



Final Report

Entries and exits from homelessness: a dynamic analysis of the relationship between structural conditions and individual characteristics

authored by

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for the

Australian Housing and Urban Research Institute

at RMIT University

September 2015

AHURI Final Report No. 248

ISSN: 1834-7223

ISBN: 978-1-922075-98-7



Authors	Johnson, Guy Scutella, Rosanna Tseng, Yi-Ping Wood, Gavin	RMIT University The University of Melbourne The University of Melbourne RMIT University
Title	Entries and exits from homelessness: a dynamic analysis of the relationship between structural conditions and individual characteristics	
ISBN	978-1-922075-98-7	
Format	PDF	
Key words	Homelessness, individual characteristics, structural conditions, interaction.	
Editor	Anne Badenhorst	AHURI National Office
Publisher	Australian Housing and Urban Research Institute Melbourne, Australia	
Series	AHURI Final Report; no. 248	
ISSN	1834-7223	
Preferred citation	Johnson, G., Scutella, R., Tseng, Y. and Wood, G. (2015) <i>Entries and exits from homelessness: a dynamic analysis of the relationship between structural conditions and individual characteristics</i> , AHURI Final Report No.248. Melbourne: Australian Housing and Urban Research Institute. Available from: < http://www.ahuri.edu.au/publications/projects/p53042 >. [Add the date that you accessed this report: DD MM YYYY].	

ACKNOWLEDGEMENTS

This material was produced with funding from the Australian Government and the Australian state and territory governments. AHURI Limited gratefully acknowledges the financial and other support it has received from these governments, without which this work would not have been possible.

AHURI comprises a network of university Research Centres across Australia. Research Centre contributions, both financial and in-kind, have made the completion of this report possible.

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ACRONYMS

ABS	Australian Bureau of Statistics
AQF	Australian Qualifications Framework
AHURI	Australian Housing and Urban Research Institute Limited
ASGS	Australian Statistical Geography Standard
GCCA	Greater Capital City Areas
JH	Journeys Home
NILF	Not in the Labour Force
NPAH	National Partnership Agreement on Homelessness
REIA	Real Estate Institute of Australia
SA	Statistical Area (ABS)
SHS	Specialist Homelessness Services

EXECUTIVE SUMMARY

This report examines the relationship between structural factors, individual characteristics and homelessness. Our interest in the interaction of structural conditions and individual characteristics gives rise to two secondary research questions. First, do structural factors such as housing and labour market conditions, as well as area-level poverty, matter for those individuals vulnerable to homelessness? Second, do structural factors affect those with particular individual risk factors more than others? The questions were answered by analysing an individual's probability of being homeless, the probability of the housed entering homelessness, and the probability that homeless individuals will exit homelessness.

In the first two chapters we provide background material while Chapter 3 describes our approach. We rely on economic choice theory and a housing demand and supply framework to set up the empirical approach. The research approach estimates three models that include the individuals' static homeless state, as well as the dynamics of individuals' homelessness through an examination of entry into and exit out of homelessness. The static model includes all observations in the *Journeys Home* (JH) dataset to assess the probability that an individual will be homeless at each interview. To estimate the probability of entry into homelessness, we identify all persons who are classified as housed and estimate their probability of entering into homelessness in the next six months (i.e. being classified as homeless at the next interview). To analyse the probability of exiting homelessness, we focus on those persons who are classified as homeless, and estimate their probability of becoming housed at the next wave. A random effects logit model is employed to perform the estimations in each model. In each model we present the mean marginal effects of each of the covariates to assess both the statistical significance and the magnitude of effects.

In Chapter 4 we outline our data sources and the definition of homelessness. To estimate the contribution of structural factors and individual characteristics requires both micro-level (individual) longitudinal data and area-level data that capture the conditions of social structures such as the housing and labour markets of areas. In the past, micro-level longitudinal data has not been available but this changed with *Journeys Home*, a longitudinal survey of Centrelink customers who were homeless, at risk of homelessness, or who have high propensity to be homeless (vulnerable to homelessness). The *Journeys Home* data is ideal for examining the interactions between structural conditions and individual characteristics as it includes detailed information on individuals' characteristics and housing circumstances over time, as well as biographical information prior to the survey. It also covers a representative and sizeable number of geographic areas, with the initial sample clustered across 36 areas drawn from all states and territories, and follow-up interviews attempted even when initial sample members move to areas outside of these initial clusters. Since the sample is designed to be representative of those living in insecure housing circumstances, we are analysing whether individuals belonging to a vulnerable group (due to either personal characteristics or structural factors) are at higher or lower risk of homelessness as compared to others living in insecure housing circumstances.

We draw on area-level data from the 2011 Census to establish our housing market conditions measure. The median rent of private rentals is the key measure, 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. A number of other measures such as the demand and supply of low cost housing are also tested. The indicator of local labour market conditions is the regional unemployment rate sourced from the ABS monthly *Regional Labour Force Statistics* (ABS 2014). As our housing market measure is time invariant, we average the monthly unemployment rates over the *Journeys Home Survey* period (over two-and-a-half years) to ensure the consistency between the two measures.

Housing and labour market data is provided at Statistical Area Level 4 (SA4). It is questionable whether SA4s are the appropriate classification to use when representing capital city residents

exposure to housing and labour market conditions. Thus, each of the three models is estimated using two different spatial unit definitions of the area based variables. In our preferred specifications, SA4s within the greater capital city areas have been merged, with unemployment rates and median weekly rents measured on a city-wide basis where relevant. Estimations are also performed using area-level measures in a finer spatial unit classification where the SA4 spatial unit is retained across all Australian regions, including greater capital city metropolitan areas.

In Chapter 5 we present the results. For the static model we found that men, older people (45 years plus), those with low educational attainment, the unemployed (or those outside the labour market) are at higher risk of homelessness. So too are individuals who have experienced recent violence or who have recently been incarcerated. The static model also finds that individuals experiencing episodes of primary homelessness prior to JH were also at greater risk of homelessness. Surprisingly, *regular drug use was not significantly associated with homelessness*, nor was the absence of parenting during childhood, or involvement in the child protection system. Factors correlated with these behavioural and biographical characteristics could be responsible for the elevated rates of homelessness associated with these groups. Similarly, those with diagnosed mental health issues (bi-polar or schizophrenia) are at less risk of homelessness than those without a similar condition. We speculate that *diagnosis of these conditions* makes delivery of support services more likely. There is confirmation from the estimates that people who were married, had dependent children, or who had better social support, are less likely to be associated with homelessness. After controlling for personal characteristics and risky behaviour, we find housing markets matter, but the evidence on the effects of labour markets is mixed.

The analysis of homeless status during JH provides an indication of the overall effects of structural and individual risk factors on homelessness, but the picture provided by the static analysis is far from complete. Factors that may affect an individual's likelihood of entry into and exit from homelessness may be different, and if so a more nuanced perspective on the likely effectiveness of different forms of policy intervention is required. Thus, we estimate models of the probability of entry (for the housed) and probability of exit (for the homeless) separately.

The results of the entry and exit models are also presented in Chapter 5. Our entry model provides further confirmation that vulnerable males are less likely to sustain secure housing than females. We also find that the presence of children lowers the chances of becoming homeless, regardless of relationship status. Those with resident children are 2.6 percentage points less likely than the childless adult to enter homelessness. The *Journeys Home* sample and model estimates also uncover patterns in the data suggesting that age and country of birth are not statistically important as far as entry into homelessness are concerned. There is also evidence indicating that those with relatively low levels (years) of schooling are more likely to slip out of formal housing circumstances. Somewhat surprisingly, we found that the absence of parenting does not significantly impact on pathways into homelessness. However, those who had been in state care as children are 2 percentage points more likely to enter homelessness, despite a static model finding which suggests that they are no more likely to be homeless overall. Homelessness status is the product of entries into and exits from homelessness, so these apparently puzzling results can be reconciled since exits from homelessness prove to be insensitive to state care status.

As expected, risky behaviour (drinking, smoking, and drug use) raises the chances of entering homelessness. However, the effects of ill health on entries into homelessness are mixed. While a long-term health condition increases an individual's likelihood of entering homelessness, having a diagnosed bipolar or schizophrenia condition decreases the probability of slipping out of secure housing and into homelessness. Although this finding is somewhat surprising, given people with mental illness are thought to be especially prone to homelessness, we once again think that it reflects the delivery of treatment and care (even institutionalised care), thereby

lowering the chances of entering homelessness compared to those undiagnosed, who could also have other risk factors. Both static and entry models suggest that social support is important in reducing the risk of homelessness. But those housed in any wave are more likely to become homeless in the next six months if they have had a past experience of homelessness.

Consistent with the results examining homeless status at a point-in-time (from the static model), median market rents are positively related to entry into homelessness. An increase in the median market rent of \$100, which is a 30 per cent increase at the national median weekly rent, lifts the risk of entry by 1.6 percentage points, or from a sample mean of 8 per cent to 9.6 per cent (a 20% increase in risk). So the impact is both statistically significant and sizeable. We also find that local labour market conditions are a significant cause of entries into homelessness, with a one percentage point increase in the unemployment rate raising the likelihood of homelessness entry by one percentage point.

Nonetheless, we again find confirmation that males are prone to homelessness because they are both more likely to fall into homelessness, as well as less likely to escape homelessness. There is a startling finding with respect to age—escape for those enduring a spell of homelessness is much more difficult as age increases. The marginal effect estimates are very large; the 21 to 44-year group are 23.1 percentage points less likely to escape than the reference age group (15–20 years), and individuals 45 years and older are 35.9 percentage points less likely to exit. It is worth recalling that these findings are after controlling for other observable influences.

Although individuals married or in a defacto relationship are less likely to enter homelessness, if they do fall out of secure housing there is a significantly lower likelihood of escape as compared to the reference group (singles). Current employment status does seem to be related to exits with some connection to the labour market better than none. This effect, however is only weakly significant and only relative to those not in the labour force. Although recent job loss was a significant 'footprint' marking entries into homelessness, it is curious that our model now reveals persons losing their job between 6 months and 2 years prior who were more likely to escape homelessness than others.

Unexpectedly (in view of statistically insignificant effects in static and entry models), those who had no principal caregiver at age 14 were 15.7 percentage points more likely to exit; however, it is only statistically significant at the 10 per cent level. Those recently incarcerated were less likely to exit, but not significantly so. This also appears to be the case with those drinking, smoking or using illegal substances regularly.

With respect to the impact estimates of area-level characteristics, we find that the state of both area-level housing markets and labour markets do not appear to significantly affect the propensity to exit homelessness.

Chapter 6 examines whether housing and labour markets are more important for certain types of people than others. In the entry model there is some evidence to suggest that housing market conditions are only relevant to those subgroups prone to enter homelessness for reasons other than risky behaviour, or ill health. If you have risky behavioural traits, such as recent incarceration, regular use of drugs, and so on, your chances of becoming homeless are invariably higher regardless of housing and labour market conditions. On the other hand, if these risky behavioural traits are absent, the chances of becoming homeless are greater in regions with higher median rents. For example, you are in good health and have no risky behavioural traits, but experience bad luck such as an emotionally stressful relationship break up combined with a family row that results in unexpected departure from the parental home. The expensiveness or otherwise of housing in the neighbourhood does seem to matter in such circumstances.

This conclusion on the absence of interaction effects is clearly evident with respect to incarceration, diagnosis as bipolar or schizophrenic, drug use, risky levels of drinking and

experience of violence, all of which are *statistically insignificant* when interacted with the median rent variable.

There is some evidence in the entry model for the same phenomenon with respect to labour markets, but it is weaker. Thus, higher unemployment seems to affect some groups with personal characteristics more than others. For example, females and 21–44-year-old individuals are more prone to enter homelessness in areas with higher unemployment rates. There is tentative evidence in entry models of housing market effects with respect to the same personal characteristics.

The exit model yields one curious finding. The age categories on their own have large and significant impacts on the probability of exit from homelessness (see Chapter 5, Table 4), yet the housing and labour market effects are quite heterogeneous within the same age groups and therefore insignificant statistically for all three age groups. This suggests that the higher exit rates for the young age group may be driven by services or other unobserved factors.

The regression estimates pick up some, albeit weak, signals suggesting the prospects of entering homelessness for people *without* risky behavioural traits, but vulnerable to homelessness for other (perhaps unmeasured) reasons, are differentially affected by the labour and housing market features of their region. On the other hand, while the risk of homelessness is higher among those with risky behaviours—drug use, alcohol dependence and so on—it seems that housing and labour market effects are uniform across these risk groups.

The policy implications of our findings are discussed in Chapter 8. For those with risky behaviours—drug use, alcohol dependence and so on—programs that directly address these behaviours is the optimum approach to reduce entries into homelessness. We should also note that these implications are drawn with respect to individuals housed but vulnerable to homelessness, and as such these programs should be designed as *preventative rather than reactive*. On the other hand, those persons vulnerable to homelessness, but without behavioural issues, could benefit from a location closer to job opportunities and affordable housing opportunities. Efforts to improve affordable housing and job opportunities in regions with unaffordable housing, or weak labour markets, will then aid prevention of homelessness among these groups.

1 INTRODUCTION

This report presents the results of empirical analysis that sets out to examine the relationship between structural factors, individual characteristics, and homelessness using *Journeys Home* (JH), a unique Australian longitudinal dataset on persons vulnerable to homelessness. The *Journeys Home* micro-data is ideal for examining the interactions between structural conditions and individual characteristics as it includes high levels of detail about individuals' characteristics, both current and historical. It also covers a representative and sizeable number of geographic areas, with the initial sample clustered across 36 areas drawn from all states and territories, and follow-up interviews attempted even when initial sample members move to areas outside of these initial clusters. Because JH is longitudinal, we can also go some of the way to addressing unobserved heterogeneity.

The two structural factors that interest us are the condition of housing and labour markets in the areas that the homeless and those vulnerable to homelessness are located. Individual characteristics that interest us include demographic, biographic, and behavioural characteristics. These individual characteristics range from those over which the person has no control, such as age, through to those that are the product of individuals acting independently and making their own decisions (agency). Most individual characteristics lie between these two extremes.

Our interest in the interaction of structural conditions and individual characteristics gives rise to two secondary research questions:

1. Do structural factors such as housing and labour market conditions, as well as area-level poverty, matter for those individuals vulnerable to homelessness?
2. Do structural factors affect those with particular individual risk factors more than others?

Our study is the first, local or international, to link micro-level longitudinal data (JH) collected in a number of areas across the country, with area-level measures of housing and labour market variables and social deprivation. Using this linked data, we estimate a model that more accurately explains the magnitude of housing market effects on individual risks of homelessness relative to other structural and individual characteristics. As such, the findings from this project make a significant contribution to the Australian and indeed the international housing, homelessness and social policy literature.

There are eight chapters in the report, which is structured as follows. Chapter 2 identifies the importance of structural and individual explanations in the homelessness literature. The chapter argues that researchers recognise that theoretical explanations of homelessness are best when they incorporate the interaction of structural factors with individual characteristics. The next part of the chapter summarises findings from studies that draw on area-level data and studies that draw on individual level micro-data to examine the effects of structural factors and individual characteristics on rates of homelessness. The final part of the chapter highlights the lack of micro-level longitudinal data as a key reason why researchers have not been able to adequately assess the contribution of both individual and structural factors.

In Chapter 3 we outline our approach. We draw on established economic choice theory and a demand and supply of housing framework to set out hypotheses that are amenable to scrutiny with the JH dataset. We then provide details of our empirical model. First, we describe the static choice model. This model is used to determine what factors influence the likelihood that an individual is homeless in any given wave in JH. We then consider homelessness more dynamically by outlining our reasoning for, and approach to, examining factors linked to entries into homelessness, as well as exits out of homelessness. Chapter 4 describes the JH study, how we define homelessness and presents the key variables used in our analysis. Chapter 4 also contains descriptive statistics drawn from the JH dataset. The results of the analysis are presented in Chapter 5. There are three sections in this chapter. First, we examine the probability of being homeless at any wave in the JH study. In the analysis we first identify

individual factors before examining area-level characteristics. Next we turn our attention to entries into homelessness, and finally exits from homelessness. In both sections we follow a similar approach—we start by examining individual factors and then turn to area-level characteristics. We find that in the entry model there are eight variables that are statistically significant, but discover that only four variables achieve the same threshold in the exit model.

Chapter 6 presents modelling results that examine whether housing and labour market conditions are more important for certain types of people than others. While we find this to be the case, the picture is a nuanced one. Chapter 7 presents the results of our sensitivity analysis, and Chapter 8 concludes with a number of policy recommendations.

2 BACKGROUND

Over the last two decades numerous theories or viewpoints about homelessness have emerged. Two opposing perspectives that feature strongly in the literature are structural explanations and individual theories (Elliott & Krivo 1991; Main 1998; Johnson & Jacobs 2014). Individual accounts are based on the view that homelessness is a result of certain individual characteristics. This approach draws on empirical evidence that a lack of social capital and/or behavioural problems, such as mental health and substance misuse, are more prevalent among the homeless. On the other hand, structural accounts explain homelessness as a result of factors beyond an individual's control such as the condition of housing and labour markets.

The separation of structural conditions and individual characteristics has, however, been criticised as a misleading division, 'more reflective of the institutional organisation of knowledge than of social experience' (Katz 1993, p.441). As a way of overcoming the limitations of both approaches, researchers have argued that theoretical explanations are most incisive when they incorporate the interaction of structural factors with individual characteristics (Main 1998; O'Flaherty 2004).

The basic premise of an 'interactional' approach is that at any given time, structural factors create different risk levels among certain populations. Within these external constraints, certain individual characteristics increase an individual's vulnerability to homelessness. This approach does not reject the possibility that structural or individual characteristics on their own may cause homelessness, but rather it emphasises how the process of becoming homeless (or avoiding homelessness) is mediated through the interaction of individual characteristics and social and economic structures.

Attempts to develop an integrated theoretical framework have met with limited success. Indeed, sociological studies that have tried to explain how social structures affect homelessness through individual 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).

Economists have also been influenced by the ideas of structural and individual factors, but they have moved in a slightly different direction with greater emphasis on empirical approaches to analysing the drivers of homelessness. This is important as our analysis draws on economic theories that likely understand interactions between individuals and structural factors quite differently from the way researchers in others fields understand and apply the term. In the empirical literature, structural factors usually examined are housing and labour market conditions, economic cycles (booms and busts), demographic profiles and policy interventions. Individual risk factors that have been examined by economists include demographic and biographic characteristics, as well as various measures of behavioural attributes, although the latter are often proxies rather than direct measures.

Economic analysis of homelessness that *directly* examines how structural and individual factors affect the level and distribution of homelessness rely on two different units of analysis—area-level observation, such as cities, and micro-level data on individuals and their characteristics. However, as reported in other similar studies (cf Wood et al. 2014), there are relatively few economic studies. Indeed, we found only 18 such studies, with two from Australia, one from Scotland, and 15 from the US.

Of the 18 studies examining how structural and individual factors affect homelessness, 13 use areas (primarily cities) as the principal unit of analysis. In most of these studies, cross-sectional area-level data is used to explain the cross-city variations in homelessness. 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. 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, housing markets seem to matter the most, with little evidence that local labour markets or concentrations of poverty matter (Appelbaum et al. 1991; Elliott & Krivo 1991; Burt 1992; Honig & Filer 1993; Quigley & Raphael 2000; Quigley et al. 2001; Lee et al. 2003; Florida et al. 2012). In Australia, however, the situation seems reversed. 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 agree—individual characteristics do not matter a great deal.¹

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 extremely rare—we found only five studies that fit into this category (Early 1998, 1999, 2004, 2005; Early & Olsen 1998). Although the number of homeless and housed observations varies and each study applies different statistical techniques, the results are consistent—structural 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. In summary, individual-level studies produce very different findings from area-level studies—namely, that individual characteristics matter, but structural conditions do not.

Given that empirical studies of homelessness based on area-level observations (e.g. that focus on social and economic structures) get systematically different results from studies that use individual-level data, which of these sets of findings do we believe? As O'Flaherty (2004) shows, it's potentially both, as it's the conjunction of being the wrong person in the wrong place that matters. To understand the way structural factors impact on homelessness it is therefore crucial to explicitly account for their possible interaction with individual-level factors.

While economists, like sociologists, recognise the importance of accounting for the interaction of individual risk factors with area-level structural factors, the empirical literature tends to focus more on area-level (structural) factors because area-level data is often all that is available. Indeed, a lack of robust data, in particular micro-level longitudinal data, is one reason why researchers have not achieved a satisfactory synthesis 'in which the contributions of both structural and individual factors are estimated' (Lee et al. 2003, p.351). As Lee and his colleagues observe, such a data set would have to 'include pools of vulnerable people in multiple locations for whom homeless or non-homeless outcomes are recorded after contextual and individual characteristics have been measured' (2003, p.351). In the past this sort of data was unavailable, but the situation has changed with JH.

Whereas sociologists have struggled to develop a coherent and testable theoretical account of the interaction of structural factors and individual characteristics, we rely on established economic choice theory² on the demand and supply of housing to set up our empirical approach. This theory supplies hypotheses that are easily testable empirically, particularly with a dataset such as JH.³ Next we describe our approach.

¹ For a more detailed analysis of these 18 studies we refer readers to Johnson, Scutella, Tseng and Wood (2015).

² In the context of homelessness we are acutely conscious of the pejorative connotations associated with the notion of choice. In the public domain choice is often used to frame homelessness as a result of individual pathologies such as laziness, indolence, fecklessness and the like. Many people argue that a focus on choice ignores the structural constraints that give rise to and shape the homeless experience. Framing homelessness as a choice is thus seen as part of a conservative discourse that places blame on homeless people for their situation and thereby absolves the state of any responsibility. On the other hand, there are those who argue that by ignoring the issue of choice, people experiencing homelessness are treated as passive victims of forces beyond their control. Such a characterisation is seen to be both disempowering and empirically flawed. In drawing on economic choice theory, our approach recognises that individuals are active agents capable of making conscious choices, but that the choices people experiencing housing insecurity and homelessness make are done so in the context of often traumatic life experiences and restricted housing and labour market opportunities.

³ See Johnson et al. (2015) for further discussion of this.

3 APPROACH

3.1 Conceptual framework

Following Glomm and John (2002) 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.⁴ An elementary static version of this framework is developed in Appendix 1. 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.

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

⁴ There are therefore no moves and location is not an attribute over which preferences are defined.

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.⁵ 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 means that certain groups (e.g. young people) 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.

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.

These housing and labour market considerations are the commonly-cited structural causes of homelessness. However, there is perhaps a third intervening set of factors that are neither purely individual nor purely structural. We are referring here to institutional parameters governing the delivery of support services that target subgroups in the population that are vulnerable to homelessness. These institutional arrangements can vary in locally different ways. They could result in different service combinations in tight rather than slack regional housing and labour markets, and therefore shape how these structural variables impact on homelessness.

3.2 A dynamic perspective

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.

⁵ The upper end of the housing market is not as relevant as people can always obtain cheaper accommodation rather than become homeless.

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.

An additional issue that arises when taking a dynamic approach to homelessness, and one that is also considered in our final analysis, is that people can respond to housing and labour market conditions by moving. Some people may choose lower quality accommodation as a trade-off for their preferred location, where there may be better job prospects, or closer links to family and friends. Alternatively, some people might choose an area with lower housing costs but consume higher quality accommodation. That is, individuals can respond to tight housing markets by moving to cheaper areas in order to reduce their risk of homelessness or, if they are already homeless, to improve the chances of exiting homelessness.

3.3 Empirical model

To undertake our empirical analysis we will estimate a discrete choice model of each individual's housing state at a particular point-in-time. This involves modelling the probability that an individual chooses each one of a number of different specific housing states. In the basic model, two housing states, homeless and housed, will be analysed using a random effects logistic model. Both area-level structural factors, including housing affordability and labour market conditions, as well as individuals' characteristics will be included as independent variables to estimate the probability of being homeless. We also specify the model to explicitly allow for the interaction between structural factors and individual characteristics to see whether structural factors affect individuals with certain risk factors more than others.

Random effects models allow us to take into account not only the effects of observed characteristics of individuals, but also any unobserved individual characteristics that are fixed over time. A potential problem with the standard random effects model is that it assumes that any unobservable time-invariant heterogeneity is uncorrelated with other explanatory variables in the model. If, as is likely, this unobserved heterogeneity is correlated with any of the explanatory variables included in the model, the results of the estimation will be biased. Ideally, we would adopt a fixed-effects model, which does not require such a restrictive assumption. A fixed-effects model, however, requires that our explanatory variables are time-varying. Unfortunately, however, some of the area-level data that we will be using is taken from one point-in-time (Census night in 2011), and other area-level characteristics are unlikely to vary much over the short timeframe that *Journeys Home* data was collected. Therefore, we will follow the approach of Mundlak (1978). For the time-varying explanatory variables that are likely to be correlated with unobserved heterogeneity, the within-person means of these variables will be added to a standard random-effects model. We will also make an assessment of whether there is enough time-varying information for us to undertake analysis using a fixed-effects model, even if only to test the robustness of our findings.

The analysis of homeless status provides an indication of the overall effects of structural and individual risk factors on homelessness, but the picture provided by this analysis is far from complete. Factors that may affect an individual's likelihood of entry into and exit from homelessness may be different and could therefore require different forms of policy intervention. For example, current policy settings prioritise families, young people, and the long-term homeless (among others). It may be that the higher level of resources directed towards assisting these groups increases the likelihood of exiting homelessness, holding other things constant, but not the chances of entering homelessness. Although the probability of entry and exit jointly determines the probability of being homeless, understanding the dynamic process (that is entry and exit) will provide important insights for policy-makers concerned with both preventing homelessness, as well as getting people out of their homeless predicament. Thus, we will estimate the probability of entry (for the housed) and probability of exit (for the homeless) separately.

To estimate the probability of entry into homelessness, we will take all persons at an interview date (wave) that are classified as housed and estimate their probability of entering into homelessness in the next six months (i.e. being classified as homeless at the next interview). To analyse the probability of exiting homelessness, we focus on those persons at a wave that are classified as homeless and estimate their probability of becoming housed at the next wave. Again, the random effect logit model will be employed to perform the estimations.

4 DATA AND DEFINITIONS

4.1 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.

The JH sample is drawn from the Research Evaluation Database extracted from Centrelink administrative records. Since 2010, Centrelink staff have 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).

It is important to note that 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.

These protocols resulted in a total population of 139 801 individuals being identified as (1) homeless, (2) at-risk of homelessness, or (3) vulnerable to homelessness. From this population, a stratified random sample of 2992 individuals across 36 distinct locations covering all states and territories was selected for interview. Of this group, 273 were subsequently determined to be out of scope—mostly because they had moved out of the designated survey interview area prior to fieldwork commencing—leaving an effective sample of 2719. 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 (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 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. Although there have been some minor changes to the survey instrument over the course of the study, the surveys have captured 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.

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.

Journeys Home is thus ideal for the kind of analysis proposed here as it includes detailed information about individuals' characteristics, both current and historical. Also its wide geographic coverage will allow us to examine variation in housing outcomes across a range of geographical level factors, hitherto not appropriately examined.

4.2 Measuring individual 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 homeless.⁶ 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. We then classify the homeless into three categories—primary homeless (those without accommodation), secondary homeless (arrangements are short-term), and tertiary homeless (the arrangements are long-term, such as boarding houses or caravan parks).⁷

4.3 Explanatory variables

Table 1 presents a description of the key variables that will be used in our analysis. Individual characteristics examined include a standard set of demographic controls such as age, gender,

⁶ 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.

⁷ See Scutella et al, 2012 for a detailed discussion of this approach.

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. Finally, we add in an indicator reflecting whether individuals had ever experienced primary homelessness.

As discussed earlier, the key structural factor that we are interested in is the extent to which there is a housing imbalance at the area level. To pick this up, we examine the effects of a range of area-level housing market characteristics derived from the 2011 Census (ABS 2011). 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. We focus on private rental costs in our measure and, as we are using Census data, we only capture the rental prices of occupied private dwellings.^{8,9}

Note that there are caveats to the use of the Census data. As noted, the Census only provides information on the rental costs of occupied dwellings, but not vacant properties. Further, not all unoccupied dwellings are available to rent. Some are holiday homes. Therefore, we can only use occupied rental properties as a proxy to measure the market rent of rental properties. Another limitation with the Census data is that it does not capture time series variations in local housing and labour markets as it measures the characteristics of areas at one point in time, Census night in 2011.

⁸ Includes the rental costs of dwellings rented from a real estate agent or from a person who is not the relative of the resident and not living in the dwelling.

⁹ As the Census only provides rent paid in ranges we take the mid-point of the rent range when constructing the median. We also exclude observations where zero rent is paid as they are likely to be living in a non-standard type of rental arrangement.

Table 1: Variable definitions and summary statistics

Variable	Definition	Mean (total)	Mean (entry sample)	Mean (exit sample)
Homeless	Equals 1 if primary, secondary or tertiary homeless; and 0 otherwise. Based on the cultural definition of homelessness.	0.203	0.000	1.000
Entered homelessness	For those housed at current interview: equals 1 if became homeless in the next interview, and 0 otherwise.	NA	0.080	NA
Exited homelessness	For those homeless at current interview: equals 1 if became housed in the next interview, and 0 otherwise.	NA	NA	0.398
Male	Equals 1 if male, and 0 if female	0.540	0.491	0.700
<i>Age group</i>	Age determined from date of birth			
15–21 years	Equals 1 if aged 15–21 years, and 0 otherwise	0.204	0.235	0.149
21–44 years	Equals 1 if aged 21–44 years, and 0 otherwise	0.574	0.572	0.510
45+ years	Equals 1 if aged 45 years plus, and 0 otherwise	0.222	0.193	0.341
ATSI	Equals 1 if identifies as Aboriginal or Torres Strait Islander; and 0 otherwise. Options are as provided in the ABS Census.	0.173	0.161	0.188
Born in Australia	Equals 1 if born in Australia, and 0 otherwise.	0.873	0.874	0.867
Born in English-speaking country	Equals 1 if born in main English-speaking country, and 0 otherwise.	0.064	0.065	0.068
Born in non-English-speaking country	Equals 1 if born in non-main English speaking country, and 0 otherwise.	0.063	0.060	0.065
Married/defacto	Equals 1 if married/defacto, and 0 otherwise.	0.190	0.201	0.106
Have resident children	Equals 1 if have dependent children living who are living with them, and 0 otherwise.	0.248	0.286	0.104
<i>Highest educational qualification</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	0.336	0.334	0.309
Yr 12 or e.q.	Equals 1 if completed high school and does not have a post-school qualification	0.110	0.119	0.091

Variable	Definition	Mean (total)	Mean (entry sample)	Mean (exit sample)
	(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.			
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.	0.388	0.392	0.388
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.	0.166	0.155	0.212
<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	0.234	0.256	0.154
Unemployed	Equals 1 if unemployed, and 0 otherwise	0.261	0.259	0.275
Not in the labour force (NILF)	Equals 1 if not in the labour force, and 0 otherwise	0.505	0.485	0.571
<i>Work history</i>				
	Based on a series of questions capturing proportion of time since first left full-time education in paid work, unemployed and not in labour force.			
No work history	Equals 1 if has spent no time since first left full-time education in paid work; and 0 otherwise.	0.075	0.080	0.063
Time employed	Per cent of time employed since first leaving full-time education (with values greater than 0 and less than or equal to 1).	40.542	40.704	42.466
Has not experienced job loss within last 2 years	Equals 1 if has not experienced job loss in last 2 years; and 0 otherwise.	0.691	0.697	0.671
Lost job in last 6 months	Equals 1 if experienced job loss in last 6 months; and 0 otherwise.	0.119	0.121	0.117
Lost job in last 2 years but not in last 6 months	Equals 1 if experienced job loss 6 months to 2 years ago; and 0 otherwise.	0.189	0.181	0.213
<i>Family history</i>				
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	0.168	0.165	0.176

Variable	Definition	Mean (total)	Mean (entry sample)	Mean (exit sample)
No principal caregiver at age 14	Equals 1 if had no principal caregiver at age 14, and 0 otherwise	0.058	0.053	0.070
<i>Recent events</i>				
Did not experience violence in last 6 months	Equals 1 if reported not having experienced physical violence or force or sexual violence against them in the last 6 months; and 0 otherwise.	0.789	0.800	0.721
Experienced violence in last 6 months	Equals 1 if anyone has used physical violence or force or sexual violence against them in the last 6 months; and 0 otherwise.	0.171	0.161	0.238
Did not respond: violence	Equals 1 if did not respond to questions on violence; and 0 otherwise.	0.040	0.039	0.041
Incarcerated	Equals 1 if in juvenile detention, adult prison or remand in last 6 months; and 0 otherwise.	0.032	0.022	0.052
<i>Substance use</i>				
Alcohol consumption	Average number of drinks consumed per day.	0.204	0.188	0.280
Cigarette consumption	Average number of cigarettes smoked per day.	10.097	9.526	12.492
Did not use illicit drugs in last 6 months	Equals 1 if did not use any type of illicit drug in the last six months; and 0 otherwise	0.634	0.660	0.519
Used illicit drugs in last 6 months irregularly	Equals 1 if used any type of illicit drug irregularly (i.e. less than weekly) in the last six months; and 0 otherwise.	0.147	0.144	0.171
Regular user of illicit drugs in last 6 months	Equals 1 if used any type of illicit drug at least weekly in the last six months; and 0 otherwise.	0.220	0.196	0.311
<i>Health</i>				
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.	0.452	0.438	0.521
Never diagnosed with bipolar/schizophrenia	Equals 1 if have never been diagnosed, by a health professional, with bipolar affective disorder or schizophrenia; and 0 otherwise.	0.797	0.809	0.783
Ever diagnosed with bipolar/schizophrenia	Equals 1 if have ever been diagnosed, by a health professional, with bipolar affective disorder or schizophrenia; and 0 otherwise.	0.189	0.178	0.199

Variable	Definition	Mean (total)	Mean (entry sample)	Mean (exit sample)
Did not respond: bipolar/schizophrenia	Equals 1 if did not respond to questions on mental health diagnosis; and 0 otherwise.	0.014	0.012	0.018
<i>Social Support</i>	An index averaging across the following four items, with each rated on a scale ranging from 1 'Strongly agree' to 5 'Strongly disagree': 1. You often need help from other people but can't get it? 2. You have someone you can lean on in times of trouble? (reversed) 3. There is someone who can always cheer you up when you are down? (reversed) 4. You often feel very lonely?	3.507	3.567	3.251
Ever primary homeless	Equals 1 if have ever experienced primary homelessness; and 0 otherwise.	0.581	0.531	0.744
Wave 1	Equals 1 if observation from wave 1 survey; and 0 otherwise.			
Wave 2	Equals 1 if observation from wave 2 survey; and 0 otherwise.	0.156	0.186	0.182
Wave 3	Equals 1 if observation from wave 3 survey; and 0 otherwise.	0.165	0.201	0.188
Wave 4	Equals 1 if observation from wave 4 survey; and 0 otherwise.	0.165	0.198	0.183
Wave 5	Equals 1 if observation from wave 5 survey; and 0 otherwise.	0.160	0.198	0.168
Wave 6	Equals 1 if observation from wave 6 survey; and 0 otherwise.			
Combined income	[Total weekly gross income of individual and partner (if applicable)] divided by 100.	5.313	5.390	4.349
<i>Area-level characteristics</i>				
Median market rent	[Median market rent of greater capital city area or SA4 for regions outside of capital cities] divided by 100.	3.323	3.310	3.387
Average unemployment rate	Unemployment rate of greater capital city area or SA4 for regions outside of capital cities, averaged over the period September 2011 and May 2014.	5.636	5.648	5.630
Concentration of low income h/holds	[Proportion of households in greater capital city area or SA4 for regions outside of capital cities with incomes less than \$800 a week] multiplied by 10.	3.254	3.271	3.187
Availability of affordable private rental housing	[Number of low-cost private rental properties (i.e. with weekly rental costs below \$250) in a greater capital city area (or SA4 for regions outside of capital cities)	4.061	4.113	3.840

Variable	Definition	Mean (total)	Mean (entry sample)	Mean (exit sample)
	divided by the total number of low-income households (i.e. households with incomes less than \$800 a week) in that area] multiplied by 10.			
Availability of public/social housing	[Number of households in public or social housing in a greater capital city area (or SA4 for regions outside of capital cities) divided by the total number of low-income households (i.e. households with incomes less than \$800 a week) in that area] multiplied by 10.	3.557	3.485	3.743
Availability of affordable housing (private + public)	[Number of low-cost rental properties available (i.e. number of low-cost private dwellings as defined above plus number of households in public or social housing) in a greater capital city area (or SA4 for regions outside of capital cities) divided by the total number of low-income households (i.e. households with incomes less than \$800 a week) in that area] multiplied by 10.	7.630	7.610	7.595
N		7,138	4,409	1,120

Despite these problems, ABS census data has its advantages as compared to alternative sources such as that available from the Real Estate Institute of Australia (REIA). The major drawback with the REIA data (which has quarterly time series observations) is that it only includes areas in major capital cities and certain regional centres. More than 20 per cent of our sample do not have corresponding REIA-area data, either because they are not in areas covered by the REIA dataset, or they have missing information in the area covered. As there was limited time-series variation over the two-and-a-half-year panel study period, we have decided to sacrifice the small amount of time-series variation that would be available in the REIA data, for the national coverage and sample size that we gain by using the Census data.

The Census data also provides information allowing us to construct more direct proxies of the imbalance of low-cost accommodation in each area, which we use to test the sensitivity of our findings. A proxy for the availability of affordable private rental accommodation is constructed as a ratio measure of the total number of households in an area paying private rental costs¹⁰ of less than \$250 a week,¹¹ divided by the total number of low-income households in rental accommodation in an area. Households are defined as low-income if household incomes are less than \$800 a week, and they reside in either private rental or public or social housing.¹² Also, as we know that public and social housing can be important components of the total housing supply, we also design a proxy for the availability of public and social housing in each area, by constructing a ratio measure of the total number of households in an area that are in public or social housing divided by the total number of low-income renters in that area. Finally, we construct an overall measure that captures the balance of all affordable housing (whether public or private) relative to the number of low-income households in rental accommodation in that area.

In addition, and as previously discussed, we also expect the local labour market to affect individual risks of homelessness: individuals living in areas with weak labour market conditions are more likely to lose their jobs if they are employed, and less likely to find work if they are jobless. We therefore include the area's unemployment rate as an indicator of the strength of local labour markets, and this is sourced from the ABS monthly *Regional Labour Force Statistics* (ABS 2014). Although these statistics are provided on a monthly basis, to ensure consistency with our time-invariant housing market variables we take the average unemployment rate of the area over the two-and-a-half-year period. Finally, we note that the local area unemployment rate can also act as a proxy for poverty. Therefore, some sensitivity testing of alternative measures of poverty and the local labour market will be undertaken.

All the above described structural factors will be taken from data that is provided at 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

¹⁰ That is households renting their dwelling from a real estate agent or from a person who is not the relative of the resident and not living in the dwelling.

¹¹ \$250 a week was determined to be the maximum rental cost that is 'affordable' (i.e. roughly 30% of income) to those on low-incomes (i.e. those with weekly incomes below \$800).

¹² Households reporting that they rent from a Government Housing Authority/housing department or housing cooperative: community or church group.

(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, which we refer to as model 1, 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.

4.4 Descriptive statistics

The descriptive statistics of all key variables to be used in our regression models are also provided in Table 1 above.

There is a reasonably even gender split (male 54%) while Indigenous Australians make up 17 per cent of the sample. Poor levels of educational attainment are common with only 11 per cent completing year 12, and therefore it is unsurprising to find that rates of economic participation are very low—as many as three in four of the sample are unemployed or not in the labour force at any given time, and 7 per cent have never been employed. Personal risk factors are prominent; for example, 17 per cent have experienced domestic violence and 22 per cent use drugs regularly.

About 20 per cent of the sample are homeless at any one time, so the housed but vulnerable are typically the majority status. The mean rate of entry into homelessness in any wave from the pool of formally housed individuals is 8 per cent, though the rate is volatile (a coefficient of variation of 3.4). On the other hand, there is a high rate of exit with an average 40 per cent of the homeless successfully finding a pathway into formal housing at the next interview. This does not necessarily mean that there are large numbers evading and small numbers tumbling into homelessness, since the pool of homeless is a minority group in the sample.

5 MAIN RESULTS

In this chapter there are three sections. First, we report our findings from models designed to explain what factors influence whether an individual is homeless at any given wave in the panel study period. The analysis then proceeds to investigate the structural and individual factors important in tipping previously housed but vulnerable individuals into homelessness. Finally, we look at exits out of homelessness and identify variables correlated with successful routes into secure housing. In each section two specifications are presented. In model 1 (our preferred specification), SA4s within the greater capital city areas have been merged (see Chapter 4 for discussion), with unemployment rates and median weekly rents measured on a city-wide basis where relevant. In model 2, the finer SA4 classification is retained across all Australian regions, including greater capital city metropolitan areas.

Before proceeding with a description of our main findings, it is worth pausing to consider how we should interpret the model estimates. Our sample contains individuals who are insecurely housed, that is either homeless or at risk of becoming homeless. Those groups vulnerable to homelessness will be overrepresented in our sample as compared to the general population of Centrelink clients from which our sample is drawn. JH respondents are, for example, younger, more likely to be Indigenous and more likely to be recorded as having experienced mental illness (see Bevitt et al. 2014, Table 2.1). The modelling ascertains whether homelessness is more or less probable for a certain group of people as compared to *other vulnerable groups in the sample*. A particular group of people could be overrepresented in the sample, and traditionally thought prone to homelessness, but not more likely to be homeless as compared to other vulnerable groups in the sample.

5.1 Static modelling results—What factors influence whether an individual is homeless at any given wave?

Table 2 below presents the results of logistic regressions of homelessness status with random effects. As we are interested in the direction (positive or negative) of effects as well as their magnitudes, mean marginal effects are presented. For categorical variables, the marginal effect is in fact the change in predicted probability of the outcome as a result of changing from the base category to the target category. For continuous variables, the marginal effect is changes in predicted probability due to a one unit change in the explanatory variable.¹³ Three levels of statistical significance are shown from the weakest (at 10%) to the strongest (at 1%).

¹³ That is, the partial derivative of the latent probability with respect to each observed value of the continuous variable and then averaged across the sample.

Table 2: Probability of homelessness: mean marginal effects from logistic regression with random effects

	Model 1 ^a	Model 2 ^a
Male	0.062 ***	0.060 ***
<i>Age group</i>		
15–21 years (reference)		
21–44 years	0.007	0.003
45+ years	0.071 ***	0.067 **
<i>Aboriginal and Torres Strait Islander</i>		
Born in Australia (reference)		
Born in English-speaking country	-0.029	-0.034
Born in non-English-speaking country	0.002	0.003
<i>Married/defacto</i>		
Married/defacto	-0.080 ***	-0.079 ***
<i>Have resident children</i>		
Have resident children	-0.084 ***	-0.081 ***
<i>Highest educational qualification</i>		
Post-school qualification		
Yr. 12 or e.q.	-0.002	-0.006
Yr. 10 or 11	0.009	0.009
Yr. 9 or below	0.024	0.027
<i>Labour force status</i>		
Employed		
Unemployed	0.040 **	0.040 **
NILF	0.053 ***	0.054 ***
<i>Work history</i>		
No work history		
No work history	-0.056	-0.051
Time employed (%)		
Time employed (%)	0.000	0.000
Has not experienced job loss within last 2 years		
Lost job in last 6 months	-0.034 *	-0.034 **
Lost job in last 2 years but not in last 6 months	0.002	0.002
<i>Family history</i>		
Ever in state care		
Ever in state care	-0.010	-0.010
No principal caregiver at age 14		
No principal caregiver at age 14	0.002	0.005
<i>Recent events</i>		
Did not experience violence in last 6 months		
Experienced violence in last 6 months	0.031 **	0.030 **
Did not respond: violence		
Did not respond: violence	-0.005	-0.008
Incarcerated		
Incarcerated	0.097 ***	0.095 ***
<i>Substance use</i>		
Alcohol consumption		
Alcohol consumption	0.002 **	0.002 **

	Model 1 ^a	Model 2 ^a
Cigarette consumption	0.002 **	0.002 **
Did not use illicit drugs in last 6 months		
Used illicit drugs in last 6 months irregularly	0.010	0.010
Regular user of illicit drugs in last 6 months	0.009	0.009
<i>Health</i>		
Long-term health condition	0.031 **	0.032 **
Never diagnosed with bipolar/schizophrenia		
Ever diagnosed with bipolar/schizophrenia	-0.070 **	-0.070 **
Did not respond: bipolar/schizophrenia	0.100	0.106
Social support	-0.037 ***	-0.038 ***
Ever primary homeless	0.071 ***	0.071 ***
Combined income (\$00s)	0.000	-0.001
<i>Area-level characteristics</i>		
Median market rent (\$00s) ^b	0.040 ***	0.042 ***
Average unemployment rate ^c	0.007	-0.013 **
Number of individuals		
Number of observations	7,138	7,138

Notes: * p<0.10, ** p<0.05, *** p<0.01

a. Also included in the regression specification were wave indicators and Mundlak correction terms for time-varying variables.

b. Model 1 includes the median market rent of greater capital city area or SA4 for regions outside of capital cities; Model 2 includes the median market rent of SA4s for all regions.

c. Model 1 includes the unemployment rate of greater capital city area or SA4 for regions outside of capital cities; Model 2 includes the unemployment rate of SA4s for all regions.

d. Coefficients of the logistic regressions are presented in Appendix Table A1.

5.1.1 Individual risk factors

As the effects of individual risk factors vary little between our two model specifications we focus our attention on the model 1 results.¹⁴ We begin with a group of demographic variables that represent stages in the life cycle, migrant status and family background. Among the demographic groups identified, males are 6 percentage points more likely to be homeless than females. This is consistent with findings in Wood et al. (2014) who find that the male share of a region's population has a positive and large (relative to other variables) impact on point prevalence measures of homelessness. Older JH respondents (those aged 45 years plus) are more likely to be homeless than younger respondents, with persons 45 years and older 7.1 percentage points more likely to be homeless than the reference group of persons aged 15–20 years. Aboriginal or Torres Strait Islander respondents are also slightly more likely to be homeless, but with an effect that only achieves significance at the 10 per cent level. Given the rich vector of individual characteristics included in our models, these results offer some evidence in support of the view that elevated rates of Indigenous homelessness are largely due

¹⁴ There are personal characteristics, especially risky behaviours that might themselves be influenced by homelessness status. In these static models, causality could then operate in the reverse direction. This is a caveat that should be borne in mind. In the dynamic models, reverse causation is less of a concern. When we model the future chances of homelessness among a sample that are currently housed, the current personal characteristics of persons can be assumed independent of future homelessness status.

to the other specific characteristics of Indigenous Australians, rather than Indigenous status per se. There is no evidence that migrants are any more or less likely to be homeless, and this is regardless of whether born in English-speaking countries or not. Also, some subgroups in the sample are less vulnerable to homelessness. For example, those married or in a defacto relationship, and households with dependent children, have a significantly lower likelihood of homelessness. Persons married or in a defacto relationship have a probability of homelessness that is 8 percentage points lower than other persons, whereas when children are present in the household the effect is slightly stronger, with a marginal effect estimate which indicates a probability of homelessness that is 8.4 percentage points lower, no matter what the marital status.

Next come a vector of human capital and individual employment characteristics; although the magnitude of coefficients suggest that those with relatively low levels (years) of schooling are more prone to homelessness, these effects are not statistically significant. Low levels of education are very common in the estimation sample (see Table 1 above) and so lack of variation in schooling could account for these weak impacts. Labour force status on the other hand does seem to matter significantly. The jobless, whether unemployed or not in the labour force, have an elevated (and statistically significant) risk of being homeless as compared to the employed. Also, recent employment history leaves an imprint on the probability of homelessness, but in a counterintuitive way: the effects of having lost a job in the last six months, although only weakly significant, suggest that those recently unemployed are less likely to be at-risk of homelessness than those who have not experienced recent job loss. Analysis of the dynamics of homeless entries and exits, which we undertake below, may shed further light on this unexpected result.

A group of variables indicating the absence of parenting during childhood and involvement in the child protection system are insignificant, a finding that seems at odds with many studies that report the over-representation of individuals with histories of child protection involvement (Courtney et al. 2001; Cashmore et al. 2006; Johnson & Chamberlain 2008). However, risks of homelessness and recent experiences of violence are significantly and positively related. Likewise the risks of homelessness are significantly greater for those recently incarcerated, which includes those coming out of juvenile justice, adult prison or remand. The recently incarcerated variable has a relatively large marginal effect at 9.7 percentage points, despite it only affecting 3 per cent of the sample.

The model also includes a series of variables depicting risky behaviour (drinking, smoking and drug use) that are often cited as correlates of individual homelessness. These variables are particularly interesting because they are difficult to take into account in the regional macro-data panel models that are commonly estimated in US empirical studies (for one of the earliest examples, see Honig & Filer 1993). We find that an increase in average alcohol consumption of one drink per day on average results in a significantly elevated (0.2 percentage point) risk of homelessness. Likewise, an increase in average cigarette consumption by one cigarette a day increases the risk of homelessness by 0.2 percentage points. Elevated levels of alcohol and cigarette consumption are often associated with health concerns, a key link in Glomm and John's (2002) theoretical narrative around homelessness. Regular drug use features in the lives of a little over one in five of the sample, but the impact of regular drug use is not statistically significant.

The importance of health to risks of homelessness receives mixed backing from our findings (though substance abuse variables might be picking up its impact as hinted at in the previous paragraph). While those with a long-term health condition that restricts everyday activities are significantly more at-risk of homelessness, individuals that have been diagnosed bipolar or schizophrenic are at a lower risk of homelessness than those without similar diagnosed conditions. We speculate that those diagnosed are more likely to be receiving treatment and

care (even institutionalised care), thereby lowering chances of experiencing homelessness compared to those undiagnosed who might also have other risk factors.

Social support also appears to be an important protective factor in helping people avoid homelessness, with risks of homelessness reduced for those with higher levels of social support, though there is a caveat here as the direction of causation might well operate in the reverse direction. The link is highly statistically significant, and the marginal effect is large with a one unit change in the social support index (ranging from one to five) associated with a probability of homelessness that is 3.7 percentage points lower.

Gross weekly income is not significantly related to homelessness—although we note here that JH respondents are all overwhelmingly low income with a mean weekly income of \$531.30. As with the schooling variable, such a tight concentration around a low mean generates little variation from which to detect a significant effect. Over half (58.1%) of the sample have a previous experience of primary homelessness. A prior experience has a strong (marginal effect of 7.1 percentage points) and highly statistically significant impact on the chances of homelessness later on.

Controls for the wave in which individuals are interviewed have been added to the model specification, the marginal effects of which have not been included in the table for brevity. They all prove statistically insignificant; this suggests that once we control for personal characteristics, risky behaviour and area variables, the chances of homelessness are the same whether it is early or late in the study timeframe.

5.1.2 Area-level characteristics

The addition of variables capturing the housing and labour market conditions individuals are exposed to is a key component of the statistical analysis. As discussed in Section 4.3, our main housing market measure is the median rental price of an area (in hundreds of dollars) and our key labour market measure is the area unemployment rate. The direction and significance of these variables' impacts are valuable evidence of whether the chances of homelessness in the JH sample are shaped by housing and labour market conditions, after we have controlled for personal characteristics and risky behaviours. As it turns out the evidence is mixed.

Consider first the model 1 estimates. Tight housing markets with expensive private rental housing elevate the likelihood of homelessness among the JH sample. The model estimate is highly statistically significant and the marginal effect estimate is sizeable. It indicates that a \$100 increase in weekly median rent, which is equivalent to a 30 per cent increase at the national median weekly rent, lifts the probability of homelessness by 4 percentage points, or from the sample mean of 20.3 per cent to 24.3 per cent, a 19 per cent increase in the likelihood of homelessness. In model 2 with a finer spatial classification the rent coefficient is stable in size and significance.

By contrast, the unemployment rate variable does not yield consistent estimates. In model 1 it is positive and insignificant, but then negative and statistically significant (at 5%) in model 2. So the coefficient on the unemployment rate flips sign; the same change in sign is revealed in the regional panel model estimates reported in Wood et al. (2014); in ordinary least squares (OLS) and random effects models the coefficient on the unemployment rate variable is positive, but then becomes negative and insignificant in fixed effects model estimates.

The most likely explanation for these imprecise labour market area estimates is endogenous sorting within capital cities, that is 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, 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 project. 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 (model 1), at the same time flagging that this is an important area of future research.

While understanding what factors, structural or individual, influence the probability that an individual is homeless at any given wave in JH, factors that may affect an individual's probability of entering and exiting homelessness may well be different. This has potentially significant policy implications. In the next section we examine entries into homelessness before considering exits from homelessness.

5.2 Entries into homelessness

In Table 3 below we present estimates from a logistic regression model (with random effects) that analyses entries into homelessness. The model estimates the chances of entry into homelessness in the next wave (six months later) conditional on being housed. Again, we present the mean marginal effects of each of the covariates to assess both the statistical significance and the magnitude of effects. As with the static model, we combine both personal characteristics, measures of risky behaviour and area structural variables into model specifications. Once again, in model 1 capital city SA4s are merged, and individuals located within the boundaries of capital cities are assigned the housing and labour market characteristics of the greater capital city area. In model 2, the SA4 unit is used for all individuals, including those living in capital cities. Before turning to the effects of these area-level characteristics on homelessness entries, we identify the individual risk factors that are found to be important in precipitating homelessness among a sample of vulnerable individuals who were housed when interviewed six months earlier.

Table 3: Probability of homeless entry: mean marginal effects from logistic regression with random effects

	Model 1 ^a	Model 2 ^a
Male	0.026 ***	0.026 ***
<i>Age group</i>		
15–21 years (reference)		
21–44 years	-0.008	-0.008
45+ years	0.009	0.009
ATSI	0.013	0.013
Born in Australia (reference)		
Born in English-speaking country	-0.016	-0.017
Born in non-English-speaking country	-0.001	-0.001
Married/defacto	-0.012	-0.012
Have resident children	-0.026 ***	-0.025 ***
<i>Highest educational qualification</i>		
Post-school qualification		
Yr. 12 or equiv.	0.003	0.003
Yr. 10 or 11	0.016 *	0.016 *
Yr. 9 or below	0.022 *	0.021 *
<i>Labour force status</i>		
Employed		
Unemployed	-0.003	-0.003
NILF	0.003	0.002

	Model 1 ^a	Model 2 ^a
<i>Work history</i>		
No work history	0.029	0.030
Time employed (%)	0.000 *	0.000 *
Has not experienced job loss within last 2 years		
Lost job in last 6 months	0.027 *	0.028 *
Lost job in last 2 years but not in last 6 months	0.018	0.019
<i>Family history</i>		
Ever in state care	0.020 *	0.020 *
No principal caregiver at age 14	-0.001	-0.001
<i>Recent events</i>		
Did not experience violence in last 6 months		
Experienced violence in last 6 months	0.015	0.015
Did not respond: violence	0.017	0.017
Incarcerated	0.029	0.028
<i>Substance use</i>		
Alcohol consumption	0.002 *	0.002 *
Cigarette consumption	0.000	0.000
Did not use illicit drugs in last 6 months		
Used illicit drugs in last 6 months irregularly	0.015	0.014
Regular user of illicit drugs in last 6 months	0.026 **	0.025 **
<i>Health</i>		
Long-term health condition	0.003	0.003
Never diagnosed with bipolar/schizophrenia		
Ever diagnosed with bipolar/schizophrenia	-0.032 ***	-0.032 ***
Did not respond: bipolar/schizophrenia	-0.041 *	-0.040 *
Social support	-0.015 ***	-0.015 ***
Ever primary homeless	0.032 ***	0.032 ***
Combined income (\$00s) ^b	0.000	0.000
<i>Area-level characteristics</i>		
Median market rent (\$00s) ^c	0.016 **	0.014 *
Average unemployment rate	0.010 **	0.004
Number of individuals		
Number of observations	4,409	4,409

Notes: * p<0.10, ** p<0.05, *** p<0.01

a. Also included in the regression specification were wave indicators.

b. Model 1 includes the median market rent of greater capital city area or SA4 for regions outside of capital cities; Model 2 includes the median market rent of SA4s for all regions.

c. Model 1 includes the unemployment rate of greater capital city area or SA4 for regions outside of capital cities; Model 2 includes the unemployment rate of SA4s for all regions.

d. Coefficients of the logistic regressions are presented in Appendix Table A2.

5.2.1 Individual risk factors

Model 1 and 2 estimates are the same or very similar, and so illustrative marginal effect measures refer to model 1 estimates only. There is further confirmation of the importance of gender; vulnerable males are less likely to sustain secure housing than females. Married and defacto couples are this time found to be 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. The coefficient estimates imply that those with resident children are 2.6 percentage points less likely to enter homelessness than those without. The sample mean probability of entry into homelessness is 8 per cent, so the effect of resident children is very large (cutting the chances of becoming homeless by roughly one-third). But if the respondent is male, this effect is exactly offset. We find that age and country of birth are not statistically important as far as entries into homelessness are concerned.

Now consider 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 spending more time employed since they first left full-time education are less likely to enter homelessness. A somewhat stronger effect is detected with respect to more recent employment history. Those individuals losing a job in the six months prior to interview are more prone to loss of secure housing. The marginal effect is a large (given a sample mean probability of 8%) 2.7 percentage points. The abrupt income shock accompanying redundancy or sacking is then important in precipitating a descent into homelessness among the JH sample.

As with the results obtained on examining homelessness status, we find that the absence of parenting does not significantly impact on pathways into homelessness. However, now we see that even though those that had been in state care as children are not statistically more likely to be homeless overall, they are 2 percentage points more likely to enter homelessness; an effect that is weakly significant. Exposure to recent violence and recent incarceration do not appear to significantly affect the chances of sustaining secure housing, even though they are significantly correlated with homelessness status.¹⁵ Among the variables representing risky behaviour (drinking, smoking and drug use) and ill health (long-term health condition and bipolar or schizophrenia diagnosis), there are statistically significant effects. Regular drug use and heavy drinking are correlated with entries into homelessness, although the latter is only weakly significant. There is again confirmation that diagnosis of bipolar and schizophrenia conditions promote housing security among a group that are thought especially prone to homelessness (see Section 5.1.1 above for discussion). Indeed persons diagnosed with bipolar disorder or schizophrenia are 3.2 percentage points less likely to enter homelessness than those not diagnosed with these illnesses; this represents a 40 per cent reduction in the odds of slipping into homelessness.

Both static and entry models suggest that past experience of homelessness and social support is important. If there has been a prior episode of primary homelessness the individual that is housed but vulnerable is 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 3.2 percentage points, which is a large impact (40%) at the sample mean; the evidence is therefore mounting that early intervention preventing first episodes of homelessness could 'pay off'. Higher levels

¹⁵ While these results appear to be contradictory they can be reconciled since homelessness status is the product of both factors precipitating entry into, as well as exit from homelessness.

of social support seem to cement residency in secure housing, evidence supporting the positive effect detected in our static models.

5.2.2 Area-level characteristics

Consistent with the results examining homeless status at a point-in-time, median market rents are positively and significantly related to entry into homelessness: model 1 shows that an increase in the median market rent of \$100 (a 30% increase at the national median weekly rent) lifts the risk of entry by 1.6 percentage points, or from a sample mean of 8 per cent to 9.6 per cent (a 20% increase in risk).¹⁶ So the impact is both statistically significant and sizeable. Focusing on entries, we now also find that the local labour market condition is a significant cause of entries into homelessness with a 1 percentage point increase (decrease) in the unemployment rate increasing (decreasing) the likelihood of homelessness entry by 1 percentage point, or 12.5 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; once again the effect on pathways into homelessness is therefore roughly similar to that of market rents in the local housing market. In model 2, where all SA4 regions are defined and area variables assigned accordingly, the direction of both effects is the same, but they are weaker in both size and significance: median market rents are now only significant at the 10 per cent level, whereas the unemployment rate is no longer significant at all.

5.3 Exits from homelessness

A pathway into homelessness is one of two journeys along which homeless individuals can travel; the other is a pathway out of homelessness. Homelessness status in our sample at any point in time will reflect movement along both pathways. Table 4 below lists results from a logit model (with random effects) of factors associated with transitions out of homelessness, conditional on initially being homeless. We repeat our practice of presenting mean marginal effect estimates from our models 1 and 2 which use different classifications of areas. A potentially interesting dimension of our findings is the light they shed on similarities (or otherwise) in the processes shaping escapes from homelessness as compared to those tipping previously housed (though vulnerable) individuals into homelessness.

¹⁶ The point elasticity estimate is 0.87.

Table 4: Probability of homeless exit: mean marginal effects from logistic regression with random effects

	Model 1 ^a	Model 2 ^a
Male	-0.112 *	-0.108 *
<i>Age group</i>		
15–21 years (reference)		
21–44 years	-0.231 ***	-0.222 ***
45+ years	-0.359 ***	-0.346 ***
<i>ATSI</i>		
Born in Australia (reference)	0.022	0.021
Born in English-speaking country	-0.032	-0.023
Born in non-English-speaking country	-0.040	-0.046
<i>Married/defacto</i>		
Married/defacto	-0.138 **	-0.137 **
Have resident children	0.243 ***	0.231 ***
<i>Highest educational qualification</i>		
Post-school qualification		
Yr. 12 or equiv.	0.086	0.089
Yr. 10 or 11	0.053	0.055
Yr. 9 or below	0.054	0.046
<i>Labour force status</i>		
Employed		
Unemployed	-0.059	-0.064
NILF	-0.137 *	-0.137 *
<i>Work history</i>		
No work history		
No work history	0.105	0.103
Time employed (%)		
Time employed (%)	0.000	0.000
Has not experienced job loss within last 2 years		
Has not experienced job loss within last 2 years		
Lost job in last 6 months		
Lost job in last 6 months	0.063	0.071
Lost job in last 2 years but not in last 6 months		
Lost job in last 2 years but not in last 6 months	0.096 *	0.095 *
<i>Family history</i>		
Ever in state care		
Ever in state care	-0.031	-0.028
No principal caregiver at age 14		
No principal caregiver at age 14	0.157 *	0.151 *
<i>Recent events</i>		
Did not experience violence in last 6 months		
Did not experience violence in last 6 months		
Experienced violence in last 6 months		
Experienced violence in last 6 months	0.014	0.014
Did not respond: violence		
Did not respond: violence	-0.022	-0.016
Incarcerated		
Incarcerated	-0.070	-0.066
<i>Substance use</i>		
Alcohol consumption		
Alcohol consumption	-0.006	-0.006 *

	Model 1 ^a	Model 2 ^a
Cigarette consumption	-0.001	-0.001
Did not use illicit drugs in last 6 months		
Used illicit drugs in last 6 months irregularly	0.005	0.006
Regular user of illicit drugs in last 6 months	-0.057	-0.050
<i>Health</i>		
Long-term health condition	0.039	0.042
Never diagnosed with bipolar/schizophrenia		
Ever diagnosed with bipolar/schizophrenia	-0.043	-0.042
Did not respond: bipolar/schizophrenia	0.140	0.146
Social support	0.003	0.004
Ever primary homeless	0.025	0.025
Combined income (in \$00s) ^b	0.009	0.009
<i>Area-level characteristics</i>		
Median market rent (in \$00s) ^c	-0.011	-0.005
Average unemployment rate	0.003	0.032
Number of individuals		
Number of observations	1,120	1,120

Notes: * p<0.10, ** p<0.05, *** p<0.01

a. Also included in the regression specification were wave indicators.

b. Model 1 includes the median market rent of greater capital city area or SA4 for regions outside of capital cities; Model 2 includes the median market rent of SA4s for all regions.

c. Model 1 includes the unemployment rate of greater capital city area or SA4 for regions outside of capital cities; Model 2 includes the unemployment rate of SA4s for all regions.

Coefficients of the logistic regressions are presented in Appendix 2, Table A3.

5.3.1 Individual risk factors

Curiously the exit model results in far fewer statistically significant individual risk factors than does the entry model. In the entry model, eight variables are statistically significant at 5 per cent or better, but only four variables achieve the same threshold in the exit model. This is in part a statistical artefact, because the sample size used to estimate the exit model (1120) is much smaller than that used to estimate the entry model (4409).¹⁷

We nevertheless obtain confirmation that males are prone to homelessness because they are both more likely to fall into homelessness, as well as less likely to escape homelessness. There is a startling finding with respect to age, and this is in part down to a conspicuous asymmetry in the results generated by entry and exit models. While all age groups appear equally likely to tumble into homelessness, escape for those enduring a spell of homelessness is much more difficult as age increases. The marginal effect estimates are very large; the 21 to 44-year group are 23.1 percentage points less likely to escape than the reference age group (15–20 years), and individuals 45 years and older are 35.9 percentage points less likely to exit¹⁸ It is worth recalling that these findings are after controlling for other observable

¹⁷ This is because the pool of vulnerable but housed individuals in the JH sample is bigger than the pool of homeless in all waves.

¹⁸ At the sample mean probability of exit (39.8%) the 21–44-year age group's chances of escape are 42 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 10 per cent of the young's (15–20 years).

influences; so, for instance, these large differences cannot be attributed to past episodes of primary homelessness that are more common among the older homeless individuals. This is a particularly notable discovery, and we return to a discussion of its significance in the concluding chapter.

Although individuals married or in a defacto relationship are less likely to enter homelessness, conditional on entering they are significantly less likely to exit than the reference group (singles). Perhaps this reflects an increased difficulty in finding housing to meet the additional needs of a couple relative to a single person. On the other hand, individuals with children are substantially more likely to find pathways out of homelessness (by 24.3 percentage points), and this might reflect service support that is targeted on families.

Country of birth is again insignificant, as is the effect of identifying as Aboriginal or Torres Strait Islander; the overseas born are only just over 5 per cent of the sample, but the Aboriginal or Torres Strait Islanders account for nearly 20 per cent of the sample. We now have three model estimates (the static, entry and exit models) where Indigenous status is statistically insignificant, firming up evidence that other personal characteristics 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. Current employment status does, however, seem to be related to exits with some connection to the labour market better than none. This effect, however, is only weakly significant and only relative to those not in the labour force. Although recent job loss was a significant precursor to homelessness entries, it is now interestingly, persons who lost their job between six months and two years prior who were more likely to escape homelessness than others. We speculate that this may have something to do with the way employment services target support.

While individuals with a history in foster care or residential care are less likely to exit homelessness, this is not statistically significant. Unexpectedly (in view of statistically insignificant effects in static and entry models), those who had no principal caregiver at age 14 were 15.7 percentage points more likely to exit; however, it is only statistically significant at the 10 per cent level. Those recently incarcerated were less likely to exit, but not significantly so. This also appears to be the case with those drinking, smoking or using illegal substances regularly. Though Table 4 reveals a finding that those diagnosed with bipolar or schizophrenia illnesses are less likely to exit, the effect is not statistically significant. It therefore seems that their lower chances of entering homelessness are responsible for our static model finding that those with such illnesses are less likely to be homeless. Social support, while important in helping people avoid homelessness, does not seem to assist the homeless to escape their condition. Likewise, prior experiences of primary homelessness are not significantly related to the likelihood of exiting homelessness, nor are gross incomes.

5.3.2 Area-level characteristics

Turning now to the impact estimates of area-level characteristics in Table 4, we see that the state of area-level housing markets and labour markets do not appear to significantly affect the propensity to exit homelessness.

Why might we see a difference in the way these characteristics relate to entries relative to exits? We suspect that this may be related to the way that services respond to individuals at-risk in Australia. We return to this discussion further in Chapter 8 when we discuss the policy implications of our findings.

6 ARE THE HOUSING AND LABOUR MARKETS MORE IMPORTANT FOR CERTAIN TYPES OF PEOPLE THAN OTHERS?

In this section we report the modelling results which examine whether housing and labour markets are more important for certain types of people than others. 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 elaborate.

6.1 Detailed findings

Table 5 below 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 and a 1 percentage point increase in the unemployment rate respectively. Marginal effect estimates obtained for variables representing personal characteristics and risky behavioural traits are presented for the static probability of homelessness status model, and then the probabilities for entries into, and exits from homelessness.

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

	Static		Dynamic			
	Probability		Entries		Exits	
	Median rent	Unemp rate	Median rent	Unemp rate	Median rent	Unemp rate
Overall	0.040 ***	0.007	0.016 **	0.010 **	-0.011	0.003
Males	0.066 ***	-0.001	0.017	0.007	-0.008	0.032
Females	0.013	0.009	0.015	0.012 **	-0.012	-0.056
15–20 yrs	0.025	0.008	0.004	0.003	-0.084	0.000
21–44 yrs	0.034 ***	0.004	0.017 *	0.014 **	-0.045	-0.012
45 yrs +	0.079 *	0.009	0.027	0.005	0.120	0.040
Aboriginal and Torres Strait Islander	0.058	0.021	0.055 *	0.025 *	0.030	-0.006
Non-Aboriginal and Torres Strait Islander	0.037 ***	0.001	0.011	0.008	-0.019	0.010
Children	0.002	0.005	0.014	0.011 *	0.268 *	0.145 **
No children	0.056 ***	0.003	0.017 *	0.009	-0.034	-0.013
Employed	0.035 **	0.010	0.037 **	0.019 **	0.147	0.071
Unemployed	0.025	-0.007	0.011	0.013	-0.085	-0.013
NILF	0.055 ***	0.012	0.010	0.004	0.001	0.000
Incarcerated	-0.045	-0.033	0.023	0.076	-0.052	0.041
Not incarcerated	0.042 ***	0.007	0.016 **	0.009 *	-0.010	0.000
Long-term health condition/disability	0.056 ***	0.003	0.002	0.008	-0.051	-0.020
Do not have	0.029 **	0.007	0.029 ***	0.012 **	0.024	0.025

	Static		Dynamic			
	Probability		Entries		Exits	
	Median rent	Unemp rate	Median rent	Unemp rate	Median rent	Unemp rate
Diagnosed with bipolar or schizophrenia	0.038	-0.010	0.007	0.012	-0.023	-0.046
No diagnosis	0.044 ***	0.011	0.019 **	0.009 *	0.012	0.019
Did not use drugs	0.033 ***	0.006	0.021 **	0.007	-0.019	-0.027
Used	0.045 *	0.010	-0.012	0.014	-0.005	0.049
Used regularly	0.061 **	-0.001	0.022	0.019	-0.005	0.032
Risky drinkers	0.075 **	0.019	0.022	0.013	-0.053	0.022
Don't drink at risky levels	0.032 ***	0.003	0.014 *	0.009 **	0.003	-0.009
Experienced violence	0.065 **	0.003	0.007	0.015	-0.100	-0.017
Did not experience violence	0.033 ***	0.004	0.015 *	0.010 **	0.013	0.017
Didn't respond to violence questions	0.072 *	0.033	0.066 *	-0.017	0.163	-0.038

Note: * p<0.10, ** p<0.05, *** p<0.01 (results of testing whether marginal effects are statistically different from zero for each group).

The results for each set of interaction terms are estimated from separate equations. That is, the results in this table are generated from 36 different equations. Individual characteristics and risk factors are also included as controls in underlying logistic regressions. Regression results are available from the authors upon request.

Note that the estimates presented in Table 5 above 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 the male gender category. The static probability model suggests that males have elevated probabilities of being homeless, and also that the housing market significantly increases the risk of homelessness for all persons on average. But it could also be that males are particularly prone to homelessness if they are living in areas where unemployment is high. To detect whether this is indeed the case we add an interaction term that is the product of the male indicator variable (that equals 1 when male, 0 otherwise) and the average unemployment rate. The marginal effects presented in the table are the effects of a one unit change in the unemployment rate for females (male=0) and for males (male=1).

If the marginal effect is x/100 for males and y/100 for females, it means that an increase in the unemployment rate of one percentage point increases the probability of homelessness by x percentage points for males and y percentage points for females. Statistical test results on whether each subgroups estimated marginal effect is significantly different from zero are also presented. Similarly, we also list the marginal effects of an increase in median rents of \$100 a week on the changes in the probability of homelessness for different subgroups.

6.1.1 *Static model estimates*

The static model results examining the effects of housing and labour markets on homelessness status can be found in the first two columns of Table 5 above. While we find an overall significant positive association between median rents and risks of homelessness, when we examine the relationship for certain subgroups of the population we find that the relationship is stronger for some subgroups than others. Indeed, for some subgroups the state of the housing market appears to have little or no effect on risks of homelessness.

Males appear to be more sensitive to housing markets than females for instance. Males are 6.6 percentage points more likely to be homeless if they face a \$100 increase in median market rents. Females, on the other hand, face a (statistically) similar risk of homelessness regardless of the state of the housing market. Individuals 21 years and over are also more sensitive to the housing market than their younger counterparts with those 21 to 44 years facing a 3.4 percentage point higher (lower) chance of homelessness if median market rents rise (fall) by \$100, and those 45 years or older facing a 7.9 percentage point higher chance of homelessness with the same change in market rent. Note, however, that although the magnitude of the effect for older persons (45 years plus) is larger, it is only statistically significant at the 10 per cent level, whereas the effect for those 21 to 44 years is strongly significant.

Although the marginal effect of a change in median rents is larger for Indigenous respondents than for other respondents, it is not statistically significant. This might reflect considerable differences in housing market effects across individuals; for example, the effects of a given rise in median rents might be different on the Indigenous living in urban areas as compared to remote areas. The marginal effect for non-Indigenous respondents is, however, significant. Individuals without dependent children living with them are also more at risk of homelessness in areas with tight housing markets. Interestingly it is the employed and those not in the labour force that are significantly more at risk of homelessness in areas with tight housing markets, whereas the unemployed have the same chances of homelessness regardless of place.

Housing market conditions have no statistically significant effect on persons recently incarcerated. But those who have not recently been incarcerated are 4.2 percentage points more at risk of homelessness with every \$100 increase in an area's median market rent. Likewise, there is no statistically significant effect for persons diagnosed with bipolar or schizophrenia, yet those not diagnosed are more at risk if located in tighter housing markets. Higher median market rents significantly elevate risks of homelessness for all of the other groups identified (both those with and without a long-term health condition or disability, both drug users and non-users, and both those experiencing recent violence and those not experiencing violence).

The housing market findings contrast with those obtained with respect to interaction variables formed using unemployment rates. Here we find that labour market conditions seemingly have a uniform zero impact on the probability of homelessness in the JH sample.

6.1.2 *Entry and exit model estimates*

We know, however, that the results from static models can hide some of the more dynamic ways that housing and labour markets affect entries into, and exits from homelessness. Thus, attention now turns to a discussion of the results generated by our dynamic models where we examine factors associated with entries into homelessness, and then exits out of homelessness.

Our results from the entry model specification are in many ways similar to the results from the static model discussed above, at least when we examine the relationship between median rental costs and homelessness entry. As we saw earlier, a key difference is that when we isolate the effects of entering homelessness from those associated with homelessness exit, the

local labour market appears to make a much more significant contribution to homelessness entry overall. And, from Table 2 we see that the labour market seems to matter most if an individual is employed. A one percentage point increase in the local unemployment rate increases the chances of employed but housed persons slipping into homelessness by 1.9 percentage points. The marginal effect for those not in the labour force or unemployed is also positive but not statistically significant. Persons with long-term health conditions are more likely to be out of the labour force, and this might explain why these groups are not affected by local labour market conditions. We also find statistically insignificant effects for those engaging in risky behaviours (drinking, drug use and recent incarceration); this is consistent with results obtained for median rents in local areas. People with risky behaviours are more likely to lose secure housing and become homeless, regardless of labour market conditions. We do find a difference with housing market findings when we examine subgroups identified by the absence of risky behaviours; statistically significant effects are only detected (for non-drinkers and persons not recently incarcerated) at the 10 per cent level, and limited to those not drinking at risky levels, or suffering recent incarceration.

The exit model results are distinctive. As noted in Chapter 5, the homeless in the JH sample seem to have the same likelihood of escaping their homeless condition regardless of housing and labour market conditions. Nor do they affect the chances of any of the JH sample subgroups that are examined separately in Table 2. For some groups the sign of the effect is in the expected direction but the result is not statistically significant, perhaps due to the small sample numbers involved. For instance, consider the subgroup experiencing recent violence; although the marginal effect of a \$100 increase in an area's median market rent is a 10 percentage point reduction in the likelihood of exiting homelessness (conditional on initial homelessness), this effect is not statistically significant.

6.2 Summary of key findings

In summarising the results of this section, although we find evidence that the housing market has a significant effect on homelessness overall, an effect that looks largely driven by its effects on homelessness entries, it is more important for some groups than others. Labour market conditions (as measured by the average unemployment rate) are also a noticeable influence on certain subgroups in the entry model, with statistically significant effects for interactions representing 11 subgroups. But just as with housing market conditions, the unemployment rate is a peripheral influence on all subgroup pathways out of homelessness. In short, housing market and labour market conditions have differential effects on some subgroups' pathways into homelessness, but not their pathways out of homelessness.

In the entry model, there is some evidence to suggest that housing market conditions are only relevant to the subgroups that are prone to enter homelessness for reasons other than risky behaviour, or ill health. If you have risky behavioural traits such as recent incarceration, regular use of drugs, and so on, your chances of becoming homeless are invariably higher, regardless of housing and labour market conditions. On the other hand, if these risky behavioural traits are absent, the chances of becoming homeless are greater in regions with higher median rents. This conclusion is clearly evident with respect to incarceration, diagnosis as bipolar or schizophrenic, drug use, risky levels of drinking and experience of violence, all of which are *statistically insignificant* when interacted with the median rent variable.

There is some evidence in the entry model for the same phenomenon with respect to labour markets, but it is weaker. Higher unemployment also seems to affect some groups with personal characteristics more than others. For example, females and 21–44-year-old individuals are more prone to enter homelessness the higher an area's unemployment rate. There is tentative evidence in entry models of housing market effects with respect to the same personal characteristics.

The exit model yields one curious finding. The age categories on their own have large and significant impacts on the probability of exit from homelessness (see Chapter 5, Table 4), yet the housing and labour market effects are quite heterogeneous within the same age groups and therefore insignificant statistically for all three age groups. This suggests that the higher exit rates for the young age group may be driven by services or other unobserved factors.

The regression estimates pick up some albeit weak signals suggesting the prospects of entering homelessness for people *without* risky behavioural traits, but vulnerable to homelessness for other (perhaps unmeasured) reasons, are differentially affected by the labour and housing market features of their region. On the other hand, while the risk of homelessness is higher among those with risky behaviours—drug use, alcohol dependence, and so on—it seems that housing and labour market effects are uniform across these risk groups. This raises some important policy issues, which we discuss in Chapter 8.

7 SENSITIVITY ANALYSIS

Our main housing market measure is the median market rent of private rental housing in an area. It is commonly used as an indicator of the tightness of housing markets because higher rents reflect tighter markets. However, it is a crude measure of access to affordable rental housing since it is exclusively drawn from the private rental sector. A region could have high market rents, but affordable rental housing is accessible because it has a large stock of public housing. Furthermore, the level of the median market rent tells us that 50 per cent of rental properties attract a rent at or below this level, but not whether the number of low-income households 'chasing' rental properties in this market segment is large (or otherwise) relative to supply.

In this section, we add more sophisticated housing market variables to our models that are once again based on census data. We allow for the balance of affordable rental housing relative to low-income households in rental accommodation by adding the number of private rental dwellings with rents below \$250 per week to the number of public and social housing units, and expressing this sum as a proportion of the total number of low-income households in rental accommodation in a region. This proportion is also calculated separately with respect to affordable private rental housing and social housing; the latter could have a different effect on homelessness in a region, as in Wood et al. (2015) for example. Detailed definitions and sources for these measures can be found in Chapter 4.

There is a second important addition to the empirical analyses in this section. Area level disadvantage could impact on the likelihood of homelessness if spatial concentrations of poverty have a place-based effect that precipitates homelessness among vulnerable groups, or makes it more difficult to escape homelessness. We allow for this possibility by adding each region's proportion of households with weekly incomes less than \$800 to our models of homelessness.

The results of logistic regression (with random effects) models estimating the probability of homelessness, entry into homelessness (conditional on initially being housed) and exit from homelessness (conditional on initial homelessness) that include these alternative area-level characteristics are presented in Tables 6 to 8 respectively. Estimates are reported from our preferred area-level classification in which area-based variables for metropolitan SA4 regions are defined on a city-wide basis (see Chapter 4). Model 1 estimates include the median market rent and the unemployment rate variables and so results replicate those reported in the earlier Tables 2 to 4. They act as a reference point to assist with comparisons. Model 3 then examines the impact of introducing our measure of area-level disadvantage (i.e. the concentration of low-income households in each area). Model 4 drops this and the median market rent variables, but replaces the latter by the ratio of low-cost private rental housing to low-income households in rental housing, and the ratio of public and social housing to low-income households in rental housing. Finally, in model 5, we omit the distinction between social and private rental housing, and instead insert the variable measure that merges affordable private rental housing and social housing. As with previous tables, mean marginal effects are presented.

Table 6: Sensitivity of probability of homelessness status to other housing supply variables: mean marginal effects from logistic regression with random effects

	Model 1	Model 3	Model 4	Model 5
Median market rent of GCCA (SA4 for other regions)	0.040***	0.015		
Unemployment rate of GCCA (SA4 for other regions)	0.007	0.012	0.003	-0.006
Proportion of households with weekly incomes less than \$800		-0.030		
Ratio: low-cost private dwellings/low-income renters			-0.007*	
Ratio: public & social housing/low-income renters			0.011*	
Ratio: all low-cost rental dwellings/low-income renters				-0.040
Number of observations	7,138	7,138	7,138	7,138

Note: All other controls from Table 2 are also included in underlying logistic regression. Regression results are available from the authors upon request.

Table 7: Sensitivity of probability of homelessness entry to other housing supply variables: mean marginal effects from logistic regression with random effects

	Model 1	Model 3	Model 4	Model 5
Median market rent of GCCA (SA4 for other regions)	0.016**	0.019		
Unemployment rate of GCCA (SA4 for other regions)	0.010**	0.009*	0.008*	0.005
Proportion of households with weekly incomes less than \$800		0.004		
Ratio: low-cost private dwellings/low-income renters			-0.004*	
Ratio: public & social housing/low-income renters			0.002	
Ratio: all low-cost rental dwellings/low-income renters				-0.031
Number of observations	4,409	4,409	4,409	4,409

Note: All other controls from Table 3 also included in underlying logistic regression. Regression results are available from the authors upon request.

Table 8: Sensitivity of probability of homelessness exit to other housing supply variables: mean marginal effects from logistic regression with random effects

	Model 1	Model 3	Model 4	Model 5
Median market rent of GCCA (SA4 for other regions)	-0.011	0.077		
Unemployment rate of GCCA (SA4 for other regions)	0.003	-0.015	0.004	0.009
Proportion of households with weekly incomes less than \$800		0.113		
Ratio: low-cost private dwellings/low-income renters			-0.008	
Ratio: public & social housing/low-income renters			-0.017	
Ratio: all low-cost rental dwellings/low-income renters				-0.096
Number of observations	1,120	1,120	1,120	1,120

Note: all other controls from Table 4 also included in underlying logistic regression. Regression results are available from the authors upon request.

The model 3 results offer no evidence that individuals living in areas of disadvantage are any more or less at risk of homelessness than those living in other areas, regardless of whether we look at homeless status (Table 6), entries to homelessness (Table 7) or exits from homelessness (Table 8). It takes an unexpected sign in two (status and exit) of the models, though marginal effect estimates are always statistically insignificant. There is also a noteworthy impact on the other area-level variables when modelling homeless status, with median market rents becoming insignificant and the unemployment rate variable nearly doubling in size (though still insignificant). Correlation between the area disadvantage measure and median market rents and/or the unemployment rate could be responsible.

When we examine whether the overall availability of low-cost housing is related to homelessness—as revealed in the model 5 set of results in Tables 6 to 8 for homeless status, entries and exits respectively—we see no apparent significant relationship. However, when we differentiate between publicly-provided and privately-provided low-cost housing, as in model 4, the two seem to work in the opposite direction. As expected, larger supplies of affordable private rental accommodation relative to the number of low-income households reduce the probability of homelessness in the JH sample, though it is only weakly significant (see Table 6). This effect seems to be coming through because shortages of affordable housing in the private rental market precipitate entries into homelessness (see Table 7), the effect on pathways out of homelessness being statistically insignificant (see Table 8). But even the impact on entries into homelessness is small; a 10 percentage point increase (decrease) in the availability of affordable private rental accommodation decreases (increases) the risk of entering homelessness by 0.4 percentage points.

Now consider our area-based measure of the availability of public/social housing. It turns out to have a positive relationship with the likelihood of homelessness status, though it is only weakly significant at 10 per cent. Thus, individuals living in areas with little (abundant) public/social housing face a lower (higher) risk of homelessness. However, the availability of public housing/social is not significant in the dynamic entry and exit models.

These results offer patchy confirmation of our earlier findings that housing markets have a significant impact on individual risks of homelessness, with individuals living in areas characterised by tighter private housing markets at an elevated risk of homelessness. There is also endorsement of earlier findings in that housing market effects seem to come about because they impact on the risks of entering homelessness.

But there are intriguing angles to be explored in these findings. It is the supply of affordable private rental housing that matters in terms of reducing homelessness. Increases in its

availability to low-income households will reduce the incidence of homelessness by cutting the probability of housed but vulnerable individuals entering homelessness. This effect likely comes through because those losing their home have a better chance of a 'soft landing' given better alternative housing options in the private market. On the other hand, the probability of homelessness status in static models is estimated to be higher in areas with relatively large stocks of public housing. Why might this be the case? We can think of three potential reasons.

1. It could be that areas with higher concentrations of public and social housing act as magnets to those most vulnerable, as they are also areas with higher levels of other housing and homelessness-related services.¹⁹
2. It could be that levels of public and social housing in most Australian cities and regions are just too low to have any measurable effect, though we do obtain weakly significant estimates in static models, so there is a caveat here.
3. It could be that evictions from public and social housing are causing at least part of the homelessness that occurs in these areas.

¹⁹ Unfortunately, we could not test this proposition as the costs associated with access to AIHW data on specialist homelessness services by SA4 fell well outside the project budget.

8 CONCLUSION AND POLICY IMPLICATIONS

Homelessness policy in Australia remains broadly tied to the policy framework set out in *The Road Home*, the Federal Government's White paper on homelessness released in 2008 (FaHCSIA 2008). The *Road Home* emphasised the importance of prevention and early intervention, as well as increased attention to breaking the cycle of longer term homelessness. Each state and territory subsequently signed off on the National Partnership Agreement on Homelessness (NPAH) which articulated the policy goals as well as targets against which progress was to be measured. Recently, the Federal Government extended funding for projects launched through the NPAH, signalling a commitment (in the short term at least) to the policy directions outlined in *The Road Home*. While all states and territories are signatories to the NPAH, it is also the case that each state and territory have implemented their own responses to the policy directions laid out in *The Road Home*.

Our project is the first to examine the relationship between structural factors and individual characteristics. Thus, the project represents the start of a broader program of research that seeks to shed light on the dynamics of homelessness. While previous Australian research has touched on the dynamic patterning of homelessness, it has generally relied on qualitative data and small samples drawn from a limited number of locations. Because this study draws on quantitative longitudinal data from numerous areas and links it to area-level measures, it can provide more robust evidence on what factors contribute to entries, and how (or indeed if) they differ from those factors that contribute to exits from homelessness.

Before we consider the policy implications of our findings in detail, three broad points emerge from our analysis. First, while the findings highlight the importance of interventions designed to prevent homelessness among identified high risk groups, we also found that exiting homelessness is trickier for certain groups than others. Getting the right balance between prevention and reactive services that assist homeless people to exit more rapidly is, however, a significant and ongoing challenge facing policy-makers. Second, and relatedly, our results emphasise the importance of thinking about entries and exits from homelessness separately. This is particularly crucial given the asymmetry in many of our results—some groups that are at a higher risk of entering homelessness have less difficulty exiting homelessness (e.g. young under 20-year-olds). Other groups at less risk of becoming homeless, are, conditional on being homeless, at increased risk of remaining homeless (e.g. married and de facto couples). Finally, housing and labour markets matter but their impact varies—for some of those with behavioural problems or biographies marked by acute disadvantage, the risk of homelessness remains high irrespective of the condition of housing and labour markets. In contrast we have discovered that there are individuals without behavioural issues (e.g. regular drug use), serious health issues (e.g. bipolar or schizophrenia) or biographical signals (e.g. absence of parenting) that are commonly associated with homelessness, who are nevertheless at higher risk of homelessness where housing markets are tight and labour markets slack. In short, our findings show that individual characteristics and structural factors matter but in quite different ways. As such, our findings offer important insights, both theoretical and empirical, missing from studies that rely solely on area or individual-level data.

Turning our attention now to more specific findings, the report provides important empirical evidence that supports existing policy directions, but it also identifies areas where policy approaches need to be strengthened. More specifically, our modelling results confirm that men are more likely to enter homelessness and less likely to exit homelessness than women. This confirms findings from previous studies that indicate men are over-represented in the homeless population. The ABS (2012) for instance has repeatedly found that men account for approximately 56–60 per cent of the homeless population, yet they account for approximately 40 per cent of those who use Specialist Homelessness Services (AIHW 2014). This likely reflects the high concentration of services that target family and domestic violence. The key

policy point here is not to redistribute existing funding to better reflect the empirical evidence, but rather to consider options that broaden the availability of support services for at risk and homeless men.

The link between homelessness and incarceration has long been recognised by service providers, policy-makers and researchers, both in Australia and overseas. Our modelling results confirm that the risk of homelessness is high among people who have been recently incarcerated (a marginal effect at 9.7 percentage points), despite it affecting only a relatively small number of people in our sample (approximately 3%). One policy goal is to reduce exits into homelessness from the Justice and Child Protection systems. From a policy perspective, our findings suggest the need for further work to improve the level of integration between Justice Systems and the Homelessness Support system. More effective integration that focuses on building relationships with prisoners prior to their release (in reach) would enable prisoners to transition into stable, permanent accommodation. Reducing the number of ex-prisoners who become homeless may also have an indirect impact on the level of recidivism, which is high among homeless ex-prisoners (Metraux & Culhane 2006). Similarly, although the risk of entering homelessness among those with a background in the state care system is only weakly significant, the findings nonetheless confirm that post-care support services which aim to prevent homelessness among this group is the optimal approach.

Other demographic factors that we examined further underscore the importance of understanding that homelessness is a dynamic process. For instance, although individuals married or in a de facto relationship are less likely to enter homelessness, conditional on entering they are significantly less likely to exit. The longer people remain homeless, the more complex and costly their circumstance become. Increasing support options specifically for homeless married /de facto couples without children could improve their prospects of exiting homelessness.

The asymmetry in entry and exit results is also evident when we consider age. While all age groups appear equally likely to fall into homelessness on controlling for other personal characteristics, getting out of homelessness becomes more difficult as age increases—individuals 45 years and older are 35.9 percentage points less likely to exit than their younger counterparts (15–20 years). It is likely that these results reflect, in part, the relatively high level of funding directed towards assisting homeless young people. Indeed, the results tentatively support the conclusion that the current policy focus on intervening early among homeless young people is making a difference. However, there is clearly a gap in service provision for older homeless people who are less likely to exit homelessness regardless of the condition of housing and labour markets. Some of this gap in service provision will have been addressed by programs working with the chronically homeless individuals, who tend to be older. However, not all older people experience chronic homelessness. Further, ABS results suggest that the number of older people experiencing homelessness is increasing. Thus, both preventative strategies targeting older people at risk, as well as services designed to work specifically with homeless older people are required.

Our modelling also presents some puzzling results. It is generally agreed that the prevalence of poor physical health and mental health issues is higher among the homeless than the general population, and we did find that those with a long-term health condition that restricts everyday activities are significantly more at-risk of homelessness. However, individuals diagnosed with bipolar or schizophrenic are at a lower risk of homelessness than those without similar diagnosed conditions. This is primarily due to a lower likelihood of entering homelessness. 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. We think a possible reason for this is that those diagnosed are more likely to be receiving treatment and care (even institutionalised care), thereby lowering the chances of experiencing homelessness compared to those undiagnosed but with other risk factors. Moreover, this argument implies that those

diagnosed 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 health services play in the prevention of homelessness among people with a severe mental illness. However, the results also show that for individuals in poor physical health there is still room to improve and further strengthen connections between the homelessness and health systems, if the level of risk among this group is to be reduced.

Our modelling also emphasises the importance of social support in terms of preventing homelessness. Among 'at risk' and homeless young people there has been a strong emphasis in program design to strengthen support networks, primarily but not exclusively, with family. Our findings also show that social support is an important protective factor for adults as well. Policy-makers need to consider ways in which the social support available to adults and families can be strengthened. Such an approach may yield additional benefits beyond reducing entries into homelessness (and all the associated costs). Through improved access to social and economic resources, individuals are better able to enjoy the full benefits of civic participation.

A crucial finding is that a prior experience of homelessness has a strong (marginal effect of 7.1 percentage points) and highly statistically significant impact on the chances of homelessness later on, mainly driven by increasing the likelihood of entering homelessness. This cycling in and out of homelessness, which is potentially explained by either occurrence dependence (a form of state dependence), or adaptation to homelessness, raises a number of important policy issues. First, initial assessments of at risk individuals should seek to determine whether a person has had a prior experience of primary homelessness. Such a question would be easy to ask and relatively unobtrusive, yet yield positive results by identifying people more likely to cycle back into the homeless population. Assisting them to secure stable housing outcomes *before they become homeless* could do much to reduce the burden on existing homelessness services that target individuals prone to rough sleeping.

While it is clear that demographic factors and biographical circumstances matter as determinants of homelessness, a key aspect of our analysis was to try and better understand how these individual characteristics interacted with housing and labour markets of areas. We find evidence that housing markets have a significant impact on individual risks of homelessness, with individuals living in areas with tighter housing markets at an elevated risk of homelessness relative to those in areas with looser housing markets. What seems to contribute most to individual risks of homelessness is the state of the private rental market. People living in areas with tighter private housing markets and fewer affordable housing options in the private rental market are most at risk. We do not find evidence that the availability of public and social housing offsets this risk however. Why might this be the case? We can think of three potential reasons.

1. It could be that areas with higher concentrations of public and social housing act as magnets to those most vulnerable as they are also areas with higher levels of other housing and homelessness-related services.
2. It could be that levels of public and social housing in most Australian cities and regions are just too low to have any measurable effect.
3. It could be that evictions from public and social housing are causing at least part of the homelessness that occurs in these areas.

Crucially though, despite finding a positive association between median rents and the risk of homelessness, the relationship is stronger for some groups than others, and that its effect is largely driven by entries into homelessness. People with some risky behaviours are more likely to lose their housing irrespective of the condition of the housing and labour markets. For those with risky behaviours—drug use, alcohol dependence and so on—programs that directly address these behaviours is the optimum approach to reduce entries into homelessness. We

should also note that these implications are drawn with respect to individuals housed but vulnerable to homelessness, and therefore these programs should be designed as *preventative rather than reactive*.

On the other hand, the homelessness prospects of people *without* risky behavioural traits, but vulnerable to homelessness for other (perhaps unmeasured) reasons, seem to be especially affected by the labour and housing market features of their region. There are potentially important policy implications—those persons vulnerable to homelessness, but without behavioural issues, could benefit from locations closer to job opportunities and affordable housing opportunities. Efforts to improve affordable housing and job opportunities in regions with unaffordable housing, or weak labour markets, will then aid prevention of homelessness among these groups.

With respect to the labour market, it seems to matter most if an individual is employed or looking for work, but only for homeless entries. However, in the static and exit models of homelessness, labour market conditions, as represented by the unemployment rate, are found to be unimportant. We think that the geographical pattern of homelessness support services might obscure labour market effects, since these services tend to be located in regions with high unemployment rates. There is some evidence to support this; in fiscal year 2011–12, there was statistically significant (at 1%) correlation coefficient of 0.34 between the unemployment rate and the per capita number of clients receiving support from homelessness services agencies, as measured nationally using the SA3 spatial unit of measurement.²⁰

We do not find strong evidence that either the housing or labour market significantly effects exits from homelessness overall, nor for any of the groups examined separately. It is not entirely clear why this is the case, but a plausible explanation may be that services are reactive rather than preventative. Since they are more prevalent in areas where labour markets are weak, or housing is more expensive, they are more likely to assist escapes from homelessness in these areas. Services are an omitted variable and could therefore mask the ‘true’ influence of housing and labour market variables. On the other hand, we can more readily detect the influence of housing and labour market variables on pathways into homelessness because services oriented to prevention are relatively scarce.

The policy implications of our findings are indeed broad, but they reinforce the importance of thinking about homelessness as a dynamic process. Understanding how entry and exit differ can assist policy-makers to craft more finely-tuned interventions. Similarly, understanding the differential impact of housing and labour market conditions can equally assist in the development of more effective policy responses. Clearly, a strong case can be made that prevention is the best approach. And, while it is possible to target high risk groups, it is important to point out that prevention strategies are always likely to be less than 100 per cent accurate in respect to who is targeted—that is, some individuals may well be targeted who would never have become homeless. The point to bear in mind here is that we cannot predict with certainty which individuals in any high risk groups will become homeless. Thus, there will always be a need for services that work with the homeless. The key policy point here is that although getting the right balance between preventative and reactive services is tricky, it should always be uppermost in the minds of policy-makers.

8.1 Future research directions and concluding comments

Journeys home is a rich data source that will be capable of yielding insights across a broad range of research questions, and this project has addressed just a few of these possible research questions. Rather than outline new research questions, we highlight how the present analysis might be extended in potentially fruitful ways.

²⁰ We are grateful to Deb Batterham for computational assistance.

While conducting this research, we invariably had an important caveat at the back of our minds. This was the absence of information on the spatial pattern of homelessness services. At various points in the analysis, we feared that the absence of this information was preventing a more precise quantification of housing and labour market effects. While service measures are available for sub-national spatial units (SA3), we were designing and computing variable measures for a different spatial unit (SA4), and algorithms to achieve concordance at a different level of spatial disaggregation could not be obtained and implemented in the study timeframe. Integrating homelessness service measures into the vector of structural variables is a priority future research requirement.

The service measures will yield particularly rich insights into mobility patterns among the homeless and those insecurely housed. One of this project's important discoveries is the very high mobility of the homeless across labour market boundaries. This may come as no surprise to qualitative researchers, but it is nevertheless an important finding because it is a general pattern evident in a large sample, and across a lengthy study timeframe. We can be confident that this is a result that can be generalised across the population of those vulnerable to or actually in a homeless condition. A richer understanding of mobility patterns is another research priority. The work we have completed so far has failed to unearth any strong and systematic patterns across housing and labour markets. There are roughly equal numbers moving to cheaper housing markets as are moving to more expensive housing markets; and similarly, there are roughly equal numbers moving to lower unemployment areas as are moving to higher unemployment areas. The geography of homelessness services could be acting as a magnet that masks or even overrides housing and labour market push and pull factors. We need a little more investigation here, but we feel that with modest resource outlay considerable progress can be made on this front.

There are also some methodological innovations that could yield improved identification of the causal relationships shaping homelessness outcomes. The JH data set is a longitudinal survey and offers opportunities for panel modelling that allow researchers to address the statistical problems associated with unmeasured heterogeneity. But it also has a second important feature—it is a spatial dataset because it has a sample design drawn from different locations. This has not been allowed to influence the modelling approach. In recent years there have been important advances in spatial modelling techniques (LeSage & Pace 2009) that offer the prospect of more efficient estimates based on spatial patterns in the data, and especially with respect to the error term in regression models.

Advocacy of mixed research methods might be wishful thinking given their high resource cost, but the returns from combining large sample surveys and in-depth interviews with a subsample from the same survey are potentially large. There are times when modelling large data sets uncover patterns in the data that can be interpreted in a richer way with the aid of qualitative research. There are various points in the analysis where multiple explanations of a statistical result are possible, especially when personal motives underlying behaviour are concerned. Qualitative methods can come to the aid of a program of research in such circumstances. In future large-scale panel surveys this option may well be worthy of consideration.

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APPENDICES

Appendix 1: A theoretical framework

Consider the following 'well behaved' utility function:

$$U = U(C, H) \tag{1}$$

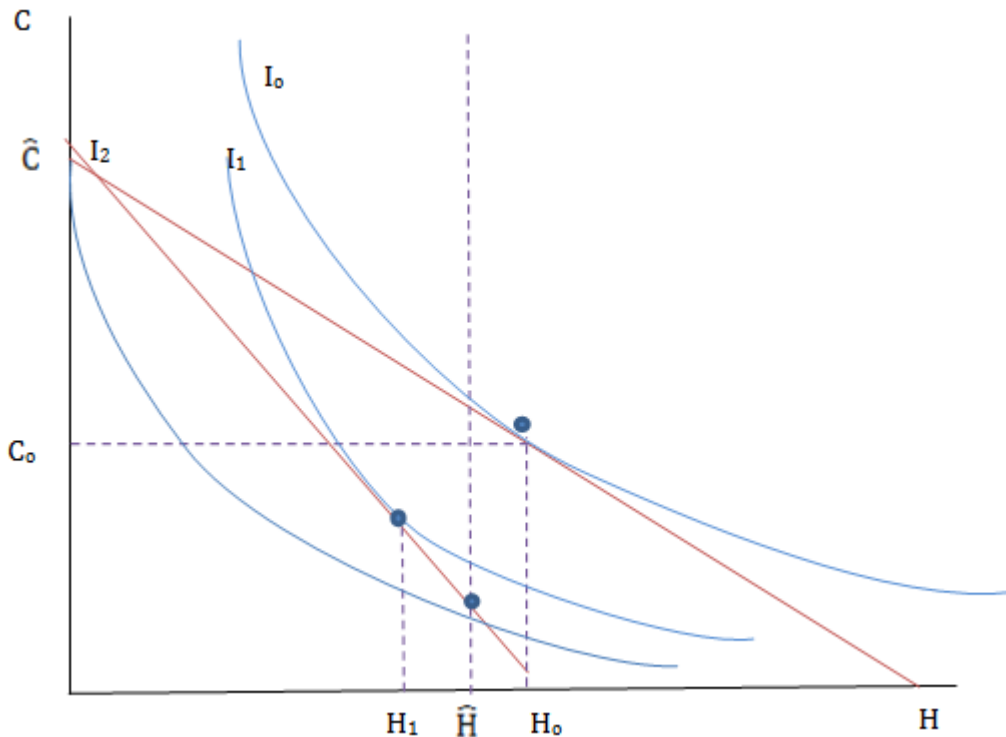
Where H is housing services supplied by landlords (assuming no owner occupied housing) and C is a composite good. The utility function in (1) is maximised subject to:

$$Y \geq p_c C + p_h H \tag{2}$$

$$H \geq \hat{H} \tag{3}$$

Where Y is income, P_c is the price per unit of the composite good and P_h is the rent per unit of housing, all exogenously determined. The novel aspect of the model is \hat{H} , it is a minimum standard of housing that building standards and land use regulation define. The best feasible combination of C and H with respect to the budget constraint is H_0, C_0 , with \hat{H} non-binding in Figure A1. Now consider a housing market shock that increases housing rents and shifts the budget constraint to $\hat{C} - H_0$. At the new lower level of housing consumption H_1 the housing standards constraint is binding, and H_1 is unattainable. The rise in housing rents in this case leaves the individual indifferent between homelessness (O, \hat{C}) and consumption of housing at \hat{H} as both combinations lie on the same I_2 indifference curve. Any further increase in P_h will precipitate homelessness.

Figure A1: Homelessness in a choice theoretical framework with supply constraints



Appendix 2: Results of logistic regression with random effect

Table A1: Logistic regression results on probability of homelessness

	Model 1 ^a		Model 2 ^a	
	coef.	P value	coef.	P value
Male	0.710	0.000	0.691	0.000
<i>Age group</i>				
15–21 years (reference)				
21–44 years	0.096	0.617	0.054	0.779
45+ years	0.748	0.006	0.708	0.010
<i>Aboriginal and Torres Strait Islander</i>				
Born in Australia (reference)				
Born in English-speaking country	-0.345	0.296	-0.415	0.212
Born in non-English-speaking country	0.019	0.954	0.034	0.918
<i>Married/defacto</i>				
Married/defacto	-1.073	0.000	-1.066	0.000
<i>Have resident children</i>				
Have resident children	-1.156	0.000	-1.104	0.000
<i>Highest educational qualification</i>				
Post-school qualification				
Yr. 12 or equiv.	-0.020	0.937	-0.064	0.808
Yr. 10 or 11	0.098	0.587	0.099	0.583
Yr. 9 or below	0.263	0.244	0.287	0.205
<i>Labour force status</i>				
Employed				
Unemployed	0.499	0.040	0.507	0.038
NILF	0.646	0.008	0.664	0.007
<i>Work history</i>				
No work history				
No work history	-0.746	0.217	-0.686	0.253
Time employed (%)				
Time employed (%)	0.001	0.946	0.001	0.854
Has not experienced job loss within last 2 years				
Lost job in last 6 months	-0.403	0.063	-0.412	0.058
Lost job in last 2 years but not in last 6 months	0.037	0.837	0.035	0.848
<i>Family history</i>				
Ever in state care				
Ever in state care	-0.108	0.607	-0.114	0.592
No principal caregiver at age 14				
No principal caregiver at age 14	0.034	0.917	0.066	0.839
<i>Recent events</i>				
Did not experience violence in last 6 months				
Experienced violence in last 6 months	0.317	0.016	0.316	0.016
Did not respond: violence				
Did not respond: violence	-0.031	0.903	-0.069	0.791
Incarcerated				
Incarcerated	0.889	0.001	0.889	0.001

	Model 1 ^a		Model 2 ^a	
	coef.	P value	coef.	P value
<i>Substance use</i>				
Alcohol consumption	0.423	0.004	0.429	0.004
Cigarette consumption	0.021	0.010	0.020	0.013
Did not use illicit drugs in last 6 months				
Used illicit drugs in last 6 months irregularly	0.092	0.584	0.100	0.554
Regular user of illicit drugs in last 6 months	0.077	0.663	0.078	0.661
<i>Health</i>				
Long-term health condition	0.333	0.015	0.350	0.011
Never diagnosed with bipolar/schizophrenia				
Ever diagnosed with bipolar/schizophrenia	-0.876	0.033	-0.884	0.033
Did not respond: bipolar/schizophrenia	0.906	0.309	0.966	0.283
Social support	-0.411	0.000	-0.425	0.000
Ever primary homeless	0.840	0.000	0.846	0.000
Combined income (\$00s)	-0.004	0.779	-0.005	0.737
<i>Area-level characteristics</i>				
Median market rent (\$00s) ^b	0.071	0.363	-0.145	0.016
Average unemployment rate ^c	-4.421	0.000	-3.104	0.001
Panel level standard deviation	2.179		2.190	
Prop. of variance contributed by panel-level variance	0.591		0.593	
Likelihood-ratio test of rho=0 (P value)	-2690.4		-2673.6	
Log likelihood	1557		1557	
Number of individuals	7138		7138	
Number of observations	0.710	0.000	0.691	0.000

Notes:

a. Also included in the regression specification were wave indicators and Mundlak correction terms for time-varying variables

b. Model 1 includes the median market rent of greater capital city area or SA4 for regions outside of capital cities; Model 2 includes the median market rent of SA4s for all regions.

c. Model 1 includes the unemployment rate of greater capital city area or SA4 for regions outside of capital cities; Model 2 includes the unemployment rate of SA4s for all regions.

Table A2: Logistic regression results on homeless entry

	Model 1 ^a		Model 2 ^a	
	coef.	P value	coef.	P value
Male	0.471	0.004	0.468	0.004
<i>Age group</i>				
15–21 years (reference)				
21–44 years	-0.144	0.449	-0.150	0.432
45+ years	0.138	0.597	0.145	0.578
<i>Aboriginal and Torres Strait Islander</i>				
Born in Australia (reference)				
Born in English-speaking country	-0.319	0.313	-0.337	0.287
Born in non-English-speaking country	-0.009	0.977	-0.009	0.976
<i>Married/defacto</i>				
Married/defacto	-0.222	0.260	-0.220	0.264
<i>Have resident children</i>				
Have resident children	-0.510	0.010	-0.504	0.011
<i>Highest educational qualification</i>				
<i>Post-school qualification</i>				
Yr. 12 or eq	0.069	0.788	0.065	0.798
Yr. 10 or 11	0.290	0.098	0.289	0.098
Yr. 9 or below	0.384	0.072	0.378	0.077
<i>Labour force status</i>				
<i>Employed</i>				
Unemployed	-0.045	0.859	-0.056	0.825
NILF	0.060	0.796	0.040	0.865
<i>Work history</i>				
No work history	0.443	0.100	0.450	0.094
Time employed (%)	-0.006	0.054	-0.006	0.052
<i>Has not experienced job loss within last 2 years</i>				
Lost job in last 6 months	0.439	0.045	0.449	0.040
Lost job in last 2 years but not in last 6 months	0.307	0.111	0.317	0.099
<i>Family history</i>				
Ever in state care	0.329	0.068	0.331	0.066
No principal caregiver at age 14	-0.017	0.955	-0.014	0.962
<i>Recent events</i>				
<i>Did not experience violence in last 6 months</i>				
Experienced violence in last 6 months	0.247	0.123	0.247	0.123
Did not respond: violence	0.289	0.354	0.274	0.379
Incarcerated	0.435	0.216	0.418	0.234
<i>Substance use</i>				
Alcohol consumption	0.028	0.061	0.028	0.059

	Model 1 ^a		Model 2 ^a	
	coef.	P value	coef.	P value
Cigarette consumption	0.007	0.351	0.007	0.333
Did not use illicit drugs in last 6 months				
Used illicit drugs in last 6 months irregularly	0.263	0.157	0.258	0.165
Regular user of illicit drugs in last 6 months	0.429	0.012	0.414	0.016
<i>Health</i>				
Long-term health condition	0.061	0.683	0.056	0.707
Never diagnosed with bipolar/schizophrenia				
Ever diagnosed with bipolar/schizophrenia	-0.663	0.001	-0.660	0.001
Did not respond: bipolar/schizophrenia	-0.910	0.196	-0.900	0.202
Social support	-0.269	0.002	-0.268	0.002
Ever primary homeless	0.602	0.000	0.598	0.000
Combined income (\$00s)	0.005	0.843	0.004	0.880
<i>Area-level characteristics</i>				
Median market rent (\$00s) ^b	0.279	0.042	0.245	0.058
Average unemployment rate ^c	0.174	0.040	0.072	0.261
Constant	-4.756	0.000	-4.023	0.000
Panel level standard deviation	1.016		1.014	
Prop. of variance contributed by panel-level variance	0.239		0.238	
Likelihood-ratio test of rho=0 (P value)	0.000		0.000	
Log likelihood	-1133.5		-1134.4	
Number of individuals	1334		1334	
Number of observations	4409		4409	

Notes:

a. Also included in the regression specification were wave indicators.

b. Model 1 includes the median market rent of greater capital city area or SA4 for regions outside of capital cities; Model 2 includes the median market rent of SA4s for all regions.

c. Model 1 includes the unemployment rate of greater capital city area or SA4 for regions outside of capital cities; Model 2 includes the unemployment rate of SA4s for all regions.

Table A3: Logistic regression results on homeless exit

	Model 1 ^a		Model 2 ^a	
	coef.	P value	coef.	P value
Male	-0.527	0.049	-0.512	0.058
<i>Age group</i>				
15–21 years (reference)				
21–44 years	-1.067	0.001	-1.032	0.002
45+ years	-1.661	0.000	-1.614	0.000
Aboriginal and Torres Strait Islander	0.105	0.728	0.104	0.733
<i>Born in Australia (reference)</i>				
Born in English-speaking country	-0.156	0.740	-0.111	0.814
Born in non-English-speaking country	-0.196	0.688	-0.228	0.644
Married/defacto	-0.702	0.046	-0.706	0.046
Have resident children	1.150	0.002	1.101	0.004
<i>Highest educational qualification</i>				
<i>Post-school qualification</i>				
Yr. 12 or eq	0.414	0.318	0.437	0.295
Yr. 10 or 11	0.259	0.342	0.268	0.327
Yr. 9 or below	0.262	0.431	0.225	0.501
<i>Labour force status</i>				
<i>Employed</i>				
Unemployed	-0.279	0.447	-0.302	0.413
NILF	-0.653	0.057	-0.658	0.056
<i>Work history</i>				
No work history	0.501	0.283	0.497	0.290
Time employed (%)	0.001	0.762	0.001	0.761
<i>Has not experienced job loss within last 2 years</i>				
Lost job in last 6 months	0.306	0.352	0.347	0.293
Lost job in last 2 years but not in last 6 months	0.462	0.083	0.462	0.085
<i>Family history</i>				
Ever in state care	-0.151	0.614	-0.138	0.647
No principal caregiver at age 14	0.750	0.084	0.728	0.096
<i>Recent events</i>				
<i>Did not experience violence in last 6 months</i>				
Experienced violence in last 6 months	0.069	0.761	0.066	0.771
Did not respond: violence	-0.109	0.810	-0.079	0.862
Incarcerated	-0.348	0.421	-0.326	0.453
<i>Substance use</i>				
Alcohol consumption	-0.031	0.107	-0.032	0.102

	Model 1 ^a		Model 2 ^a	
	coef.	P value	coef.	P value
Cigarette consumption	-0.004	0.703	-0.004	0.700
Did not use illicit drugs in last 6 months				
Used illicit drugs in last 6 months irregularly	0.024	0.929	0.031	0.908
Regular user of illicit drugs in last 6 months	-0.277	0.254	-0.247	0.312
<i>Health</i>				
Long-term health condition	0.192	0.363	0.206	0.330
Never diagnosed with bipolar/schizophrenia				
Ever diagnosed with bipolar/schizophrenia	-0.210	0.472	-0.204	0.487
Did not respond: bipolar/schizophrenia	0.668	0.369	0.708	0.344
Social support	0.015	0.897	0.019	0.873
Ever primary homeless	0.124	0.635	0.122	0.644
Combined income (\$00s)	0.043	0.124	0.043	0.128
<i>Area-level characteristics</i>				
Median market rent (\$00s) ^b	-0.055	0.805	-0.027	0.893
Average unemployment rate ^c	0.013	0.921	0.157	0.143
Constant	1.053	0.485	0.077	0.953
Panel level standard deviation	1.580		1.595	1.580
Prop. of variance contributed by panel-level variance	0.431		0.436	0.431
Likelihood-ratio test of rho=0 (P value)	0.000		0.000	
Log likelihood	-665.6		-663.7	
Number of individuals	575		575	575
Number of observations	1120		1120	1120

Notes:

a. Also included in the regression specification were wave indicators.

b. Model 1 includes the median market rent of greater capital city area or SA4 for regions outside of capital cities; Model 2 includes the median market rent of SA4s for all regions.

c. Model 1 includes the unemployment rate of greater capital city area or SA4 for regions outside of capital cities; Model 2 includes the unemployment rate of SA4s for all regions.

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