereas homeless exits, which are only defined for those who are homeless at time t , takes a value of 1 if the person makes a transition from being homeless at time t to become housed at time $t+1$, and zero otherwise.

2.5. Overview of Journeys Home respondents and their homeless experience

As expected with such a vulnerable population group, the profile of JH respondents is very different to that of the general population (Scutella et al. 2013). Respondents are on average younger, more likely to be single, have no dependent children, Australian born and much more likely to be Indigenous Australian than in the general population. JH respondents also have much lower levels of education on average and the vast majority are not in the labour force. The incidence of mental illness is also higher than that of the general population and smoking, drinking at 'risky' levels and drug use more widespread.

Table 1 presents rates of homelessness and homelessness entry and exit rates for JH respondents by wave. The entry rate is defined as the total number of people who were housed in one wave but become homeless in the next wave divided by the total number who were initially housed (i.e., entered homelessness/remained housed + entered homelessness). The exit rate is defined as the number of people who were homeless in one wave but were housed in the next wave divided by the total number of people who were initially homeless (i.e., exited homelessness/remained homeless + exited homelessness). The same method is applied to each wave to wave transition.

As the sample is such a vulnerable group rates of homelessness are considerably higher than population based estimates of homelessness, with around 20 per cent of the sample homeless on average. On average around 9 per cent of the sample, conditional on being initially

housed, enter homelessness between waves. Likewise, conditional on initially being homeless, over 40 per cent exit homelessness between waves.

2.6. Homeless entry and exit rates by median rental price and unemployment rate

In Figures 1 and 2 we present some descriptive material on the relationship between entry and exit rates of homelessness at an area level and the housing rents and unemployment rates of those respective areas. In these figures rents are grouped into ranges of \$10 and unemployment rates into ranges of 0.1 percentage points. Thus the first data point in Figure 1a for example is showing the proportion of persons entering homelessness between t and $t+1$ in areas with real median rents between \$200 and \$210, the second data point the proportion entering homelessness in areas with real median between \$210 and \$220. And so on. Likewise the first data point in Figure 2a is showing the proportion of persons entering homelessness between t and $t+1$ in areas with an unemployment rate of between 3 and 3.1 per cent, and so on. Figures 1b and 2b then show the corresponding proportions of those exiting homelessness.

In Figure 1a we see that there is a slight positive relationship between homeless entry rates and median rents of areas but the slope of the fitted line is not steep and there is much variation around the fitted line. Figure 1b shows a clearer relationship between exit rates and median rents with exit rates lower in tighter housing market conditions as represented by relatively high median rents. Figure 2a shows a slight positive relationship between the unemployment rate of an area and rates of transition into homelessness, but as was the case with median rents the slope of the fitted line is not steep. While Figure 2b shows a stronger positive relationship between exit rates and area level unemployment rates there is considerable variation around the fitted line.

From these figures it is difficult to say with much confidence that there is a clear relationship between homelessness entry rates and housing and labour markets. There does appear to be a stronger relationship between exit rates and housing and labour markets, but there is much variation around the general pattern.

3. Estimation strategy

3.1. Conceptual framework

Following O'Flaherty (1996 & 2012), Early (1999) and Glomm and John (2001) we describe homelessness as one consequence of decision-making under extreme income constraints. We

assume that individuals must make decisions between housing and non-housing consumption under typically austere income constraints, and at a single point in time and place.³ Crucially, we assume that individuals are price-takers and therefore cannot influence the price of housing (as well as the price of non-housing consumption). Income is determined ‘outside the model’ (exogenous) and treated as fixed. Individuals have preferences over housing and non-housing consumption. *In principle*, individuals can trade-off consumption of one good for the other in order to reach different bundles of housing and other consumption, while continuing to satisfy income constraints that in the absence of borrowing and lending prevent a ‘spend’ exceeding income. When income is very low these preferences can be driven by urgent needs. The affordable options can therefore shrink allowing consumption of very low quality housing that absorbs a large portion of income, or increased consumption of other necessities with zero housing expenditure (that is homelessness).

Using this framework, a few important hypotheses linking individual characteristics and homelessness can be made. First, the less income an individual has, the fewer resources they have for housing consumption. Therefore, the risk of homelessness is higher. We can also expect local labour market conditions to affect individual risks of homelessness, as those in areas with weak labour markets are more likely to experience negative income shocks associated with unemployment. Second, at a given income level, individuals with a higher need for other goods will have less income left over for housing consumption. For example, people with health problems and higher associated health expenditures will have less money to pay for housing. Therefore, they are at greater risk of homelessness. Third, people who experience some shock (e.g. family breakdown, job loss or natural disaster) that results in unexpected loss of income, savings, the equity accumulated in their homes, or in the rental property they leased, are more likely to become homeless, as it is costly and time consuming to resolve major disruptions in housing circumstances. Finally, certain groups of people can also become homeless for reasons that the standard economic theory of consumer behaviour cannot readily explain. For instance, some individuals might have difficulties accessing housing because of discrimination. There is evidence to suggest that Indigenous people, families on income support, people with mental health problems, as well as young people, are routinely discriminated against by landlords (Walsh, 2011). Our a priori expectation is that these groups of people will have higher risks of homelessness.

³ There are therefore no moves and location is not an attribute over which preferences are defined.

In addition to the influence of individual characteristics on risks of homelessness, the framework outlined above provides the rationale for how we might expect housing market characteristics to affect individual risks of homelessness, holding all else constant. Rents (prices) that must be paid for housing help determine the severity of income constraints experienced by 'at risk' groups. Real rent levels (prices) are believed to have exhibited a long run upward trend in Australia since the late 1980s, tightening income constraints, especially those confronting the poor. Rents and prices also vary across regions, with differentials reflecting regional demand pressures and housing supply constraints. Supply constraints can arise due to topographical features (e.g. areas with steep inclines or flood plains are more costly to develop), regulation of land and buildings and bottlenecks within the building construction industry (e.g. skill shortages), and planning system. These supply constraints can be binding in some regions but not in others. For example, some coastal cities are hemmed in by mountain ranges that curb radial urban expansion, while others are favoured by a flat topography that aid low cost housing development on greenfield sites. A shortage of affordable housing for low-income households is more likely where supply constraints bind. Shortages are also more likely when large numbers of households with low incomes are competing for housing in markets with high rental prices and low vacancy rates. That is, there is excess demand for low cost accommodation.⁴ The model therefore predicts that risks of experiencing homelessness will be higher in areas with exclusionary land use zoning (Fischel 2004), high costs of housing *and* high concentrations of poverty - high rents and prices alone do not cause homelessness if people in the area have sufficient income for housing.

We also expect that certain groups will be more vulnerable to homelessness in tighter housing markets than others. For instance, it may be the case that discrimination is more likely to occur in tight regional housing markets, as landlords have more choices over potential tenants. This may mean that certain groups (for example ex-offenders) in these areas will be more likely to enter homelessness and less likely to exit homelessness than those in the same groups who live in areas where the housing market is slack. Alternatively, it could actually be that those with serious risky behaviours (e.g. alcohol and drug dependency) are equally prone to homelessness, regardless of the housing market, as private landlords will be reluctant to lease even if their property is vacant.

⁴ The upper end of the housing market is not as relevant as people can always obtain cheaper accommodation rather than become homeless.

Likewise we might expect that certain groups will be more vulnerable to weaker labour markets than others. For example, work opportunities are unlikely to be offered to those with drug and alcohol problems even if they were available. On the other hand, those vulnerable to homelessness because of an unexpected job loss, are less likely to become homeless if housing is inexpensive and labour market opportunities are abundant in their region. These benign housing and labour market conditions will facilitate adjustment to unexpected shocks. It is therefore important to account for these potential interactions of individual and area level characteristics in our estimation model.

The approach outlined above is based on a static model of homelessness. But the pool of homeless individuals at any point in time is determined by the flows of people becoming homeless or escaping homelessness at that time, as well as the numbers with an enduring homeless status. There are reasons to expect that area-level characteristics will have different effects on entries into homelessness than they do on exits from homelessness. For instance, tight housing markets may have more of an effect on exits from homelessness than on entries. Those vulnerable but housed have the protection of a lease (if renting) that insulates them in the short term from the vagaries of housing market pressures. And if they occupy public housing the protection is secure in the long term. But individuals who are homeless and seeking affordable housing are exposed to the effects of varying housing market conditions - thus pathways out of homelessness are more likely to be influenced by the cost and availability of housing. Alternatively, housing markets may have a bigger effect on entries than exits if there are no services available to assist at risk households who find themselves in trouble, or if services are more reactive than preventative and are targeted to those already homeless. Similarly, one might expect the state of the labour market to be more important for entries than exits. Differences in these variables could also be more of an issue for some groups than others. For example, older people may well be reluctant to leave their home in tight housing markets, while older homeless persons with limited social and economic resources to draw on might find it difficult to exit homelessness in tight housing markets.

3.2. Estimation models

To allow risk factors to have different effects on homeless entries and exits, we model the transitions into and out of homelessness separately. However, there may be unobserved factors that affect both homeless entry and exit, we therefore jointly estimate the two type of transitions allowing the time-invariant unobserved heterogeneity to be correlated between the two equations. More specifically, we use a joint random effect probit specification to

estimate the homeless entry transition (equation 1 below) and homeless exit transition (equation 2 below).

$$H_{it}^* = X_{it}\beta_H + Z_{at}\gamma_H + \mu_i + e_{it} \quad (1)$$

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

$$L_{it}^* = X_{it}\beta_L + Z_{it}\gamma_L + v_i + \varepsilon_{it} \quad (2)$$

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

Where H_{it}^* represents an unobserved latent variable relating to homeless entries and H_{it} is the observed binary outcome variable on homeless entry as defined in section 2.1. Similarly, L_{it}^* and L_{it} represent an unobserved latent variable and the observed binary outcome reflecting homeless exit respectively. The error terms in the model comprise of permanent components (μ_i and v_i) and transitory components (e_{it} and ε_{it}). The transitory components are assumed to be normally distributed with means of zero and variances of 1. The transitory components are also assumed to be independent of the time invariant components and of one another. The permanent components (time-invariant individual heterogeneity) are assumed to be normally distributed with means of zero and variances of σ_H^2 and σ_L^2 and may be correlated with the correlation coefficient ρ_{HL} .

The explanatory variables include both individual characteristics, X_{it} , and area level characteristics, Z_{it} , that individual i is residing in at the time interviewed. Individual characteristics examined include a standard set of demographic controls such as age, gender, marital status and the presence of children, country of birth and whether people identify as Aboriginal or Torres Strait Islander. Gross household incomes of respondents are also included to capture the financial resources available to each individual. Variables designed to capture the human capital of individuals are also included. These comprise the highest level of education obtained, current labour force status, employment history and variables capturing the health of individuals. To account for whether individuals grew up in a particularly adverse environment we also enter an indicator of whether individuals had ever been placed in the Child Protection system. An index of current levels of social support is also embraced. In addition, we include indicators capturing recent experiences of violence, recent incarceration and engagement in risky behaviours such as substance use and the risky consumption of alcohol. We also include variables reflecting whether individuals are residents of public or social housing. Finally, we add in an indicator reflecting whether

individuals had ever experienced primary homelessness. The definition of variables and summary statistics are presented in Appendix Table A1. To allow the effects of housing and labour market conditions to differ by subpopulation, we interact Z_{it} with individual characteristics (one at a time to avoid problems with small sample sizes).

4. Main results

Table 2 presents marginal effect estimates from equation 1 (entry model) and equation 2 (exit model) using our preferred housing and labour market measures discussed in Section 2. It is important to reinforce that our sample contains individuals who are vulnerable to homelessness. The modelling therefore estimates whether a given group of individuals is more or less likely to enter (exit) homelessness as compared to *other vulnerable groups*. A particular group such as the mentally ill are traditionally thought prone to homelessness, but might be no more likely to become homeless (or escape homelessness) as compared to other vulnerable groups in the sample.

Consider first the entry model estimates. From demographic variables in the entry model we learn that vulnerable males are much less likely to sustain secure housing than females. Married and defacto couples are no more prone to tumble out of secure housing than singles. However, the presence of children lowers the chances of becoming homeless, regardless of relationship status. Our estimates suggest that resident children lower the probability of entry by 2 percentage points. The sample mean probability of entry into homelessness is 8 per cent, so the effect of resident children is large (cutting the chances of becoming homeless by roughly one-quarter), and with roughly the same marginal impact as gender (males are 2.1 percentage points more likely to become homeless). But since males are 49% of the entry sample while those with resident children are a much lower proportion, at 29% of the entry sample, gender is clearly a relatively more prominent influence. We find that age, indigenous status and country of birth are not statistically important as far as entries into homelessness are concerned.

Next we turn to the vector of human capital and individual employment characteristics; those with relatively low levels (years) of schooling are more likely to slip out of formal housing circumstances, but the effects are only just statistically significant at 10 per cent. Though contemporaneous employment status turns out to be unimportant, there is weak evidence that employment history matters; those with no record of employment since they first left full-time education are more likely to enter homelessness, a marginal effect estimate of 4.1

percentage points, but again significance is at only 10%. Equivalised income proves to be statistically insignificant.

Turning now to family history and markers of severe disadvantage, a recent experience of violence and being a past custodian of state care stand out with marginal effects of 2.0 and 2.3 percentage points respectively. However, in both cases these variables are only weakly significant. Incarceration, whether recent or at some point in the past, is unexpectedly insignificant though only 2.2% of the entry sample has been in juvenile detention, adult prison or remand in the last 6 months and a somewhat larger 28% have ever been incarcerated in the past.

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 heavy drinking seem to precipitate entries into homelessness, although the latter is only weakly significant⁵.

The health variables yield some unexpected and interesting findings. Those with long term health conditions are no more likely than the fit and healthy to become homeless; moreover individuals with *diagnosed* mental health conditions have a substantially lower probability of homelessness. The effect is both statistically significant and large (a 2.6 percentage point marginal effect). We speculate that their diagnosis signals medical treatment and that these individuals are likely prioritised by support services that enhance their capacity to maintain housing. On the other hand those with undiagnosed mental health problems and other risk factors are likely to be more precariously positioned in relation to homelessness.

Social support, past experience of homelessness, and current housing circumstances are considerably important. Higher levels of social support help cement residency in secure housing. If there has been a prior episode of primary homelessness the individual that is housed but vulnerable is considerably more likely to slip back into homelessness. Whether this is due to a scarring effect (past experience has a debilitating effect that adversely impacts resilience), or learning effect (previous experience facilitates adaptation to homelessness), is uncertain. Either way, its influence lifts the chances of slipping out of secure housing by 3.7

⁵ Roughly 20% use illicit drugs at least weekly over the last 6 months. But the average daily consumption of alcohol is only 1.5 units per day

percentage points, which is a large impact (roughly 46%) at the sample mean; there is a suggestion here that programs designed to sustain the housing of formerly homeless persons could 'pay off'. Our estimates suggest that security of tenure in affordable public housing also offers very effective protection against homelessness. Residence in public housing lowers the (conditional) probability of homelessness by 5.9 percentage points. This is comfortably the most important indicator variable in the entry model and offers evidence in support of its role in preventing homelessness. While a powerful influence, public housing protects only a small minority of the entry sample (17%)

Housing and labour market conditions do seem to matter, especially the former. Median market rents are positively and significantly related to entry into homelessness; an increase in an area's median market rent of \$100 (a 30% increase at the national median weekly rent) lifts the risk of entry by 1.9 percentage points, or from a sample mean of 8 per cent to 9.9 per cent (a 24% increase in risk)⁶. We also find that a 1 percentage point increase (decrease) in a region's unemployment rate increases (decreases) the likelihood of transitions into homelessness by 1.3 percentage points, or 16.3 per cent at the sample mean probability of entry. There is a 5.6 per cent mean unemployment rate across SA4 regions, so an increase to 6.6 per cent would represent an 18 per cent lift in the unemployment rate at the mean; the effect on risk of entry into homelessness is therefore roughly similar to that of market rents in the local housing market, though the unemployment rate variable is only significant at 5%.

Table 2 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 there are fewer degrees of freedom and the standard errors reported 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 a little over one third, compared to just under one fifth of the entry sample. Married people share of the entry sample (20%) is nearly twice their share of the exit sample (11%); there is an even more marked divergence with respect to resident children, with their presence in the entry sample nearly three times that in the exit sample. Current employment status 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

⁶ The point elasticity measure is 0.87.

the exit sample has a stronger representation of older single males with risky behaviours and episodic homelessness profiles.

In view of the differences in size and composition of the sample it is perhaps unsurprising to find that the processes apparently driving escapes from homelessness are different from those tipping previously housed individuals into homelessness. Most conspicuous is the lack of statistically significant variables in the exit model.

While males are more likely to become homeless they are no less likely to escape homelessness than females; although the marginal effect in the exit model is relatively large at -7.9 points (the mean probability of exit is 40%).⁷ The standard error is quite large thus we cannot reject the hypothesis that the marginal effect is zero. Also the findings with respect to age are in stark contrast to those in the entry model. While all age groups appear equally likely to tumble into homelessness, as is consistent with studies such as Allgood & Warren (2003) and Cobb-Clark et al (2016) escape for those enduring a spell of homelessness is much less probable as age increases. The marginal effect estimates are large; the 21 to 44-year group are 21.2 percentage points less likely to escape than the reference age group (15–20 years), and individuals 45 years and older are 32.4 percentage points less likely to exit.⁷ Past episodes of homelessness are more common among older homeless individuals, so scarring or experience effects could be relevant, but these are controlled for in the model⁸. This is a notable finding and we return to its interpretation and wider significance in the concluding section.

Strongly significant and large marginal effects (22.7 percentage effects) in the anticipated direction are detected with respect to resident children. This could reflect the targeting of homeless families by service supports. Country of birth is again insignificant, as is the effect of identifying as Aboriginal or Torres Strait Islander; those born overseas are just over 5 per cent of the sample, but the Aboriginal or Torres Strait Islanders account for nearly 20 per cent of the sample. Indigenous status is found to be statistically insignificant in both entry and

⁷ At the sample mean probability of exit (39.8%) the 21–44-year age group's chances of escape are 47 per cent of those of the young (15–20 years), while the 45 years and older age group have chances of escape that are only around 19 per cent of the young's (15–20 years).

⁸ Very nearly three quarters of the exit sample have had a prior episode of homelessness, so this is not the first experience of homelessness for most of those homeless in any given wave. The lack of sample variation in this variable might be responsible for its statistical insignificance in the exit model.

exit models, firming up evidence that other personal characteristics as well as housing and labour market conditions are responsible for their elevated rates of homelessness.

While education among the housed but vulnerable offers (weak) protection against the risk of entering homelessness, once homeless, higher educational attainment does not appear to hasten exit from homelessness. Similarly the employment variables are statistically insignificant, and so employment status and history appears to play a more important role in preventing homelessness than in offering a pathway out of homelessness. Only 15% of the exit sample is employed. However, over one half is not in the labour force and their unattached labour force status is found to have a large impact (a marginal effect of -12.3 percentage points), but fails to achieve significance.

Unexpectedly, those who had no principal caregiver at age 14 were 12.9 percentage points more likely to exit, but once again this estimate is statistically insignificant. Also surprising is the absence of any significant effects from risky behaviours and family history markers of severe disadvantage and trauma. Health variables and social support also gather no support. Finally, the state of area-level housing markets and labour markets do not appear to significantly affect the propensity to exit homelessness. This is yet another contrast with the entry model. It could be that the attachment of homeless people, especially the primary homeless, to employment and housing pathways becomes so weak that the condition of housing and labour markets is irrelevant to their prospects of escape. Perhaps the availability and targeting of support services matters most in the exit sample. This could be why younger people are so much more likely to find pathways out of homelessness. However, an alternative interpretation can be offered. Younger people are more mobile and adaptive and therefore more likely to have access to a wider range of housing and labour market opportunities.

5. Sensitivity of main results

5.1. Housing and labour market measures

The main set of results takes area level measures of housing markets from SQM. As discussed in Section 2 an alternative housing market measure is available in the 2011 Australian Census. Although there are significant limitations to the use of Census data we test whether our results are sensitive to the alternative data sources in this section.

We continue to utilise the ABS monthly *Regional Labour Force Statistics* (ABS 2014) to construct our regional unemployment rate measure. However as the Census data only reflects the characteristics of areas at one point in time, Census night in 2011, we take the average unemployment rate of the area over the two and a half year period as our local labour market measure to ensure consistency with our now time-invariant housing market measure.

In addition we undertake analysis to examine whether our main findings are sensitive to the choice of spatial unit. The main set of results presented in the previous section defines housing and labour market measures at the capital city area for greater capital city regions, but continues to use the SA4 spatial unit for areas outside of capital cities. In this section we undertake sensitivity analysis to examine whether our main results vary if we take the SA4 as the spatial unit for individuals in all areas, both those within greater capital city regions and those in areas outside the capital cities.

Table 3 compares the marginal effects of housing and labour markets on individual risks of homelessness using these alternative measures. We suppress the marginal effects of all other control variables as they are very similar across the various specifications. In both entry and exit models the Census data based measures also generate similar results for housing and labour market effects, both qualitatively and quantitatively. Median market rents are a positive and significant influence on entry into homelessness: an increase in an area's median market rent of \$100 (a 30% increase at the national median weekly rent) lifts the risk of entry by 1.7 percentage points when utilising the Census data, an effect very similar to that found using our preferred specification (i.e. a marginal effect of 1.9 percentage points). Likewise entries to homelessness are similarly positively affected by the regions unemployment rate with a 1 percentage point increase (decrease) in a region's unemployment rate increasing (decreasing) the likelihood of transitions into homelessness by 1 percentage point (compared to a marginal effect of 1.3 percentage points estimated using our preferred specification). On turning to exit model estimates we once again find that the marginal effects of both median rents and the unemployment rate remain insignificantly different from zero.

By contrast the choice of spatial unit does seem to impact on our findings. A smaller spatial unit dampens the impact of median rents on entries to homelessness marginally (from 1.9 to 1.3 percentage points). However the effect remains statistically significant. On the other hand, the effect of the unemployment rate variable on entry into homelessness becomes statistically insignificant when deploying the finer spatial unit classification in both capital and non-capital city areas.

The most likely explanation for these imprecise labour market area estimates is endogenous sorting within capital cities, i.e. while the poor and the most vulnerable tend to live in the cheapest areas, for a given rental price people will choose to live in areas that have better services and amenities. These tend to be in areas with lower unemployment rates thus dampening the overall true effect that the labour market has on risks of entering homelessness. Thus if you were to use this kind of classification it is important to account for endogenous location choice. This however is outside the scope of this paper. Thus, to minimise the problems that location choice has on our estimates our preferred specification is that using the broader area classification within capital cities, at the same time flagging that this is an important area of future research.

5.2. Excluding public housing residents

The rents of public housing residents in Australia are typically set at 25% of their assessable household incomes and therefore diverge from those of the private rental market. Until recently public housing tenants also had ‘lifetime’ security of tenure, at least in practice, and as such were unaffected by increases in market rents and prices.⁹ Retaining public housing residents in our sample will mask housing market effects on vulnerable individuals not fortunate enough to access public housing opportunities. Thus, in this subsection, we examine the effects of excluding public housing residents from our analysis (see table 4).

Public housing appears to shield people from the effects of housing markets, as the marginal effect of median rents is quite a bit larger on the probability of entering homelessness when public housing residents are excluded from the analysis (2.4 percentage points compared to our previous estimate of 1.9 percentage points). Excluding public housing residents from the sample also results in a slightly larger marginal effect for the unemployment rate in our entry model (1.5 percentage points compared to the previous estimate of 1.3 percentage points). But exit model estimates are unaffected by the sample re-design, further confirming the view that the homeless become so detached from housing and labour markets that differences in market opportunities become irrelevant to pathways out of homelessness.

⁹ Probationary leases and fixed-term leases for public-housing tenants have recently been introduced in many Australian States.

6. Heterogeneity in housing and labour market effects

An important innovation in this paper is that in addition to examining the overall effects of housing and labour markets on individual risks of homelessness, we also examine whether housing and labour markets are more important for certain types of people than others. In this section we report the modelling results which address this question. The short answer is yes, certain subgroups within the vulnerable population are more prone to homelessness in areas without job opportunities and/or a lack of affordable housing (place). We now discuss this in further detail.

Table 5 summarises the modelling results when we allow for heterogeneous effects of median rents and the unemployment rate, presenting, for each group, the average marginal effect of a \$100 increase in the median rent (column 1) and a 1 percentage point increase in the unemployment rate (column 2) on the probability of entering homelessness. Note that the estimates presented in Table 5 have been calculated for separate logistic regressions, where we include all of the covariates from our earlier models, plus covariates of interactions between the individual risk factor of interest and both the median market rent and the unemployment rate respectively. We do not add all interaction terms simultaneously in one single equation because we are concerned that reduced degrees of freedom will result in imprecise estimates. The addition of interactions is conducted sequentially - that is we detect for (say) a gender interaction effect, and once estimated the gender interaction term is discarded and we replace it by an interaction term representing a different individual risk factor (e.g. indigenous status). Consider, for instance, interaction effects with respect to whether people have ever been diagnosed with a mental illness. Table 2 suggests that those diagnosed have lower probabilities of entering homelessness, and also that higher median rents significantly increases the risk of homelessness for all persons on average. But it could be that those with diagnosed mental illnesses are much more prone to homelessness if they are living in areas with tight housing markets and high median rents. To detect whether this is indeed the case we add an interaction term that is the product of the ever diagnosed with mental illness indicator variable (that equals 1 when diagnosed, zero otherwise) and median rents. The marginal effects presented in the table are the effects of a \$100 a week increase in median rents on the changes in the probability of entry into homelessness for those ever diagnosed (ever diagnosed =1), and for those never diagnosed (ever diagnosed=0). Similarly, we also list the marginal effects of a 1 unit change in the unemployment rate on the changes in the probability of homeless entry for different subgroups. Statistical test results on whether

each subgroup's estimated marginal effect is significantly different from zero are also presented.

As we found in Section 5 that public housing appears to protect people at risk of homelessness from the effects of housing and labour markets, in columns 3 and 4 we also present comparable estimates where public housing residents have been excluded from the estimation sample. Sample sizes get quite small when we start looking at exits from homelessness for subgroups. Coupling this fact with the overall insignificance of median rents and unemployment rates on exits from homelessness, we only undertake analysis for entries into homelessness.

First we focus on the results over the full sample (i.e. in columns 1 and 2 of Table 5). If we look at whether the marginal effects of housing markets and labour markets are significantly different from zero or not, it looks like housing and labour markets are not having a significant effect on persons with particular risk factors (early school leavers, those not in the labour force, with a long term health condition or disability, with a diagnosed mental illness, drug users, and experiences of violence). They are however significant for groups that do not experience these risk factors. The only risk factor where this pattern differs relates to histories of incarceration. If we focus simply on the magnitude of the estimated marginal effects it appears that individuals that have been incarcerated seem to be particularly affected by local housing and labour markets, especially those recently incarcerated.

However, if we formally test for differences in the marginal effects between groups we find that the only significant differences in the effect of the housing market occurs between early school leavers and those completing secondary schooling, and between those ever diagnosed with a mental illness and those never diagnosed. Early school leavers are less sensitive to the housing market and those with higher levels of education more sensitive. Likewise persons diagnosed with a mental illness look like they're insensitive to the housing market, whereas those never diagnosed are more sensitive to it. The only significant difference in the effect of the labour market occurs between those with a history of incarceration and those without. Here it actually seems like it's those that have recently been incarcerated that are particularly affected by the local labour market; a one unit increase in the local unemployment rate increases the likelihood of entering homelessness by 12.9 percentage points for those that had been incarcerated in the previous 6 months.

When public housing residents are excluded from the sample however, we do see some slight, but important differences. Overall, the marginal effect of the housing market tends to increase in magnitude, even if only by a small amount. Thus, consistent with our earlier general findings, the housing market has a larger effect on individual risks of homelessness when public housing house residents are excluded. The only group where this isn't seen is for those with dependent children, where the marginal effect becomes small and negative when public housing residents are excluded. Likewise, the local labour market tends to have a larger effect on most groups when public housing residents are excluded.

The exclusion of public housing residents from the sample also appears to effect conclusions regarding whether there are differential effects of housing and labour markets between the various groups examined. For instance, there is no significant difference in the marginal effects of a change in median rents or the unemployment rate between those with dependent children and those without when we consider the full sample. However when public housing residents are excluded from the analysis the difference becomes significant when considering the effect of median rents. Column 3 shows that a \$100 increase (decrease) in median rents per week increases (decreases) the chance of entering homelessness by 3.6 percentage points for those without dependent children who are not in public housing, whereas the housing market has no significant effect on the risks of homelessness for those with dependent children.

Also, when public housing residents are excluded, early school leavers become more sensitive to median rents and the difference between the two education groups becomes insignificant.

When looking at the results using the full sample persons diagnosed with a mental illness are insensitive to the housing market whereas those never diagnosed are more sensitive. On the hand, when public housing residents are excluded the marginal effect of median rents is larger for those diagnosed with a mental illness relative to those that had never been diagnosed. The difference in the marginal effects between the two groups becomes insignificant, at least in a statistical sense.

Using the restricted sample the probability of homelessness for those with a history of incarceration becomes considerably more sensitive to housing market conditions (relative to persons never incarcerated). This is in line with our earlier hypothesis that ex-offenders

would face particular risks of homelessness in tight housing markets due to landlord discrimination.

7. Conclusion/Policy implications

Journeys Home (JH) is a panel data set that offers unique opportunities to study the dynamics of homelessness. The JH sample contains individuals who are either homeless or have a high propensity of becoming homeless. The paper aims to estimate whether a given group of individuals is more or less likely to enter (exit) homelessness as compared to *other vulnerable groups in the sample*.

We combine the JH micro-level longitudinal data set with area-level observations of housing and labour market conditions to explore the relationship between structural conditions, individual characteristics and transitions into and out of homelessness. Findings from jointly estimated entry and exit probit equations are reported. In entry models we employ a sample design that selects those housed in each wave of the panel data set, and then models their homelessness status at the next wave (6 months later). The average rate of entry (wave on wave) is 8%. Exit models are based on a sample of those that are homeless in each wave, and models their homelessness status at the next wave. The average rate of exit is 40%. The majority of the JH sample is formally housed in each wave.

Two model specifications are estimated. In the first we assume that each of the explanatory variables has an independent impact on the conditional probability of becoming homeless, or climbing out of homelessness. A second allows for interaction effects between housing and labour market measures on the one hand, and individual characteristics on the other; because sample numbers are relatively small the exit model results for this second specification are unreliable, and so only entry model results are reported.

In the independent effects entry model specification we discover that risky behaviours and life experiences such as regular use of drugs, heavy drinking and the experience of violence are at a higher risk of becoming homeless. Vulnerable people with biographies marked by acute disadvantage (e.g. fewer years of schooling, no previous record of employment, 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 become homeless. However, the presence of children lowers the chances of becoming homeless, regardless of relationship status. The estimates also suggest that the risk

of becoming homeless is greater in regions with higher median rents and slack labour markets; but residence in public housing has a strong protective effect. The priority status of mentally ill individuals on public housing waiting lists, might then account for the unexpected finding that those with *diagnosed* mental health conditions are less likely to tumble out of housing and into homelessness.

The processes shaping pathways out of homelessness appear to be very different from those shaping entries into homelessness. This conclusion highlights the importance of separately analysing transitions into and out of homelessness. Our results suggest that personal characteristics and housing and labour market conditions are a generally unimportant influence on pathways out of homelessness. Age is one exception to this proposition. Older homeless people are found to be much less likely to escape their predicament. These results suggest that when an older individual is homeless they become disconnected from housing and labour markets. Age could be the key influence because young people are more adaptable as well as more mobile, and hence have access to a wider range of housing and labour market opportunities.

The models including interaction variables suggest that individuals vulnerable to homelessness but not engaging in risky behaviours (e.g. regular drug users), or possessing particular risk characteristics (e.g. long term health condition), are more likely to be tipped into homelessness when housing market conditions tighten and labour market conditions weaken. This could be because persons with particular risk factors have become so disconnected from formal labour market and housing markets that their chances of entering homelessness are the same regardless of housing and labour market conditions. These findings will also reflect their priority status in terms of access to public housing. This is confirmed by modelling based on a restricted sample which excludes those occupying public housing.

The exception to this overarching conclusion is that group of individuals with histories of incarceration, especially a recent episode. It could be that this is a neglected group as far as support services are concerned. They might also be prone to discrimination in private rental housing markets that landlords are more able to express when rents are rising and there is a buoyant demand for rental housing.

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Figure 1 Homelessness entry and exit rates by real median rent of area

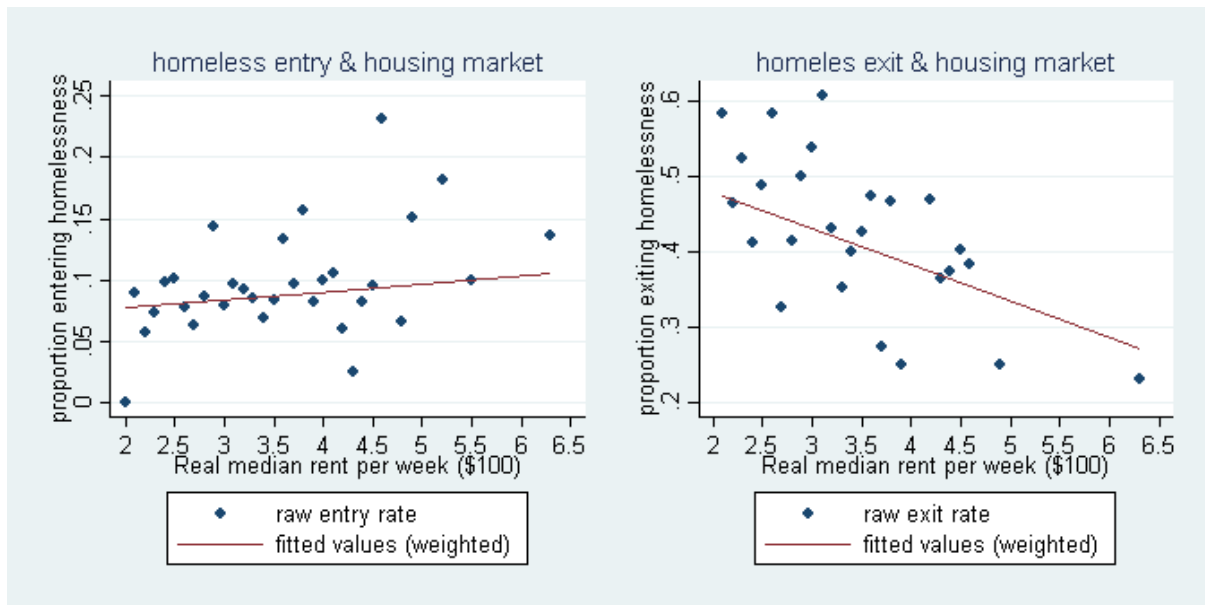


Figure 2 Homelessness entry and exit rates by unemployment rate of area

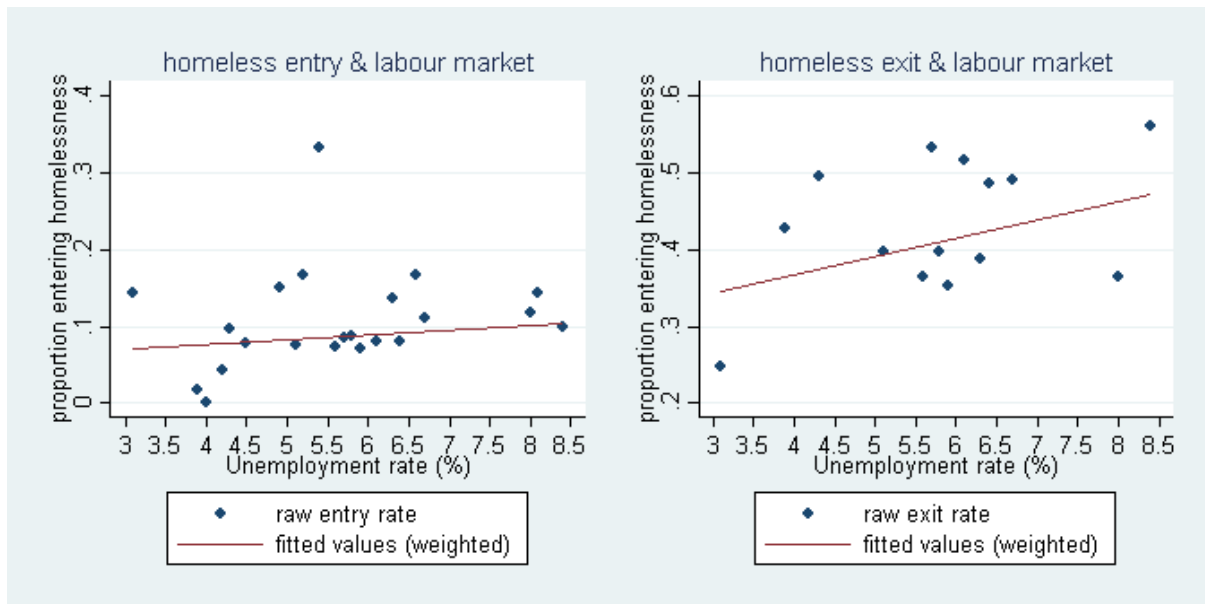


Table 1 Homeless rates, entry rates and exit rates by wave

	Homeless rates	Entry rates	Exit rates
Wave 1	0.256	0.093	0.443
Wave 2	0.204	0.099	0.425
Wave 3	0.200	0.087	0.394
Wave 4	0.192	0.077	0.402
Wave 5	0.185	0.077	0.375
Wave 6	0.181		
Total	0.205	0.087	0.411
Total numbers of observations	8829	5425	1386

Table 2 Probability of homeless entry and exit: mean marginal effects from probit with random effects

	Entry	Exits
Male	0.021** (0.009)	-0.079 (0.056)
<i>Age group (reference=15-21 years)</i>		
21-44 years	-0.003 (0.011)	-0.212*** (0.069)
45+ years	0.021 (0.017)	-0.324*** (0.083)
ATSI	0.019 (0.013)	0.014 (0.060)
<i>Country of birth (reference=AUS)</i>		
Born in English speaking country	-0.014 (0.015)	-0.022 (0.088)
Born in non-English speaking country	0.003 (0.019)	-0.035 (0.092)
Married/defacto	-0.009 (0.010)	-0.067 (0.068)
Have resident children	-0.020** (0.010)	0.227*** (0.076)
<i>Educational (reference=post school qualification)</i>		
Yr 12 or eq	0.005 (0.013)	0.050 (0.080)
Yr 10 or 11	0.014 (0.010)	0.036 (0.053)
Yr 9 or below	0.024* (0.013)	0.047 (0.065)
<i>Labour force status (reference=employed)</i>		
Unemployed	0.002 (0.015)	-0.068 (0.090)
Not in the labour force	0.009 (0.014)	-0.123 (0.083)
<i>Work history</i>		
never employed	0.041* (0.022)	0.094 (0.094)
lost job in the last 2 years	0.015 (0.011)	0.067 (0.053)
Time employed sine left FT education (%)	-0.000 (0.000)	0.001 (0.001)
<i>Family history</i>		
Ever in State care	0.023* (0.012)	-0.011 (0.056)
No principle caregiver at age 14	-0.004 (0.016)	0.129 (0.086)
<i>Violence or multiple threat of violence (reference= Did not experienced)</i>		
Experienced violence or multiple threat of violence	0.020* (0.012)	0.030 (0.051)
Did not respond violence questions	0.015 (0.022)	-0.072 (0.101)
<i>Incarceration (reference=never incarcerated)</i>		
Ever (but not recently) incarcerated	-0.002 (0.010)	-0.045 (0.050)

incarcerated in the last 6 months	0.026 (0.029)	-0.092 (0.091)
Alcohol consumption per day	0.002* (0.001)	-0.005 (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 (0.012)	0.016 (0.061)
Used drugs once a week or more	0.027** (0.012)	-0.049 (0.051)
<i>Health</i>		
Activity limiting Long term health condition	0.005 (0.009)	0.028 (0.046)
Ever diagnosed with mental illness	-0.026** (0.011)	0.048 (0.049)
Average social support score	-0.017*** (0.005)	0.006 (0.026)
Ever primary homeless	0.037*** (0.009)	0.016 (0.051)
Lived In public housing	-0.059*** (0.007)	
Lived in social housing	-0.010 (0.013)	
Equivalised income (\$100/ per week)	-0.001 (0.002)	0.003 (0.011)
Median rent	0.019*** (0.007)	-0.019 (0.035)
unemployment rate	0.013** (0.005)	0.002 (0.029)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3 Sensitivity of housing and labour market effects using alternative area level measures (mean marginal effects)

	Hybrid SA4 main results (SQM)		hybrid SA4 Census		SA4 SQM	
	entry	exit	entry	exit	entry	exit
Median rent	0.019*** (0.007)	-0.019 (0.035)	0.017** (0.008)	0.008 (0.046)	0.013** (0.005)	-0.017 (0.025)
Unemployment rate	0.013** (0.005)	0.002 (0.029)	0.010** (0.005)	0.017 (0.027)	0.003 (0.003)	0.021 (0.014)

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Table 4 Sensitivity of housing and labour market effects to excluding public housing residents (mean marginal effects)

	Hybrid SA4 main results (SQM)		Hybrid SA4 Exclude public housing	
	entry	exit	entry	exit
Median rent	0.019*** (0.007)	-0.019 (0.035)	0.024*** (0.008)	-0.020 (0.035)
Unemployment rate	0.013** (0.005)	0.002 (0.029)	0.015** (0.006)	0.003 (0.029)

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Table 5 Allowing for heterogeneity in area-level effects: mean marginal effects of median rent and unemployment rate from probit with random effects

	Full sample		Sample excluding public housing residents	
	median rents (1)	ue rates (2)	median rents (3)	ue rates (4)
No children	0.0270*** (0.0101)	0.0172** (0.00789)	0.0362*** (0.0114)	0.0201** (0.00892)
Children	0.00755 (0.0105)	0.00769 (0.00732)	-0.00338 (0.0134)	0.00293 (0.00924)
Year 12 or equivalent	0.0411*** (0.0126)	0.0274*** (0.00901)	0.0473*** (0.0147)	0.0335*** (0.0105)
Early school leaver	0.0121 (0.0111)	0.00841 (0.00865)	0.0165 (0.0129)	0.00553 (0.0103)
Employed	0.0296*** (0.0109)	0.0201** (0.00913)	0.0319*** (0.0117)	0.0193* (0.00984)
Not in the labour force	0.0120 (0.0127)	0.00540 (0.00975)	0.0145 (0.0162)	0.00646 (0.0125)
Do not have long-term health condition or disability	0.0303*** (0.00964)	0.0186** (0.00758)	0.0305*** (0.0105)	0.0182** (0.00838)
Long-term health condition or disability	0.00680 (0.0130)	0.00955 (0.00969)	0.0169 (0.0164)	0.0128 (0.0122)
Never diagnosed with mental illness	0.0405*** (0.0134)	0.0217** (0.0103)	0.0414*** (0.0145)	0.0186 (0.0114)
Ever diagnosed with mental illness	0.0110 (0.00970)	0.0108 (0.00748)	0.0170 (0.0118)	0.0144 (0.00907)
Did not use drugs	0.0245*** (0.00846)	0.0120* (0.00644)	0.0277*** (0.00977)	0.0124* (0.00752)
Used drugs	0.0132 (0.0160)	0.0213* (0.0124)	0.0205 (0.0186)	0.0246* (0.0145)
Never incarcerated	0.0142* (0.00843)	0.0131** (0.00654)	0.0171* (0.00953)	0.0151** (0.00746)
Ever (but not recently) incarcerated	0.0398** (0.0180)	0.0143 (0.0132)	0.0608*** (0.0227)	0.0198 (0.0168)
Incarcerated in the last 6 months	0.0813 (0.0721)	0.129** (0.0615)	-0.0263 (0.0783)	0.0569 (0.0657)
Did not experience violence last 6m	0.0192** (0.00838)	0.0148** (0.00641)	0.0220** (0.00893)	0.0167** (0.00679)
Experienced violence last 6m	0.0228 (0.0251)	0.0216 (0.0187)	0.0349* (0.0189)	0.0242* (0.0125)
Did not answer violence questions	0.0554 (0.0347)	-0.0109 (0.0296)	0.0718* (0.0367)	-0.0288 (0.0302)
Numbers of observations	5,499	5,499	4,748	4,748

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Bold font indicates significant difference in marginal effects between sub-groups.

Also examined were possible heterogeneous effects by sex, age, Indigeneity and levels of alcohol consumption but differences between groups were not found to be significant.

Appendix Table 1. 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	NA	NA
Exited Homelessness	For those homeless at current interview: equals 1 if became housed in the next interview, and zero otherwise.	NA	NA	0.396	0.489
Male	Equals 1 if male, and 0 if female	0.490	0.500	0.692	0.462
<i>Age group</i>	Age determined from date of birth				
15-20 years	Equals 1 if aged 15-21 years, and 0 otherwise				
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	0.335	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	0.186	0.389
<i>Country of birth</i>					
Born in Australia	Equals 1 if born in Australia, and 0 otherwise.	0.875	0.330		
Born in English speaking country	Equals 1 if born in main English speaking country, and 0 otherwise.	0.065	0.246	0.069	0.254
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	0.246
Married/defacto	Equals 1 if married/defacto, and 0 otherwise.	0.204	0.403	0.105	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	0.308
<i>Education</i>					
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	0.314	0.464
Yr 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 Yr 10 schooling completed; and 0 otherwise.	0.119	0.324	0.093	0.290

Yr 10 or 11	Equals 1 if has completed at least Yr 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	0.388	0.487
Yr 9 or below	Equals 1 if has not completed Yr 10 at school and has not completed any other AQF recognised qualifications; and 0 otherwise.	0.156	0.362	0.206	0.405
<i>Labour force status</i>					
	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	0.362
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	0.573	0.495
<i>Work history</i>					
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 sine left FT education (%)	Per cent of time employed since first leaving full-time education (with values greater than 0 and less than 100).	40.687	30.806	42.748	30.577
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	0.333	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	0.182	0.386
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
<i>Recent violence</i>					
Did not experienced	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	0.722	0.448
Experienced voilence	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	0.238	0.426
Did not respond violence questions	Equals 1 if did not respond to questions on violence; and 0 otherwise.	0.039	0.193	0.040	0.195
<i>Incarceration</i>					
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	0.568	0.495

Ever incarcerated 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	0.378	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	2.640	5.791
<i>Illicit drug use</i>					
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	0.271	0.519	0.271
Used drugs less than once a week	Equals 1 if used any type of illicit drug irregularly (i.e. less than weekly) in the last six months; and 0 otherwise.	0.144	0.351	0.171	0.377
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	0.310	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	0.522	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	0.655	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) You often feel very lonely?	3.566	0.808	3.253	0.855
Ever slept rough	Equals 1 if have ever experienced primary homelessness; and 0 otherwise.	0.530	0.499	0.740	0.439
In public housing	Equals 1 if living in public housing; and 0 otherwise	0.171	0.377	NA	NA
In social housing	Equals 1 if living in social housing; and 0 otherwise	0.085	0.280	NA	NA
Real Equivalised family income (\$100/ per week)	Family Income / square root (family size) deflated by CPI	4.176	2.924	3.810	2.342

Real Median rent (\$100/ per week)	[Median rent of greater capital city area or SA4 for regions outside of capital cities] divided by 100; 3 months centered moving average; deflated by CPI	3.382	0.774	3.509	0.869
Unemployment rate (%)	Unemployment rate of greater capital city area or SA4 for regions outside of capital cities; 3 months centered moving avarage	5.649	1.002	5.635	1.064
numbers of observations		4391		1112	