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Neha Swami

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Neha Swami
Melbourne Institute of Applied Economics and Social Research and
Department of Economics
University of Melbourne
Melbourne, VIC 3010 Australia
nswami@student.unimelb.edu.au

Abstract

This paper provides new insights into the association between homelessness and poor employment outcomes by examining how homelessness affects employment transitions. The study uses longitudinal data from the Journeys Home survey and methods that address concerns related to reverse causality and endogenous selection into homelessness. The findings reveal that low levels of employment among homeless people can be attributed primarily to their higher probabilities of exiting employment. The negative association between homelessness and employment entry is much weaker in both magnitude and significance. This finding contrasts with what one would expect given the perception in the literature, i.e. that the difficulty of finding employment is a major contributing factor behind the poor rates of employment among homeless people. The significant positive association between homelessness and the probability of exiting employment seems to be mainly driven by unobserved person-specific characteristics, which increase a person's chances of being homeless and of leaving employment. Once the effect of these unobserved confounding characteristics is considered, homelessness per se has no significant impact on either employment entry or exit.

JEL classification: J1, J2
Keywords: Homelessness, employment entry and exit, correlated random effects, Journeys Home survey

* This paper uses data collected from the Journeys Home project, a longitudinal survey-based study managed by the Melbourne Institute of Applied Economic and Social Research on behalf of the Australian Government Department of Social Services (DSS). The findings and views reported in this paper are solely those of the author, and they should not be attributed to either DSS or the Melbourne Institute. The .do files used to analyse the data are available upon request. The author sincerely thanks her supervisors Professor David Ribar and Professor Jenny Williams for their guidance and helpful feedback. The author also thanks participants at several seminars for their helpful comments. The author is thankful for the funding provided by the university in the form of an Australian Training Program Scholarship, Postgraduate Award (APA) and a Melbourne Study Scholarship.

1. Introduction and Motivation

Homelessness means a lack of not only shelter for people but also safety and stability that permits physical, psychological and economic well-being (ABS, 2012). In addition, from an economic perspective, the public cost of caring for homeless people is argued to be substantially higher than for a typical person in the general population; according to an OCDE (2015) report, this cost is up to seven times higher. Hence, preventing homelessness is both ethically and economically desirable for governments and policy makers (OCDE, 2015). Participation in the labour market can help people move out of homelessness (Bakos, 2007; Shaheen & Rio, 2007; Taskforce, 2008). Employment can help homeless people break the cycle of homelessness by providing income to maintain stable housing and take control of their lives (Shaheen & Rio, 2007). Many OECD countries, including Australia, have introduced targeted plans and policy actions to reduce homelessness and achieve social inclusion for disadvantaged populations by maximizing their opportunities to participate in the labour market and the community more broadly (Taskforce, 2008).

Evidence suggests that contrary to popular belief, people experiencing homelessness are no less motivated to find and engage in work than other individuals and that they see paid work as having both financial and non-financial benefits (Hulse, Saugeres, & Housing, 2008; Porat, Marshall, & Howell, 1997; Radey & Wilkins, 2010). Burt et al. (1999) reported that almost half the clients sampled in the National Survey of Homeless Assistance Providers and Clients (NSHAPC) in the United States did some paid work in the 30 days before being interviewed. Similarly, according to the Australian Bureau of Statistics (ABS) Estimating Homelessness 2011 report, of the 70,624 homeless Australians aged 15 or older who reported their labour force status in the 2011 census, 32,030 (45%) were in the labour force and 20,931 (30%) were working (ABS, 2011). The rate of employment among homeless people, however, remains low compared to the general population.

The literature highlights that homeless people face multiple sources of disadvantages and several challenges in terms of finding and engaging in employment, which might be consequences of their homelessness, contributors to their homelessness or both. These include health issues that hinder the ability of homeless people to find and keep employment, including poor physical health (Bakos, 2007; Grace, Batterham, & Cornell, 2008; Zuvekas & Hill, 2000), mental illness (Bakos, 2007; Grace et al., 2008; Lenz-Rashid, 2006), and substance abuse (Ferguson, Bender, Thompson, Maccio, & Pollio, 2012; Zlotnick, Robertson, & Tam, 2002). Several studies also reported that compared to the general population, very low levels of education and formal training among homeless people act as important barriers to gaining stable employment (Bakos, 2007; Grace et al., 2008; Hulse et al., 2008; Nunez & Fox, 1999; Radey & Wilkins, 2010). There is also evidence that factors such as a lack of social support and social integration (Brown & Mueller, 2014; Hulse et al., 2008) and difficulty in maintaining personal hygiene act as barriers to securing employment (Mavromaras, King, Macaitis, Mallett, & Batterham, 2011). Moreover, a lack of affordable childcare or the presence of very young dependent children (Hulse et al., 2008; Nunez & Fox, 1999) and the inability to afford transportation (Hulse et al., 2008; Kerr & Dole, 2005; Mavromaras et al., 2011; Nunez & Fox, 1999) are also commonly cited challenges to homeless people's ability to get and keep employment. Altogether, the experience of homelessness can make it difficult to find and keep a job, thereby pushing individuals into a homelessness trap (Glomm & John, 2002).

While we now have a better understanding of the numerous challenges and barriers that homeless people encounter when attempting to obtain and maintain paid employment, only a handful of studies have directly examined the impact of homelessness on employment, and the evidence they provide is inconclusive. Lei (2013) used data on sheltered homeless persons from the NSHAPC in the United States and estimated binary logit models with controls for several demographic and health characteristics. The results indicate that homeless people have significantly lower odds of working in regular jobs. However, due to the cross-sectional nature of the data employed, the study does not account for the issue of unobserved confounders. More importantly, the study does not address the issue of reverse causality. There is a strong possibility that employment problems lead to housing problems (Morris, Judd, & Kavanagh, 2005; Shlay & Rossi, 1992). Given these issues, the study cannot provide a causal interpretation of the association between homelessness and employment.

Chigavazira et al. (2014) addressed the issue of common confounders. The authors analysed data from the Journeys Home (JH) survey, a large-scale longitudinal survey of housing-insecure people in Australia, which is also used in this study. The authors estimated fixed-effects models to examine the impact of homelessness at time t and $t-1$ on the probability of being employed at time t. The study found no conclusive evidence of a negative effect of lagged or current homelessness on the current rate of employment.

A recent study by Desmond & Gershenson (2016) provided empirical evidence on the association between housing loss and job loss by using county-level data from Milwaukee, Wisconsin. To account for unobserved heterogeneity among respondents, the authors employed matching methods and a fixed-effect discrete hazard model with repeat failures (per respondent). The findings revealed that involuntary housing loss is a statistically significant predictor of subsequent job loss. However, the authors restricted the sample to people living in private rental housing. Hence, it is hard to generalize the findings to the broader homeless population.

The aim of my study is to expand the scope of our current understanding by examining the effect of homelessness on employment entry and exit using national longitudinal data on housing-insecure Australians from the Journeys Home (JH) survey. Job search and job turnover theoretical models guide the conceptual framework used to understand how homelessness can affect employment entry and exit. The implications from the conceptual framework show that several challenges or factors associated with homelessness are likely to influence employment entry and exit decisions. However, the extent and direction of the effect of these factors might be different across the two processes. For example, a low level of education may matter more to finding a job compared to keeping a job, while factors such as frequent changes in housing may adversely affect job continuation more without necessarily affecting job finding.

This study makes two important contributions to the literature. First, by examining job entry and exit separately, it provides useful insights into the effect of homelessness on the dynamics of employment. Hence, it informs the development of appropriate interventions and targeted policies. Until now, empirical analyses have largely focused on examining the effect of homelessness on the level or rate of employment. Dynamic labour supply models, however, suggest the presence of inherent conceptual differences between the nature of the two employment processes and their determinants. The overall effect of homelessness observed on employment levels is the net effect of entry and exit processes, which can lead to misspecification if the effects of homelessness on each employment process do not reinforce each other or could lead to null effects if they work in opposite directions.

Second, I overcome the issue of reverse causality by studying the impact of homelessness in the previous period on current-period employment outcomes. Furthermore, I address the concerns related to endogenous selection into homelessness by using a correlated random effects framework. Together, the use of timing of homelessness and employment and the correlated random effects framework enable my empirical findings to have more causal interpretation regarding the effect of homelessness on employment entry and exit.

I find that the low level of employment among homeless people can be attributed primarily to their higher probability of exiting employment or job loss. The association between homelessness and employment entry is much weaker. In fact, I find that homelessness has no significant impact on employment entry. This finding contrasts with what one would expect given the perception in the literature, i.e. that the difficulty in finding employment is a major contributing factor to poor rates of employment among homeless people. I also find that the significant positive association between homelessness and the probability of exiting employment seems mainly to be driven by unobserved person-specific characteristics, which increase a person's chances of both being homelessness and leaving employment. Once the effect of these unobserved confounding characteristics is considered, homelessness per se has no significant impact on employment exit.

This paper is organized as follows. Section 2 presents the conceptual framework, and section 3 describes the dataset, variables and analysis sample. Section 4 discusses the empirical approach and identification strategy. The results of the descriptive and empirical analyses are presented in sections 5 and 6, respectively. I test the sensitivity of the results in section 7. The paper ends with concluding remarks in section 8.

2. Conceptual Framework

To explain how homelessness might affect employment entry and exit for a person, the paper draws on two separate theoretical models: a search model for finding a job and a learning model for job turnover.

I begin by considering how homelessness might affect job entry using the standard partial equilibrium job search theory (Cahuc, Carcillo, Zylberberg, & McCuaig, 2014; Mortensen, 1986). The central idea of the job search model is that there is uncertainty and imperfect information over the exact location of one's best job opportunity. Thus, a job search is seen as an investment to acquire information. The unemployed worker, however, knows the wage offer distribution of the given set of available jobs and the act of search results in a random draw from this known wage offer distribution. In this framework, the level of search effort depends on the direct cost of search and on the utility associated with unemployment. The utility associated with unemployment captures payments conditional on unemployment, other welfare payments generally available and the value of home production or non-market time. The optimal strategy involves comparing the value of continuing the job search with the value of the current wage offer. This gives rise to the decision rule that the worker enters a job if the wage offer is greater than his/her reservation wage and he/she keeps searching if the wage offer is less than the reservation wage. Finally, the framework assumes an exogenous probability of job separation.

It follows that in the job search model, the job finding rate depends on the probability of obtaining a job offer (therefore, the search effort) and the probability that a random job offer is accepted (therefore, the wage offer and the reservation wage). Therefore, factors that affect the search effort, the mean of the wage offer distribution and the reservation wage directly and indirectly will affect the job finding rate.

The job search model implies that a decrease in the mean of the wage offer distribution decreases the job finding rate. An increase in the utility associated with unemployment decreases the job finding rate by reducing the search effort and increasing the reservation wage. In addition, given the reservation wage, an increase in the search cost decreases the search effort and therefore the job finding rate, which is a direct effect. However, an increase in search costs also decreases the reservation wage, resulting in a positive effect on the job finding rate, which is an indirect effect. Thus, the job search model highlights the role of the wage offer distribution, search costs and utility associated with unemployment in determining the probability of entering employment (i.e. the job finding rate).[1]

The job search framework allows us to think of several ways in which the factors associated with homelessness may influence the transition into employment by affecting several parameters in the job search model. For example, factors such as poor mental and physical health, drug use and low level of education may decrease the mean of the wage offer distribution, which will reduce the job finding rate. Issues related to mental and physical health and drug use may also increase the utility associated with unemployment or the value of non-market time, which will result in a decline in the job finding rate. Health issues, drug problems and a lack of social support may increase the cost of the job search, which will again reduce the job finding rate given the reservation wage. However, an increase in the search cost will indirectly reduce the reservation wage, which will increase the job finding rate, offsetting some of the negative direct effect of a higher search cost on employment entry. Overall, we see several explanations for why the experience of homelessness may reduce the probability of finding employment.

[1] For brevity, I do not consider the implications related to the discount rate.

To understand how the experience of homelessness might affect the probability of exiting employment, I draw on the learning model of job turnover. The job turnover model provides an intuitive, appealing framework to study transitions out of employment (Jovanovic, 1979). In this framework, the worker-firm match is modelled as an 'experience good', where the quality of the match is initially uncertain to both sides of the market and job turnover occurs when the quality of the match, as revealed gradually over time by output performance, falls below a certain threshold. The quality of the match, therefore, depends crucially on factors such as a worker's productivity, which is influenced by characteristics that are likely to be observable after some time on the job, e.g. a worker's skills, reliability, absenteeism and working style with respect to the job. The model therefore highlights the potential for job separation to occur if the worker's revealed productivity is deemed too low, leading to a lower match quality.

This framework suggests that many factors associated with homelessness could adversely affect a worker's productivity. These include high levels of mental stress, poor physical health, drug abuse, lack of proper time structure and problems associated with the condition of homelessness itself, such as frequent moves and living in affordable but sub-standard housing in inconvenient locations. All these challenges are likely to harm a worker's productivity at work, thus reducing the quality of the job match as measured by output performance and increasing the probability of job loss.

Many of the factors discussed above are also likely to adversely affect job finding for homeless people. Some factors, however, are likely to matter more to retaining a job. For example, drug problems, frequent moves, the inability to afford transportation or a lack of time are likely to have a much worse effect on retaining a job compared to finding one. On the other hand and as mentioned previously, factors such as the level of education are more important for entry decisions but are unlikely to affect job loss outcomes. Therefore, it is important to consider the effect of homelessness on employment entry and exit separately.

Overall, the observed empirical relationship between homelessness and employment entry and exit can stem from personal demographic and socio-economic factors, such as the level of education; factors such as health (mental and physical), drug use and social networks, which could be related to both homelessness and employment, thus becoming potentially endogenous; personal unobserved time-invariant factors that can affect homelessness and employment outcomes, such as workers' preferences, motivation, ability to cope with stressful life situations and self-esteem; and several aspects of homelessness itself, such as frequent moves, difficulty ensuring sufficient personal hygiene and living in inconvenient locations. My empirical model controls for time-invariant unobservable factors and many of the observable demographic, socio-economic, health and social network factors, thus minimizing the possibility of omitted variable bias. This study also addresses the possibility of reverse causation by modelling the impact of homelessness in wave *t* on employment transitions from wave *t-1* to *t*, thus allowing an examination of the causal effect of homelessness on employment entry and exit.

3. The Journeys Home Data and Measures

In Australia, income support payments (e.g. unemployment, family benefits, disability support payments, rent assistance or housing benefits) are provided through one central agency called Centrelink. The targeted population for Journeys Home (JH) survey was identified by the Melbourne Institute researchers as all Centrelink customers (1) aged 15 years or above; (2) in receipt of any social support payment at any time during the 28 days preceding 27 May 2011; and (3) flagged by Centrelink as homeless or at risk of homelessness or identified by Melbourne Institute researchers as having characteristics that made them vulnerable to homelessness (Wooden et al., 2012).[2] These rules resulted in a total in-scope population of 138,091 people, from which a stratified random sample of 2,992 people was selected for an interview. Of these, 1,682 people (response rate: approximately 62%) agreed to participate in the wave 1 interviews. The wave 1 interviews were conducted in September–November 2011, and five follow-up interviews were conducted at approximately 6-month intervals. The initial response rate of 62% is high compared with other national and international studies targeting disadvantaged populations (O'Callaghan et al., 1996; Randall & Brown, 1996; Weitzman, Knickman, & Shinn, 1990). Given that a large majority of homeless people in Australia or those vulnerable to homelessness receive some form of social assistance from Centrelink, the JH sampling frame has an advantage in that it provides a much wider representation of the population at risk of homelessness. JH respondents are amongst the most disadvantaged group of Australians. They

[2] Centrelink defines a person as homeless if he or she is without conventional accommodation (e.g. sleeping rough, squatting or living in a car) or is living in short-term temporary arrangements (e.g. emergency accommodations, youth shelters or with friends or family). People who are 'at risk' of homelessness are defined as those living in a boarding house, caravan park or any accommodation that falls below minimum community standards on a medium- or long-term basis. However, Centrelink might miss people who are not prepared to disclose their details and/or who do not engage with Centrelink frequently and thus are less likely to be flagged. Therefore, Melbourne Institute researchers used statistical techniques to augment the homeless and 'at risk' of homelessness populations flagged by Centrelink with a group of Centrelink customers who had not been flagged as homeless or 'at risk' of homelessness by Centrelink but nonetheless who had characteristics similar to those who had been flagged.

have considerably worse housing and non-housing outcomes than the general Australian population (for a detailed description of the JH sampling frame, see Wooden et al. (2012)).

Each wave of the JH survey contains rich information on respondents' past and present housing situations, including their experiences of homelessness between waves and their homelessness status at the interview date. The JH survey also contains information about respondents' employment experiences, such as their current employment status. It also collects information on several other factors, including demographic characteristics, family background and personal circumstances, such as health and incarceration. All these features of the JH survey data provide a unique opportunity to examine the causal effect of homelessness on employment transitions. My analysis draws on data from all six waves of the JH Survey.

3.1 Measuring Employment

My outcome measures are binary indicators of entry into and out of employment, respectively. I define a person's employment status at time/wave t using a binary indicator that takes a value of 1 if the person was employed at the time of the interview and a value of 0 if the person was not employed. I then use the binary measure of being employed at wave t to define wave-by-wave transitions in employment status.

In this framework, people who are not employed at wave t-1 will constitute the sample at risk of transitioning into employment at wave t, and people who are employed at previous wave t-1 will constitute the sample at risk of transitioning out of employment at wave t. Consequently, my two main outcome variables are as follows: (1) transition into employment that takes a value of 1 if a person transitioned from non-employment at wave t-1 to employment at wave t and a value of 0 if he/she remained unemployed at both the waves and (2) transition out of employment that takes a value of 1 if a person transitioned from employment at t-1 to non-employment at wave t and a value of 0 if he/she remained employed at both the waves.

These employment data have some limitations. When examining the employment transition outcomes, it is ideal to examine all the spells of employment and unemployment. In JH survey data, I can observe the respondents' employment status at each wave. However, I cannot observe all the instances of job holding and job loss during the reference period for the respondents, i.e. the JH data lack detailed information on respondents' employment histories. If the employment spells are short, my employment measure will not capture all the employment a respondent might have held between interviews. Therefore, the employment measure I use in this analysis is not the perfect measure. The results of the analysis in this study thus must be cautiously interpreted due to some of the instances of employment and unemployment spells unobserved due to the data collection method.[3]

3.2 Measuring Homelessness

There is no universally accepted definition of homelessness. I follow Chamberlain & MacKenzie, (2008) and adopt a "cultural" definition of homelessness and use the Melbourne Institute's broad point-in-time measure of homelessness (Bevitt, Chigavazira, Scutella, Tseng, & Watson, 2014). Hence, the binary measure of point-in-time homelessness takes a value of 1 (= yes) if a respondent was primary (without accommodations), secondary (staying rent-free with relatives or friends temporarily or staying temporarily in accommodations that fall below community standards, such as caravan, boarding house, hotel or crisis accommodation) or tertiary homeless (staying in a caravan, boarding house, hotel or crisis accommodations on a long-term basis) at the date of the interview and takes a value of 0 otherwise.

The Melbourne Institute's measure of homelessness has many advantages. Unlike the ABS's point-in-time measure of homelessness (Bevitt et al., 2014), it incorporates broad housing situations, such as living in a caravan or boarding houses on a long-term basis, that are not considered to meet minimum community standards as per Australian society. However, it also has some limitations. If spells of homelessness are brief and people tend to move in and out of homelessness frequently (Cobb-Clark, Herault, Scutella, & Tseng, 2016), my point-in-time measure might miss some episodes of homelessness that people might have experienced in between waves and that could have affected employment.

Accordingly, in a sensitivity analysis, I consider the 6-month homeless measure available in the JH data, which is a binary indicator for experiencing homelessness at any point during the reference period. However, one limitation of this 6-month measure of homelessness is that apart from including people experiencing primary, secondary and tertiary homelessness (as with my primary homeless measure), it also considers people living with friends or relatives on a long-term basis as homeless. Consequently, the incidence of homelessness is considerably higher when this measure is used. In the sensitivity analysis, I also consider the ABS's point-in-time measure provided in the JH data. As mentioned earlier, the ABS measure excludes

[3] The JH survey also includes a question that asks respondents to recall the proportion of time they spent without paid employment in last 6 months before the JH survey for wave 1 and between the interviews for waves 2–6 (ENY6MP and ENYRPP). However, there is a large amount of missing data for these proportion-based measures because fewer people answered the proportion these questions in the JH data; thus, I could not use this measure to estimate my econometric model due to the small cell size.

housing situations such as living in a caravan or boarding houses on a long-term basis from the definition of homelessness, unlike my primary homeless measure.

3.3 Explanatory Variables

Several studies suggest that men and women differ noticeably in their incidences and experiences of homelessness (Cobb-Clark & Zhu, 2015; Diette & Ribar, 2015; McVicar, 2016) and employment outcomes (Cobb-Clark & Zhu, 2015). Unfortunately, preliminary analyses suggested that the sample size is not large enough to estimate models separately for men and women for this study. Hence, I carry out all my empirical analysis for the pooled sample of men and women and include a control for gender. In addition, in a sensitivity analysis, I estimate models that examine the interaction effect of homelessness status and gender on employment transitions.

The literature suggests that a range of personal and background factors are likely to be associated with employment entry and exit. These include the respondents' demographic characteristics and childhood experiences, which could affect a person's job search and suitability for a job as well as the quality or 'experience' of the job match. The rich nature of the JH data allows me to account for many of these factors in my multivariate model.

I control for time-invariant factors that include an indicator for identifying as Aboriginal or a Torres Strait Islander; an indicator for migrating from a non-English speaking country; an indicator for being lesbian, gay or bisexual; an indicator for being incarcerated before the JH survey; an indicator for whether the respondent experienced any physical and sexual violence in childhood from someone the respondent lived with or someone else; and an indicator for childhood homelessness. In addition, I include an indicator for whether information on childhood sexual violence was missing for the person.

I further account for the respondent's age (with a quadratic in age) and three indicators for the respondent's level of education (completing a university degree, completing year 12 and completing years 10–11). I also control for job market conditions by including the measure of the person's current SA4 area of residence to link each observation for the person to the area's 6-month average unemployment rate for the current period.

The conceptual framework also points to many observable personal characteristics, such as health, drug use and family characteristics that are likely to impact finding and keeping employment. However, each of these variables is potentially endogenous and possibly influenced by employment outcomes. Therefore, I measure these time-varying variables at wave *t-1*, i.e. I include lagged values of these variables in my model. These include indicators for living in a rural or bounded area or in a small city at *t-1* (the reference category is living in a large city at *t-1*); an indicator for being in formal or de facto marriage at *t-1*; the number of children under 18 living with the respondent at *t-1*; and an indicator for having a long-term health and disability condition at *t-1*. I include a binary control for whether information on long-term disability status is missing at *t-1*. I also include variables to account for physical health, mental health and substance abuse measured at wave *t-1*. These include an indicator of self-assessed poor health at *t-1*, an indicator for whether the respondent has ever been diagnosed with a psychological disorder at *t-1*, a measure for the number of times in the previous month the respondent had five or more alcoholic drinks in a day at *t-1* and an indicator for marijuana use one or more days per month at *t-1*. I also include two binary variables indicating that information on the person's psychological diagnosis and that drinking behaviour is missing at *t-1*. Finally, I also include lagged values of an indicator for having employed friends to capture network advantage and an indicator for whether the person is registered with a job agency at *t-1*.

3.4 Analysis Sample

This study investigates employment transitions; therefore, I only select persons who participated in interviews for at least three consecutive waves of the JH survey, who were at least 18 years old at wave t-1 and less than 55 years old at the time of an interview, who completed the interviews without assistance from family or friends, and who have non-missing information on employment and homelessness measures used in the analysis. To maximize the remaining sample size, I assign a zero for missing values and include dummy controls for missing responses for variables with more than 50 missing responses (including the measures for childhood sexual abuse, long-term disability, psychological diagnosis and drinking behaviour). For other measures with lower levels of item non-response, I drop observations with missing values. These criteria result in an analysis sample of 1,291 unique people with 5,326 person-wave observations.

4. Descriptive analysis

I begin by analysing the different patterns of employment observed among JH respondents for the analysis sample. I examine the incidence of four types of employment patterns: [4](1) those who were never employed at the interview times in all waves for which they reported their employment statuses; (2) those who were always employed at the interview times in all waves for which they reported their employment statuses; (3) those who were not employed in the majority (less than 50% of the time employed) of waves at the interview times for which they reported their employment statuses; and (4) those who were employed in the majority (greater than or equal to 50% (but < 100%) employed) of waves at the interview times for which they reported their employment statuses.

Table 1. Different patterns of employment for the analysis sample

Employment patterns among JH respondents over six waves	Frequency (Person-wave)	Frequency (Person)	Percent (Person)
Never employed	2,611	646	50.0
Always employed	371	85	6.6
Not Employed more than half of time	1,301	316	24.5
Employed half or more than half of the time	1,043	244	18.9
Total	5,326	1,291	100

Notes: The statistics reported in the table were calculated using unweighted longitudinal data from the JH survey.

Table 1 shows the incidence of these employment patterns.[5] For a person to contribute to the multivariate analysis, he/she needs to have had experienced one or more transitions in employment state. As seen in Table 1, it is clear that 731 (646+85) persons did not experience any variations in their employment states over six waves; thus, their data will not contribute any transitions to the multivariate analysis. The effective sample size for the multivariate analysis is therefore 2,344 person-wave observations on 560 persons who experienced variations in their employment statuses over six waves. Table 1 shows that JH data do provide a sufficient sample of people with within-variation in employment states to support the analysis of employment transitions.

Table 2 shows the means and standard deviations of variables used in the analysis conditional on homeless status at wave t-1 for the analysis sample. The estimates indicate that

[4] Based on a person's employment status at the time of the interview for each wave, I constructed a six-character string for each person indicating his/her employment state at the time of the interview at each wave. A value of 1 in the string indicates that a person was employed, a value of 0 indicates no employment, and a value of 9 indicates a missing response. Based on these strings, I create summary patterns of employment to analyse these four categories.

[5] Table A1 shows the proportions of time people were not employed over the waves for which they had non-missing employment data for the entire JH sample.

the incidence of homelessness is significantly higher for men. Among those who were homeless at t-1, 70% are men. Significant differences are seen in the rate of employment between housed and homeless people. Only 18.9% of those who were homeless at t-1 are employed at t compared to 29.3% of those who were housed at t-1. The overall rate of employment among JH respondents is very low. On average, around 73% of respondents report not working at the time of the interview. This figure is high compared to the general rate of unemployment in Australia, which averaged around 5.7% from 2011 until 2016 (ABS, 2016b).

Comparisons of the demographic, background and other characteristics indicate that compared to people housed at t-1, people homeless at t-1 are on average significantly more likely to be older, to have a history of incarceration, to have some disability, to be in poor health, to consume five or more drinks per day more times in a month and to use marijuana one or more times in a month. In addition, people who are homeless at t-1 are significantly less likely to be married, more likely to have fewer dependent children, more likely to be registered with a job agency and less likely to have any employed friends.

The differences in the level of education between those housed at t-1 and homeless at t-1 are statistically significant but not very different in terms of magnitude. It is worth noting that the level of education is low among all the JH respondents. Few JH respondents received education beyond high school; only 3.7% of the respondents report having a university degree, which is considerably lower than the adult Australian population. For the period from 2011 to 2016, around 25% of adult Australians on average had a bachelor degree or above (ABS, 2016a). Table 2 suggests that JH respondents are an extremely disadvantaged group that not only face or risk facing housing insecurity but also fare worse on other economic and non-economic outcomes compared to the general Australian population. Altogether, Table 2 provides evidence of the presence of many characteristics among the JH respondents that negatively impact their ability to find and keep a job.

Table 2. Summary statistics for analysis variables conditional on the homelessness status *t-1*

Variable	All Mean	All Std. Dev.	Housed *t-1* Mean	Housed *t-1* Std. Dev.	Homeless *t-1* Mean	Homeless *t-1* Std. Dev.	Min	Max
Gender (Female=1)	0.463	0.499	0.501	0.500	0.300***	0.458	0	1
Employed at the time of interview	0.273	0.446	0.293	0.455	0.189***	0.392	0	1
<u>Demographic/background variables</u>								
Abor. or Torres St. islander	0.161	0.368	0.159	0.365	0.172	0.378	0	1
Immigrant from non-Eng. country	0.063	0.243	0.065	0.247	0.055	0.228	0	1
Bi/gay/lesbian	0.078	0.269	0.080	0.271	0.073	0.260	0	1
Childhood physical or sexual violence	0.695	0.461	0.690	0.463	0.716*	0.451	0	1
Homeless as child	0.471	0.499	0.474	0.499	0.457	0.498	0	1
Hist. of incarceration before JH	0.317	0.465	0.292	0.455	0.423***	0.494	0	1
Age at interview	32.180	10.977	31.436	10.780	35.376***	11.247	18	55
Age squared / 100	11.560	7.617	11.044	7.415	13.778***	8.065	3.24	30.25
Completed Year 10 or 11	0.387	0.487	0.381	0.486	0.411*	0.492	0	1
Comp. Year 12 or more (no degree)	0.441	0.497	0.452	0.498	0.395***	0.489	0	1
Completed university degree	0.037	0.189	0.040	0.197	0.024**	0.153	0	1
Avg. Local unemployment rate (6m)	5.829	1.578	5.850	1.586	5.741**	1.542	1.5	10.883
<u>Lagged endogenous variables</u>								
Married or de-facto t-1	0.235	0.424	0.261	0.439	0.125***	0.331	0	1
Number of dep. Children t-1	0.467	0.917	0.523	0.958	0.223***	0.661	0	7
Disability t-1	0.447	0.497	0.430	0.495	0.520***	0.500	0	1
Small city t-1	0.165	0.371	0.169	0.375	0.148	0.356	0	1
Rural or boundary area t-1	0.048	0.214	0.047	0.211	0.055	0.228	0	1
Self-reported poor health t-1	0.114	0.318	0.107	0.309	0.144***	0.352	0	1
Diagnosed with psych. Condition t-1	0.686	0.464	0.684	0.465	0.698	0.460	0	1
Times 5+ drinks/day in a month t-1	3.329	6.619	3.076	6.247	4.415***	7.936	0	30
Marijuana use 1 or more days/month t-1	0.277	0.448	0.252	0.434	0.385***	0.487	0	1
Registered with any job agency to help find job t-1	0.496	0.500	0.489	0.500	0.530**	0.499	0	1
Any employed friends t-1	0.611	0.488	0.631	0.483	0.523***	0.500	0	1
Log SA4 area apartment/flat rental price (6m)	5.768	0.232	5.761	0.229	5.796***	0.245	5.187	6.394
Person-wave observations	5,326		4,321		1,005			

Note: The statistics reported in the table were calculated using unweighted longitudinal data from the JH survey. Asterisks indicate statistically significant differences in means between those housed at t-1 and homeless at t-1 based on t-test. * Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level. P-values for t-test were also computed considering the panel nature of the data (using syv mean test), and the results were qualitatively similar.

Table 3 shows the incidence of transitions into and out of employment conditional on homelessness status at t-1 for the analysis sample. I observe 486 transitions into employment from wave t-1 to t (a transition rate of 12.3%) and 410 transitions out of employment from wave t-1 to t (a transition rate of 29.7%). When examining the transitions into employment between housed and homeless persons, the table reveals that people who were homeless at t-1 report fewer transitions into employment from t-1 to t (10.6% transition rate) compared to people who were housed at t-1 (12.8% transition rate). A Pearson chi-square test, however, shows that these differences in the relationship distribution are only marginally statistically significant (p-value = 0.092). Based on this result, I find weak evidence of an association between homelessness and employment entry. In terms of transitions out of employment between housed and homeless persons, the table reveals that a larger proportion of people who were homeless at t-1 experienced transitions out of employment from t-1 to t (39.5% transition rate) compared to people who were housed at t-1 (28.3% transition).[6] A Pearson chi-square test shows that these differences in the relationship distribution are statistically significant at 1% (p-value = 0.003). Hence, there is strong evidence that homelessness is positively associated with transitions out of employment.

Table 3. Transitions into and out of employment from wave *t-1* and *t* conditional on homelessness status *t-1* (column frequencies)

	Homeless at *t-1*		
	No	Yes	Total
Transition into employment from t-1 to t			
No (0)	2,711	749	3,460
	87.2	89.4	87.7
Yes (1)	397	89	486
	12.8	10.6	12.3
Total	3,108	838	3,946
	100	100	100
Pearson chi2	P-value=0.092		
Transition out of employment from t-1 to t			
No (0)	869	101	970
	71.6	60.5	70.3
Yes (1)	344	66	410
	28.4	39.5	29.7
Total	1,213	167	1,380
	100	100	100
Pearson chi2	P-value=0.003		

Notes: The statistics reported in the table were calculated using unweighted longitudinal data from the JH survey.

[6] Note that the actual or absolute number of transition in and out of employment conditional on being homeless at t-1 is low.

5. Empirical Methodology

As discussed previously, I model the employment transitions using a discrete-time Markov process in which the transition probability of being in a specific employment state at time *t* depends on the employment state at time *t-1*. Specifically, I consider two employment statuses: Y = {0-not employed; 1-employed}. Hence, the probability of transitioning into employment in my model is the conditional probability that the individual moves into state 1 at time *t* given that he/she was in state 0 at time *t-1*. Similarly, the probability of transitioning out of employment in my model is the conditional probability that the individual moves to state 0 at time *t* given that he/she was in state 1 at time *t-1*.[7] Thus, modelling employment transitions requires conditioning the current employment status upon the past employment status which generates an endogeneity problem called the initial conditions problem, discussed in Heckman (1981a). This issue arises because the beginning of the observation period (wave 1) does not coincide with the beginning of the stochastic process generating the person's employment dynamics. Hence, one needs to make a further assumption about the relationship between Y_{i1} and unobserved heterogeneity when modelling transition probabilities. If the respondent's initial conditions are correlated with unobserved heterogeneity, as is possible in the context of my study, not accounting for the initial conditions problem will lead to overstating the level of state dependence. To deal with this issue, Heckman suggested estimating the empirical model jointly with the distribution of the initial sample observation, where the initial sample observation is modelled as a function of the pre-sample information and the individual specific component of the error term. Therefore, I control for endogenous initial conditions by applying Heckman's approach.

There are two key challenges in determining the causal effect of homelessness on employment entry and exit: the possibility of simultaneity or reverse causality and the issue of endogenous selection into homelessness based on unobservable characteristics. The endogeneity of homelessness is an issue because the unmeasured individual characteristics are likely to affect entry and exit into employment, and they might also influence a person's homelessness status, thus rendering homelessness endogenous to employment outcomes. These unmeasured characteristics could include individual preferences, self-esteem, ability to cope with stressful life events and a difficult family environment.

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[7] Hackman (1981) considered the case of a lagged binary dependent variable Y_{it-1}. My model is essentially the same, but I implement it in an alternative way. I estimate separate equations for $Y_{it-1} = 0$ (transition into employment equation) and $Y_{it-1} = 1$ (transition out of employment equation). In other words, I interact the dummy Y_{it-1} with all the explanatory variables in the entry and exit equations in my model.

To overcome the possibility of reverse causality, I focus on studying the effect of homelessness at wave *t-1* on employment entry and exit from *t-1* to *t*. Within each wave, I cannot determine whether a person's homelessness or housing status necessarily precedes his or her employment status. By ensuring that homelessness precedes movement in and out of employment, I rule out the possibility of reverse causality.[8]

To address the issue of selection based on common unobserved confounders, I estimate a model that allows for person-specific unobserved heterogeneity through correlated random effects terms (DerSimonian & Laird, 1986; Laird & Ware, 1982; Ribar, 2005; Stiratelli, Laird, & Ware, 1984). In addition, the richness of the JH data allows me to account for the confounding influences of many observable personal characteristics in my empirical model.

5.1 Empirical Model

My empirical model involves jointly estimating probit models for employment transitions along with the reduced form equation for contemporaneous homelessness to account for endogenous selection. I also estimate an equation for a person's employment status at wave 1 to account for initial conditions. A detailed description of each of these equations is as follows:

Transition into employment (from t-1 to t)

Let Y^*_{Eit} be a latent index representing a person's entry into employment in period *t* conditional on being not employed in period *t-1* such that

$$Y^*_{Eit} = H_{it-1}\beta_E + S_i\gamma_E + X_{it}\alpha_E + N_{it-1}\pi_E + \eta_{Ei} + \epsilon_{it} \quad (1)$$

The observed transition is determined as follows: Y_{Eit}=1 (the person transitions into employment) if $Y^*_{Eit} > 0$ and Y_{Eit}= 0 otherwise (the person remains unemployed). H_{it-1} is a binary indicator of a person's homelessness status at wave *t-1*; S_i is a vector of time-invariant characteristics; X_{it} is a vector of exogenous observed characteristics at time t; N_{it-1} is a vector of lagged observed endogenous time-varying characteristics; η_{Ei} is the person-specific unobserved time-invariant factors or a permanent component associated with employment entry; and ϵ_{it} is the transitory error term.

[8] An alternative empirical approach could be to perform a duration analysis and estimate hazard models for entry and exit. However, such an analysis requires detailed retrospective data on respondents' employment histories. Unfortunately, the JH survey does not provide detailed retrospective employment data to analyse spells. Hence, the estimation strategy adopted in this study is suited to the nature of the JH employment data.

Transition out of employment (from t-1 to t)

Let Y^*_{Lit} be a latent index representing a person's exit from employment in period *t* conditional on being employed in period *t-1* such that:

$$Y^*_{Lit} = H_{it-1}\beta_L + S_i\gamma_L + X_{it}\alpha_L + N_{it-1}\pi_L + \eta_{Li} + u_{it} \tag{2}$$

The observed transition is determined as follows: Y_{Lit}=1 (the person leaves employment) if $Y^*_{Lit} > 0$ and Y_{Lit}= 0 otherwise (the person remains employed). H_{it-1}, S_i , X_{it} and N_{it-1} are defined as in eq. (1); η_{Li} is the person-specific unobserved time-invariant factors or a permanent component associated with employment exit (or leaving); and u_{it} is the transitory error term.

The transitory error terms (ϵ_{it}, u_{it}) are assumed to be normally distributed random variables each with mean zero and are further assumed to be independent of each other and across waves. The permanent components (η_{Ei}, η_{Li}) are allowed to be correlated (the correlation coefficient is ρ_{EL}) with each other but are assumed to be independent of the transitory error terms: $\begin{bmatrix}\eta_{Ei}\\ \eta_{Li}\end{bmatrix} \sim N\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}\sigma_E^2 & \sigma_{EL}\\ \sigma_{EL} & \sigma_L^2\end{bmatrix}\right)$ where σ_E^2 andσ_L^2 are the variances of η_{Ei} and η_{Li}, respectively, and σ_{EL} is the covariance between η_{Ei} and η_{Li}. The presence of the permanent components or random effects allows for serial correlation in the unobserved determinants of a person's employment entry and exit, thus accounting for time-invariant, unobserved characteristics that might be associated with these employment transitions.

Probit equation for a person's homeless status at wave t

To account for the endogenous selection into homelessness (based on unobservables), I estimate equations (1) and (2) jointly with the reduced form equation for homelessness as a function of the random effects terms from the entry and exit equations. The presence of these random effects allows for correlation in the unobserved determinants of a person's employment entry and exit and homelessness and by accounting for this addresses the issue of endogenous selection into homelessness based on unobserved time-invariant confounders. Let H^*_{it} be the latent variable attached to H_{it} (a dummy variable which takes a value of 1 if a person is homeless at *t* and a value of 0 otherwise) such that:

$$H^*_{it} = S_i\gamma_H + X_{it}\alpha_H + N_{it}\pi_H + \lambda^*_E\eta_{Ei} + \lambda^*_L\eta_{Li} + \zeta_{it} \quad \text{where } H_{it} = \begin{cases} 1 & if \quad H^*_{it} > 0 \\ 0 & otherwise \end{cases} \tag{3}$$

ζ_{it} is the normally distributed error term assumed to be independent of the transitory errors in other equations and the permanent components. λ^*_E is the factor loading that represents the correlation between the individual time-invariant unobserved heterogeneity related to employment entry (from wave *t-1* to *t)* and homelessness status (at wave *t*). λ_L^* is the factor loading that represents the correlation between the individual time-invariant unobserved heterogeneity related to employment exit (from wave *t-1* to *t*) and homelessness status (at wave *t*). To achieve identification, equation (3) also includes an exclusion restriction that affects homelessness but not employment entry and exit: a log of the measure of the person's current SA4 area apartment/flat average 6-month rental price. It is important to note that this homelessness equation is an auxiliary model that is used primarily to address the endogeneity of homelessness and not a model to directly investigate the determinants of homelessness. Identification of the model is discussed in detail after the model description.

Probit equation for a person's employment state in wave 1

To account for endogenous initial employment conditions and to accommodate left-censored data, I use (Heckman, 1981b) approximate method for addressing the initial conditions problem and estimate an additional equation to model a person's employment decision at wave 1 along with equations (1), (2) and (3):[9]

Let Y_{i1}^* be a latent index representing a person's employment participation in the initial period such that:

$$Y_{i1}^* = S_1\gamma_1 + X_{i1}\alpha_1 + \lambda_E\eta_{Ei} + \lambda_L\eta_{Li} + \nu_{i1} \quad (4)$$

The actual participation is determined as follows: Y_{i1}=1 (initially employed) if $Y_{i1}^* > 0$ and Y_{i1}= 0 otherwise. ν_{i1} is the normally distributed error term assumed to be independent of the subsequent transitory errors and permanent components. λ_E, and λ_L are the factor loadings that represent the correlation between the individual time-invariant unobserved heterogeneity associated with entry and exit and employment status at wave 1, respectively.

The complete model for each person is the system consisting of four equations: employment entry, employment exit, homelessness and initial conditions. The model parameters are estimated by maximum likelihood using the *gsem* procedure available in the Stata package.

[9] An alternate approach to address the initial conditions problem when examining employment transitions is to drop ongoing spells and only examine new spells on entry and exit. However, in short panel survey such as JH, adopting this approach will lead to a substantial loss of data and could result in a less-representative sample.

5.2 Identification

Formally, the identification of my system of equations with latent variables or random effects is made possible by placing restrictions on the model parameters and covariance restrictions. Specifically, I impose parametric restrictions on the distribution of the error terms. These include the assumption of normally distributed error terms and the assumption that all transitory errors are independent of each other and permanent components. Estimation also involves using standard normalization conventions, i.e. normalizing the coefficients of the permanent components in the entry and exit equations to be one to achieve identification (Skrondal & Rabe-Hesketh, 2004).

It might, however, be considered weak to solely rely on parametric restrictions for identification. Thus, to obtain more reliable estimates, I use the timing of exogenous variables and exclusion restrictions. First, the employment entry and exit transitions depend on the contemporaneous values of the exogenous variables in the vector X (i.e. $Y_{Eit}^{*} = f(X_{it})$ and $Y_{Lit}^{*} = f(X_{it})$), whereas the lagged homelessness variable depends on the lagged or predetermined values of the exogenous variables in the vector X through equation (3) (i.e. $H_{it-1} = f(X_{it-1})$. The vector X includes six variables: age, age squared, the local unemployment rate and three measures for the level of education. However, the three education measures exhibit very limited within-variation in the JH data (see table A2), and the use of two age variables might not be considered appropriate to form instruments. These restrictions only leave the local unemployment rate variable to provide a reliable instrument. Therefore, I also include an exclusion restriction that affects homelessness but not employment entry and exit. As an exclusion restriction, I use a log of the measure of the person's current SA4 area apartment/flat average 6-month rental price. High rental costs can lead to homelessness for people who cannot afford to pay higher rents (Burt et al., 1999; Tucker, 1991). For people such as low-income earners and welfare recipients who might spend over 30% of their incomes on rent, an increase in rental rates can lead to housing stress and homelessness (ACOSS, 2015). On the other hand, the average 6-month rental rate of the area in which a person lives is unlikely to have any direct effect on a person's decision to enter or exit employment. Thus, I include rental rate as an explanatory variable for homelessness in eq. (3) but not in the employment equations (1), (2) and (4). Overall, the timing of the local unemployment rate and the inclusion of the rental rate in eq. (3) provide instruments that result in the conditions necessary for empirical identification of the effect of homelessness on employment entry (β_E) and employment exit (β_L), my two endogenous variables.

6. Multivariate Results

I begin by presenting the results from the baseline multivariate model, which includes the employment entry and exit equations (eqs. 1 and 2) and the initial conditions equation (eq. 4), followed by the results from the full multivariate model, which also includes the equation for homelessness (eq. 3).

Table 4 presents parameter estimates from two specifications of my baseline multivariate model. Each of the specifications account for endogenous initial employment conditions, time-invariant unobserved factors that might be associated with employment transitions and demographic and background factors. The first specification (Model 1), however, omits controls for potentially endogenous observable factors such as family structure, location, mental and physical health, drug use and friends' characteristics. The second specification (Model 2) includes these controls. However, both models treat homelessness as exogenous. The results from Model 1 suggest that homelessness is significantly positively associated with transitions out of employment. It is negatively associated with the transition into employment; however, the estimate is small in magnitude and not significant. The non-zero and significant values of factor loadings λ_E and λ_L indicate that the random effects (unobserved heterogeneity) in the entry and exit equations are correlated with the person's initial employment condition. Accounting for observed potentially endogenous factors, such as mental and physical health outcomes, drug abuse, family structure and friends' characteristics, in Model 2 leads to a decline in the magnitude of estimates of the effect of homelessness on employment entry and exit. However, the results remain qualitatively similar to the results from Model 1.

Table 4. Baseline model's regressions results for the effect of homelessness on employment entry and exit (treat homelessness as exogenous)

	Model 1: Without controls for lagged endogenous factors			Model 2: With controls for lagged endogenous factors		
VARIABLES	Transition into emp. t-1 to t	Transition out of emp. t-1 to t	Initially employed	Transition into emp. t-1 to t	Transition out of emp. t-1 to t	Initially employed
Homeless *t-1*	-0.061	0.376**		-0.033	0.313**	
	(0.090)	(0.148)		(0.090)	(0.143)	
<u>Demographic/background controls</u>						
Gender (female=1)	-0.606***	0.130	-0.206**	-0.425***	0.110	-0.203**
	(0.094)	(0.136)	(0.102)	(0.096)	(0.125)	(0.103)
Abor. or Torres St. islander	-0.157	0.260	-0.309**	-0.189*	0.236	-0.316**
	(0.116)	(0.191)	(0.136)	(0.112)	(0.174)	(0.137)

(Continued)

Table 4. Continued

Immigrant from non-English country	0.157	0.162	-0.208	0.091	0.249	-0.220
	(0.169)	(0.231)	(0.192)	(0.162)	(0.210)	(0.194)
Bi/gay/lesbian	0.231	0.146	0.287*	0.187	0.080	0.289*
	(0.154)	(0.207)	(0.168)	(0.147)	(0.190)	(0.170)
Childhood physical or sexual violence	-0.024	-0.049	-0.117	0.052	-0.180	-0.116
	(0.094)	(0.134)	(0.102)	(0.091)	(0.123)	(0.103)
Homeless as child	-0.212**	0.120	-0.169	-0.185**	0.098	-0.176
	(0.098)	(0.143)	(0.112)	(0.094)	(0.128)	(0.113)
Hist. of incarceration before JH	-0.267***	0.349**	-0.265**	-0.248**	0.272*	-0.267**
	(0.102)	(0.155)	(0.116)	(0.099)	(0.140)	(0.117)
Age at interview	-0.064**	-0.027	-0.045	-0.036	-0.043	-0.045
	(0.030)	(0.045)	(0.030)	(0.030)	(0.041)	(0.031)
Age squared / 100	0.041	0.051	0.060	0.019	0.066	0.060
	(0.042)	(0.064)	(0.044)	(0.043)	(0.058)	(0.045)
Completed Year 10 or 11	0.163	0.214	0.268*	0.097	0.224	0.275*
	(0.141)	(0.254)	(0.145)	(0.137)	(0.229)	(0.146)
Completed Year 12 or more (no degree)	0.778***	-0.190	0.633***	0.623***	-0.077	0.636***
	(0.144)	(0.250)	(0.149)	(0.139)	(0.223)	(0.151)
Completed university degree	1.211***	-0.114	0.771***	1.017***	0.105	0.771***
	(0.253)	(0.351)	(0.272)	(0.242)	(0.315)	(0.275)
Avg. Local unemployment rate (6m)	-0.061***	0.069**		-0.065***	0.067**	
	(0.023)	(0.033)		(0.023)	(0.031)	
<u>Lagged endogenous controls</u>						
Married or de-facto t-1				0.038	0.154	
				(0.088)	(0.120)	
Number of dep. Children t-1				-0.074	-0.031	
				(0.051)	(0.068)	
Disability t-1				-0.294***	0.332***	
				(0.080)	(0.111)	
Small city t-1				-0.133	0.063	
				(0.102)	(0.149)	
Rural or boundary area t-1				0.230	-0.238	
				(0.160)	(0.218)	
Self-reported poor health t-1				-0.195	0.190	
				(0.130)	(0.192)	
Diagnosed with psych. Condition t-1				-0.047	0.144	
				(0.088)	(0.117)	
Times 5+ drinks/day in a month t-1				-0.003	0.019**	
				(0.006)	(0.008)	
Marijuana use 1 or more days/month t-1				-0.111	0.030	
				(0.086)	(0.122)	
Registered with any job agency to help find job t-1				0.483***	0.382***	
				(0.077)	(0.095)	
Any employed friends t-1				0.277***	-0.168	
				(0.074)	(0.109)	

(Continued)

Table 4. Continued

λ$_E$	1.000 (0.000)		0.519*** (0.149)	1.000 (0.000)		0.663*** (0.201)
λ$_L$		1.000 (0.000)	-0.350*** (0.112)		1.000 (0.000)	-0.508*** (0.182)
Cov (η_{Ei}, η_{Li})		-0.2614			-0.0502	
Var (η_{Ei})		0.7152			0.5379	
Var (η_{Li})		0.9562			0.5764	
Log likelihood		-2807.0092			-2707.7513	

Note: Unweighted longitudinal data from the JH survey for 560 persons (2,344 obs.). In addition to the listed coefficients, the models include intercepts and controls for missing responses for childhood sexual abuse, long-term disability, psychological diagnosis and drinking behaviour. Standard errors in parentheses. * Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level.

The findings from Models 1 and 2 in Table 4 are qualitatively similar to the descriptive results from Table 3, where there is weak or no conclusive evidence of the negative effect of homelessness on employment entry; however, homelessness is found to be significantly positively associated with employment exit. Models 1 and 2, however, do not account for the selection (on unobservables) associated with homelessness. This issue is addressed in Model 3 in Table 5. This model not only controls for endogenous initial employment conditions and time-invariant unobserved factors that might be associated with employment transitions but also accounts for time-invariant unobservable factors that could be related to both employment transitions and homelessness through equation 3, thus addressing the issue of endogenous selection into homelessness.

Table 5. Full model's regressions results for the effect of homelessness on employment entry and exit (treat homelessness as endogenous)

	Model 3: With full set of controls and with the equation for homelessness			
VARIABLES	Transition into emp. t-1 to t	Transition out of emp. t-1 to t	Homeless at t	Initially employed
Homeless *t-1*	0.076 (0.105)	0.089 (0.161)		
<u>Demographic/background controls</u>				
Gender (female=1)	-0.373*** (0.088)	0.006 (0.109)	-0.410*** (0.096)	-0.165* (0.088)
Abor. or Torres St. islander	-0.158 (0.103)	0.152 (0.151)	0.261** (0.111)	-0.271** (0.117)
Immigrant from non-English country	0.130 (0.149)	0.196 (0.184)	-0.091 (0.179)	-0.185 (0.168)
Bi/gay/lesbian	0.130 (0.134)	0.062 (0.166)	0.018 (0.160)	0.261* (0.145)

(Continued)

Table 5. Continued

Childhood physical or sexual violence	0.075	-0.173	0.048	-0.101
	(0.084)	(0.108)	(0.095)	(0.089)
Homeless as child	-0.152*	0.059	0.089	-0.144
	(0.086)	(0.111)	(0.097)	(0.097)
Hist. of incarceration before JH	-0.214**	0.199	0.114	-0.224**
	(0.091)	(0.123)	(0.099)	(0.101)
Age at interview	-0.036	-0.054	0.007	-0.039
	(0.028)	(0.036)	(0.027)	(0.026)
Age squared / 100	0.022	0.076	0.015	0.053
	(0.039)	(0.052)	(0.038)	(0.038)
Completed Year 10 or 11	0.112	0.188	-0.198*	0.262**
	(0.127)	(0.203)	(0.114)	(0.127)
Completed Year 12 or more (no degree)	0.556***	0.044	-0.400***	0.560***
	(0.128)	(0.196)	(0.117)	(0.128)
Completed university degree	0.927***	0.209	-0.653***	0.693***
	(0.221)	(0.277)	(0.252)	(0.235)
Avg. Local unemployment rate (6m)	-0.058***	0.057**	-0.021	
	(0.022)	(0.028)	(0.020)	
<u>Lagged endogenous controls</u>				
Married or de-facto t-1	0.040	0.121		
	(0.084)	(0.108)		
Number of dep. Children t-1	-0.072	-0.050		
	(0.048)	(0.061)		
Disability t-1	-0.284***	0.304***		
	(0.076)	(0.100)		
Small city t-1	-0.139	0.084		
	(0.096)	(0.133)		
Rural or boundary area t-1	0.184	-0.211		
	(0.151)	(0.196)		
Self-reported poor health t-1	-0.168	0.194		
	(0.123)	(0.177)		
Diagnosed with psych. Condition t-1	-0.032	0.060		
	(0.082)	(0.102)		
Times 5+ drinks/day in a month t-1	-0.002	0.016**		
	(0.006)	(0.007)		
Marijuana use 1 or more days/month t-1	-0.125	0.040		
	(0.081)	(0.110)		
Registered with any job agency to help find job t-1	0.473***	0.434***		
	(0.073)	(0.087)		
Any employed friends t-1	0.267***	-0.149		
	(0.070)	(0.100)		
<u>Contemporaneous variables in homelessness eq.</u>				
Married or de-facto			-0.634***	
			(0.082)	
Number of children			-0.248***	
			(0.048)	
Disability			0.144**	
			(0.065)	

(Continued)

Table 5. Continued

Small city			0.157	
			(0.100)	
Rural or boundary area			0.301**	
			(0.126)	
Self-reported poor health			0.117	
			(0.084)	
Diagnosed with psych. cond.			-0.102	
			(0.086)	
Times 5+ drinks/day in a month			0.004	
			(0.004)	
Marijuana use 1 or more days/month			0.155**	
			(0.068)	
Registered with any job agency to help find job			0.181***	
			(0.060)	
Any employed friends			-0.219***	
			(0.058)	
Log SA4 area apartment/flat rental price			0.932***	
			(0.191)	
λ_E , λ^*_E	1.000		-4.839**	1.067**
	(0.000)		(2.359)	(0.485)
λ_L , λ^*_L		1.000	5.146**	-0.941*
		(0.000)	(2.341)	(0.496)
Cov (η_{Ei}, η_{Li})		0.3223***		
Var (η_{Ei})		0.3662		
Var (η_{Li})		0.3316		
Log likelihood		-5374.2844		

Note: Unweighted longitudinal data from the JH survey for 560 persons (2,344 obs.). In addition to the listed coefficients, the models include intercepts and controls for missing responses for childhood sexual abuse, long-term disability, psychological diagnosis and drinking behaviour. Standard errors in parentheses. * Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level.

The results from model 3 indicate no significant effects of homelessness on employment entry or exit. Once I control for the confounding influences of person-specific unobserved characteristics, the positive effect of homelessness on employment exit declines considerably and becomes insignificant, while the negative effect of homelessness on employment entry becomes positive and remains insignificant. The large, significant values of the factor loadings in the homeless equations ($\lambda_E^* \neq 0$ and $\lambda_L^* \neq 0$) indicate strong evidence of selection, i.e. the presence of a strong correlation between unobservable person-specific determinants of homelessness and employment entry and exit.

These findings highlight the importance of accounting for selection effects. The association between homelessness and poor employment outcomes is mostly driven by unobserved person-specific characteristics, which increases a person's chance of being homelessness and remaining unemployed or leaving employment. These could include factors such as a poor ability to cope with stressful situations, poor judgement and planning, a lack of self-esteem, high risk-taking behaviour and difficult family situations. Once the effect of these unobserved confounding characteristics is considered, homelessness or a lack of a stable place to live per se does not affect a person's probability to transition into or out of employment. These findings are somewhat similar to the findings from Chigavazira et al. (2014), which also used JH data to identify associations between homelessness and employment. The study found weak or inconclusive evidence regarding the effect of homelessness on employment in the descriptive analysis and in the multivariate analysis. In the multivariate analysis, the authors used the fixed-effects approach and found a negative but small, insignificant effect of homelessness at t-1 on the probability of being employed at t.

One concern that may arise is that the finding of no effect of homelessness per se on employment entry and exit may reflect the fact that my analysis compares homeless people at *t-1* to those near homelessness or those very vulnerable to homelessness at *t-1*. To investigate this concern, I examined the housing situations of people I classify as homeless at t-1 and housed at t-1 in Table A4[10]. The results from the table clearly suggest that a large majority people in my reference category (housed at t-1) have very different housing situations from those classified as homeless at t-1. More than 70% of the people in my reference group (for both the analysis sample and the sample that contributes to the empirical analysis) are in long-term stable housing situations (living in rented or owner-occupied accommodations on a long-term basis) [11]. Therefore, it is reasonable to conclude that the empirical findings of this study are not driven by the lack of noticeable differences in the housing situations of people homeless at t-1 and those housed at t-1.

<u>Effects of Covariates</u>

The results from the final model (Model 3) indicate that women are significantly less likely to enter employment; however, there are no significant differences between men and women in terms of their probability of exiting employment. Furthermore, people who have experienced homelessness as children, people who have been incarcerated in the past, people living in areas with high unemployment rates and people who reported disabilities at wave t-1 are significantly less likely to enter employment from wave *t-1* to *t*. On the other hand, people who completed year 12 or higher or who completed a university degree are significantly more likely to enter employment compared to people with no schooling. Similarly, people who had

[10] By looking at the detailed composition of HSTATUS2, the variable I have used to define my homelessness measure.
[11] The remaining are those living with friends/family on a long-term basis (marginally housed) or in short-term rental accommodations (short-term rentals).

employed friends at wave *t-1* are significantly more likely to enter employment from wave *t-1* to *t*. People living in areas with high unemployment rates, people who reported disabilities at wave t-1 and people who binge drink on more days in a month are significantly more likely to leave employment.

These findings also reveal the importance of treating employment entry and exit as a separate process. Specifically, findings show that all factors that affect entry significantly need not necessarily affect exit significantly. For example, the findings suggest that being a woman, experiencing childhood homelessness and having a lower level of education significantly negatively affect a person's probability of entering employment. However, these factors do not have any significant effect on a person's probability of exiting employment. These empirical findings suggest that there are benefits of considering employment entry and exit separately to permit the effect of homelessness, as well as other factors, to differentially impact employment entry and exit.

7. Sensitivity Analysis

I examine the sensitivity of my results to alternative measures of homelessness and measures of labour force status. First, I consider the ABS's homelessness measure (HSTATUS1), which excludes housing situations such as living in a caravan or boarding houses on a long-term basis when defining homelessness, and estimate Model 3. The resulting estimate for the association between employment entry and homelessness from doing so is negative but still insignificant, and the association between employment exit and homelessness is negative, but it remains insignificant. I also find strong evidence regarding selection. Altogether, the use of ABS's homelessness measure does not qualitatively alter my final finding of no significant association between homelessness and employment entry and exit. The results of these sensitivity analyses are provided in Appendix A4.

Second, as discussed in section 3.2, if spells of homelessness are brief and people tend to move in and out of homelessness frequently (Cobb-Clark et al., 2016), my point-in-time measure of homelessness might miss some of the episodes of homelessness people might have experienced between waves that could have affected their employment. Hence, I estimate Model 3 using a 6-month homeless measure. Specifically, I use a binary measure of homelessness that takes a value of 1 if a person experienced primary homelessness; lived in a caravan, hotel, boarding house or crisis accommodation; or lived with friends, family or other relatives at any time during the 6 months before the wave 1 interview (HHMLSRP2) or during the reference period/time between subsequent interviews for waves 2–6 (HHMLS6M). I find that the association between employment entry and homelessness is negative and stronger, but it remains insignificant. The association between employment exit and homelessness is positive but weaker, and it remains insignificant. Again, there is strong evidence of selection. Overall, the results remain qualitatively similar, and they do not qualitatively alter my final finding of no significant association between homelessness and employment entry and exit. The results of these sensitivity analyses are provided in Appendix A5.

Third, my employment transition measures do not capture the quality aspect of jobs. It could be argued that the jobs homeless people engage in are primarily of low quality (such as casual work, work lasting for a few hours, etc.); thus, there is a higher probability of losing such jobs, which could drive my results. Unfortunately, the relatively small sample size does not allow the estimation of my empirical model if I define thresholds for entry and exit based on job characteristics. Nonetheless, I examined the differences in the job profiles (contract of employment, earnings and hours worked) of homeless and non-homeless people for my analysis sample in Table A6. The table suggests that there are no significant differences in the type of contract, work earnings and hours worked (i.e. quality) between those housed at t-1 and those homeless at t-1, implying that both housed and homeless individuals in the JH sample do the same quality of jobs if employed. Hence, these factors are unlikely to drive my employment transition results. The findings shown in Table A6 are very similar to the findings reported in the JH research reports (Bevitt et al., 2015). In addition, I redefine my outcome measures to capture transitions into and out of the labour force instead of transitions into and out of employment. The results again reveal the same pattern. In models treating homelessness as exogenous, the association between homelessness and labour force entry is not significant. However, being homeless is significantly positively associated with the transition out of the labour force. Thus, homeless and non-homeless people are not significantly different in terms of their probability of entering the labour force (i.e. being employed or searching for employment), but the experience of homelessness is significantly likely to make people move out of the labour force compared to non-homeless people. Once the endogeneity of homelessness is addressed, the estimate for the effect of homelessness on transitions out of the labour force becomes insignificant with strong evidence of selection, which suggests that the results are driven by unobserved personal factors that increase people's chances of being homeless and leaving the labour market. The results of these sensitivity analyses are provided in Appendices A7a and A7b.

I also estimate the specification that includes an interaction term between gender and homelessness at wave t-1 and find no significant interaction effects. The estimates suggest that homeless women are more likely to enter and less likely to exit employment compared to homeless men, possibly because they have more social support, but none of the estimates are significant. Moreover, the inclusion of the interaction between gender and the homeless outcome does not alter the main findings of the study. Therefore, the conclusions regarding the effect of homelessness on employment entry and exit remain robust. The results of this additional analysis are provided in Appendix A8.

8. Discussion and Conclusion

This is the first study to examine how the experience of homelessness affects a person's transitions into and out of employment. By taking advantage of the unique, rich longitudinal data from the JH survey, I estimate models that address the potential for reverse causality and account for confounding influences from many observable variables and unobservable time-invariant person-specific variables that might be related to employment transitions and homelessness. Eliminating concerns related to these two important issues permits my estimates to have a plausibly causal interpretation.

The descriptive analyses reveal that compared to people housed at *t-1*, people homeless at *t-1* experience significantly higher transitions out of employment. People homeless at *t-1* experience fewer transitions into employment compared to those housed at *t-1*; however, this association is only marginally significant. Findings from the descriptive analyses further reveal that JH respondents are a considerably disadvantaged group with several economic and social problems. The regression results from the empirical models that account for reverse causality but do not address the endogeneity of homelessness are similar to the descriptive findings that homelessness is significantly positively associated with transitions out of employment but that it has no significant effect on employment entry. The results from the final empirical model, which also addresses the endogeneity of homelessness, provide strong support for selection, i.e. a strong correlation between unobservable determinants of employment entry and exit and homelessness. After accounting for reverse causality and common unobservable confounders, the findings indicate no significant effect of homelessness per se on either employment entry or exit. A potential explanation for this null finding could be that the entire JH sample (both homeless and non-homeless people) is comprised of disadvantaged people in terms of low income, poor health, poor family situation, high drug use and incarceration rates, which might place them in very similar labour market prospects and situations regardless of their housing situations.

This study has some limitations. First, my econometric approach does not allow me to examine the immediate effect of homelessness on employment. Second, the job holding rate is low in the JH survey data and the data only offers six waves, which result in only five possible transition periods. This results in a relatively fewer amount of transitions observed in the data, leading to a relatively modest effective sample size. Third, while my estimation approach allows me to control for endogenous unobservable time-invariant factors and a rich set of exogenous and potentially endogenous time-varying observed characteristics, there could be other time-varying unobserved factors that I cannot control for, leaving the possibility of endogeneity arising from omitted variables.

The results from this study have important implications for the development of policies to improve economic outcomes among the homeless population. The descriptive findings reveal a very low level of employment among the homeless population compared to the general rate of employment and show that homelessness is more strongly associated with difficulty keeping employment than with finding employment. Hence, it might be justifiable to provide homeless job seekers and employees with more targeted support from job agencies to help them not only find jobs but also retain them.

The results of the multivariate analysis highlight that as suggested by the conceptual framework, several observed factors significantly affect employment entry and exit. For example, the presence of a disability significantly impacts job finding and retention, education and social networks (i.e. having employed friends) significantly affect job finding, and drug abuse significantly affects job retention. Hence, improving education and health outcomes among the homeless population can have significant positive impacts on this population's employment prospects. Importantly, the multivariate results suggest that the unobserved time-invariant factors that negatively affect both homelessness and employment outcomes are serious barriers in achieving better employment outcomes for homeless people. These factors could include low self-esteem, a poor ability to cope with stressful life events and a difficult family environment. A large decrease occurs in the association between homelessness and employment entry and exit after I account for unobservable common confounders. In other words, homelessness or a lack of stable accommodation per se has no effect on employment transitions after I account for observable and selection effects. These findings suggest that focusing on interventions that address housing problems alone will not improve employment outcomes for people experiencing homelessness. A more effective approach may be to address the complex range of personal, psychological and social problems experienced by this vulnerable population, which would help them retain jobs, achieve stable employment and thus find stable housing.

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Appendices

Table A1. Proportions of time people were not employed (over the waves they had non-missing employment data) for the whole JH sample.

Proportion of time not employed	Freq. (Person)	Freq. (Person-year)	Percent	Cum.
0	103	618	6.12	6.12
16.66667	71	426	4.22	10.34
20	18	108	1.07	11.41
25	13	78	0.77	12.19
33.33333	85	510	5.05	17.24
40	11	66	0.65	17.9
50	99	594	5.89	23.78
60	29	174	1.72	25.51
66.66666	135	810	8.03	33.53
75	15	90	0.89	34.42
80	35	210	2.08	36.5
83.33334	156	936	9.27	45.78
100	912	5,472	54.22	100
Total	1,682	10,092	100	

Notes: The statistics reported in the table were calculated using unweighted longitudinal data from the JH survey. The patterns are defined over the time period people are observed in the survey.

Table A2. Within variation in Xs

Variable		Mean	Std. Dev.	Min	Max	Observations
Age at interview	overall	32.180	10.977	18	55	N = 5326
	between		11.067	18	55	n = 1291
	within		0.715	30.513	33.780	T-bar = 4.12548
Age squared / 100	overall	11.560	7.617	3.24	30.25	N = 5326
	between		7.636	3.24	30.25	n = 1291
	within		0.488	10.173	13.124	T-bar = 4.12548
Completed Year 10 or 11	overall	0.387	0.487	0	1	N = 5326
	between		0.480	0	1	n = 1291
	within		0.091	-0.413	1.187	T-bar = 4.12548
Comp. Year 12 or more (no degree)	overall	0.441	0.497	0	1	N = 5326
	between		0.487	0	1	n = 1291
	within		0.092	-0.359	1.241	T-bar = 4.12548
Completed university degree	overall	0.037	0.189	0	1	N = 5326
	between		0.183	0	1	n = 1291
	within		0.024	-0.563	0.704	T-bar = 4.12548

Avg. Local unemployment rate (6m)	overall	5.829	1.578	1.5	10.883	N = 5326
	between		1.258	2.8	9.7	n = 1291
	within		0.980	1.739	10.171	T-bar = 4.12548

Note: The statistics reported in the table were calculated using unweighted longitudinal data from the JH survey for the analysis sample.

A3. The detailed composition of housing situations for my lagged homelessness measure

Panel A: For the analysis (n=5,362)

	Homelessness status t-1	
Detailed housing situation t-1	Not homeless	Homeless
Primary	0	8.36
Secondary	0	39.2
Tertiary	0	52.44
Marginally housed	25.06	0
Short-term rental	1.87	0
Long-term housed / stable	73.06	0
Total	100 (n=4,321)	100 (n=1,005)

Panel B: For the sample that contributes to the multivariate analysis (n= 2,344)

	Homelessness status t-1	
Detailed housing situation t-1	Not homeless	Homeless
Primary	0	6.18
Secondary	0	43.01
Tertiary	0	50.81
Marginally housed	27.79	0
Short-term rental	1.52	0
Long-term housed / stable	70.69	0
Total	100 (n=1,972)	100 (n=372)

Note: The statistics reported in the table were calculated using unweighted longitudinal data from the JH survey.

A4. Regressions results for the effect of homelessness on employment entry and exit using ABS homelessness measure

	Model with full set of controls and with the equation for homelessness			
VARIABLES	Transition into emp. t-1 to t	Transition out of emp. t-1 to t	Homeless at t	Initially employed
Homeless *t-1(ABS measure)*	-0.081	-0.123		
	(0.126)	(0.203)		
<u>Demographic/background controls</u>				
Gender (female=1)	-0.441***	0.156	-0.369***	-0.229**
	(0.096)	(0.115)	(0.103)	(0.110)
Abor. or Torres St. islander	-0.233**	0.252	0.181	-0.337**
	(0.113)	(0.159)	(0.119)	(0.147)
Immigrant from non-English country	0.050	0.247	0.051	-0.238
	(0.162)	(0.194)	(0.187)	(0.210)
Bi/gay/lesbian	0.206	0.067	0.140	0.301
	(0.147)	(0.176)	(0.164)	(0.184)
Childhood physical or sexual violence	0.024	-0.163	0.068	-0.115
	(0.091)	(0.113)	(0.102)	(0.111)
Homeless as child	-0.201**	0.101	0.101	-0.181
	(0.094)	(0.117)	(0.103)	(0.122)
Hist. of incarceration before JH	-0.280***	0.301**	0.139	-0.287**
	(0.099)	(0.130)	(0.103)	(0.126)
Age at interview	-0.037	-0.024	0.013	-0.051
	(0.030)	(0.038)	(0.029)	(0.033)
Age squared / 100	0.020	0.041	-0.006	0.068
	(0.042)	(0.054)	(0.041)	(0.048)
Completed Year 10 or 11	0.075	0.101	-0.155	0.271*
	(0.135)	(0.205)	(0.122)	(0.157)
Completed Year 12 or more (no deg.)	0.656***	-0.296	-0.205	0.686***
	(0.138)	(0.202)	(0.125)	(0.161)
Completed university degree	1.020***	-0.123	-0.260	0.826***
	(0.239)	(0.290)	(0.259)	(0.295)
Avg. Local unemployment rate (6m)	-0.065***	0.059**	-0.038*	
	(0.023)	(0.028)	(0.023)	
<u>Lagged endogenous controls</u>				
Married or de-facto t-1	0.053	0.088		
	(0.087)	(0.110)		
Number of dep. Children t-1	-0.071	-0.019		
	(0.050)	(0.062)		
Disability t-1	-0.282***	0.319***		
	(0.078)	(0.101)		
Small city t-1	-0.124	0.049		
	(0.100)	(0.134)		
Rural or boundary area t-1	0.256*	-0.199		
	(0.155)	(0.196)		
Self-reported poor health t-1	-0.217*	0.187		
	(0.127)	(0.179)		
Diagnosed with psych. Condition t-1	-0.053	0.191*		
	(0.086)	(0.106)		
Times 5+ drinks/day in a month t-1	-0.003	0.021***		
	(0.006)	(0.007)		

Marijuana use 1 or more days/month t-1	-0.091	-0.004		
	(0.084)	(0.112)		
Registered with any job agency to help find job t-1	0.455***	0.379***		
	(0.075)	(0.089)		
Any employed friends t-1	0.266***	-0.194*		
	(0.073)	(0.101)		
<u>Contemporaneous variables in homelessness eq.</u>				
Married or de-facto			-0.641***	
			(0.095)	
Number of children			-0.344***	
			(0.060)	
Disability			0.156**	
			(0.072)	
Small city			0.014	
			(0.113)	
Rural or boundary area			-0.051	
			(0.149)	
Self-reported poor health			0.102	
			(0.092)	
Diagnosed with psych. cond.			-0.036	
			(0.093)	
Times 5+ drinks/day in a month			0.011**	
			(0.004)	
Marijuana use 1 or more days/month			0.152**	
			(0.074)	
Registered with any job agency to help find job			0.154**	
			(0.068)	
Any employed friends			-0.216***	
			(0.064)	
Log SA4 area apartment/flat rental price			0.936***	
			(0.207)	
λ_E , λ^*_E	1.000		3.837*	0.273
	(0.000)		(2.236)	(0.414)
λ_L , λ^*_L		1.000	4.436**	-0.834*
		(0.000)	(2.221)	(0.429)
cov (η_{Ei}, η_{Li})		(-)0.5324***		
var (η_{Ei})		0.5917		
var (η_{Li})		0.5409		
Log likelihood		-4777.047		

Note: Unweighted longitudinal data from the JH survey for 560 persons (2,344 obs.). In addition to the listed coefficients, the models include intercepts and controls for missing responses for the childhood sexual abuse, long-term disability, psychological diagnosis, and drinking behaviour. Standard errors in parentheses. * Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level.

A5. Regressions results for the effect of homelessness on employment entry and exit using 6-month homelessness measure

	Model with full set of controls and with the equation for homelessness			
VARIABLES	Transition into emp. t-1 to t	Transition out of emp. t-1 to t	Homeless at t	Initially employed
Homeless *t-1 (6-month measure)*	-0.107	0.022		
	(0.086)	(0.115)		
Demographic/background controls				
Gender (female=1)	-0.431***	0.131	-0.163**	-0.223**
	(0.095)	(0.116)	(0.073)	(0.111)
Abor. or Torres St. islander	-0.223**	0.292*	0.086	-0.345**
	(0.112)	(0.161)	(0.087)	(0.148)
Immigrant from non-English country	0.030	0.192	-0.122	-0.230
	(0.162)	(0.197)	(0.137)	(0.209)
Bi/gay/lesbian	0.207	0.076	0.037	0.303*
	(0.145)	(0.176)	(0.122)	(0.184)
Childhood physical or sexual violence	0.023	-0.198*	0.079	-0.114
	(0.090)	(0.114)	(0.073)	(0.111)
Homeless as child	-0.197**	0.095	0.066	-0.175
	(0.093)	(0.118)	(0.075)	(0.122)
Hist. of incarceration before JH	-0.261***	0.283**	0.171**	-0.291**
	(0.099)	(0.131)	(0.078)	(0.126)
Age at interview	-0.034	-0.027	-0.037*	-0.050
	(0.029)	(0.038)	(0.021)	(0.033)
Age squared / 100	0.015	0.045	0.039	0.067
	(0.042)	(0.054)	(0.031)	(0.048)
Completed Year 10 or 11	0.062	0.146	-0.116	0.287*
	(0.134)	(0.206)	(0.090)	(0.157)
Completed Year 12 or more (no deg.)	0.626***	-0.251	-0.295***	0.691***
	(0.137)	(0.204)	(0.092)	(0.161)
Completed university degree	0.986***	-0.011	-0.286	0.819***
	(0.237)	(0.294)	(0.187)	(0.295)
Avg. Local unemployment rate (6m)	-0.063***	0.057**	-0.023	
	(0.023)	(0.028)	(0.016)	
Lagged endogenous controls				
Married or de-facto t-1	0.043	0.107		
	(0.087)	(0.110)		
Number of dep. Children t-1	-0.081	-0.031		
	(0.050)	(0.063)		
Disability t-1	-0.276***	0.332***		
	(0.078)	(0.102)		
Small city t-1	-0.121	0.104		
	(0.100)	(0.135)		
Rural or boundary area t-1	0.256*	-0.244		
	(0.156)	(0.200)		
Self-reported poor health t-1	-0.227*	0.175		
	(0.129)	(0.179)		
Diagnosed with psych. Condition t-1	-0.050	0.196*		
	(0.086)	(0.107)		
Times 5+ drinks/day in a month t-1	-0.003	0.017**		
	(0.006)	(0.007)		

Marijuana use 1 or more days/month t-1	-0.099	-0.011		
	(0.084)	(0.112)		
Registered with any job agency to help find job t-1	0.463***	0.396***		
	(0.075)	(0.090)		
Any employed friends t-1	0.269***	-0.185*		
	(0.073)	(0.102)		
<u>Contemporaneous variables in homelessness eq.</u>				
Married or de-facto			-0.384***	
			(0.058)	
Number of children			-0.242***	
			(0.035)	
Disability			0.141***	
			(0.051)	
Small city			0.169**	
			(0.079)	
Rural or boundary area			0.360***	
			(0.105)	
Self-reported poor health			0.086	
			(0.071)	
Diagnosed with psych. cond.			-0.066	
			(0.067)	
Times 5+ drinks/day in a month			0.010***	
			(0.004)	
Marijuana use 1 or more days/month			0.108*	
			(0.056)	
Registered with any job agency to help find job			0.272***	
			(0.047)	
Any employed friends			-0.202***	
			(0.046)	
Log SA4 area apartment/flat rental price			0.417***	
			(0.153)	
λ_E , λ^*_E	1.000		2.027***	0.497**
	(0.000)		(0.671)	(0.237)
λ_L , λ^*_L		1.000	2.377***	-0.625***
		(0.000)	(0.608)	(0.207)
cov (η_{Ei}, η_{Li})		(-)0.4845***		
var (η_{Ei})		0.5621		
var (η_{Li})		0.5709		
Log likelihood		-6690.2188		

Note: Unweighted longitudinal data from the JH survey for 560 persons (2,344 obs.). In addition to the listed coefficients, the models include intercepts and controls for missing responses for the childhood sexual abuse, long-term disability, psychological diagnosis, and drinking behaviour. Standard errors in parentheses. * Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level.

A6. Employment characteristics conditional on homelessness status (% of employed) for the analysis sample

Employment characteristics	All Mean	Housed *t-1* Mean	Homeless *t-1* Mean
Type of employment contract			
Ongoing /permanent	0.3489	0.3570	0.2947*
Fixed-term	0.0563	0.0545	0.0684
Casual	0.4966	0.4921	0.5263
Self-employed and other	0.0982	0.0964	0.1105
Usual hours of work per week			
Full-time (>=35 hours)	0.4437	0.4376	0.4842
Part-time (<35 hours)	0.5467	0.5521	0.5105
Other	0.0096	0.0103	0.0053
Employment earnings			
Total gross earnings per week	587.6408	597.2891	523.3526*
	1,456	1,266	190

Note: The statistics reported in the table were calculated using unweighted longitudinal data from the JH survey. Asterisks indicate statistically significant differences in means between those housed at t-1 and homeless at t-1 based on ttest.
* Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level.

A7a. Regressions results for the effect of homelessness on labour force entry and exit from models that treat homelessness as exogenous

	Model without controls for lagged endogenous factors			Model with controls for lagged endogenous factors		
VARIABLES	Transition into Labour force t-1 to t	Transition out of labour force t-1 to t	Initially employed	Transition into Labour force t-1 to t	Transition out of labour force t-1 to t	Initially employed
Homeless *t-1*	0.150	0.181**		0.105	0.188**	
	(0.107)	(0.090)		(0.105)	(0.090)	
Demographic/background controls						
Gender (female=1)	-1.163***	0.687***	-0.554***	-0.891***	0.622***	-0.529***
	(0.145)	(0.099)	(0.101)	(0.136)	(0.097)	(0.097)
Abor. or Torres St. islander	-0.006	0.166	-0.089	0.047	0.131	-0.085
	(0.149)	(0.113)	(0.120)	(0.136)	(0.110)	(0.115)
Immigrant from non-English country	0.260	0.060	-0.039	0.235	0.110	-0.034
	(0.240)	(0.162)	(0.185)	(0.216)	(0.157)	(0.177)
Bi/gay/lesbian	0.472**	-0.356**	0.571***	0.333*	-0.345**	0.548***
	(0.225)	(0.150)	(0.176)	(0.202)	(0.145)	(0.168)
Childhood physical or sexual violence	-0.149	0.072	-0.070	-0.100	-0.059	-0.065
	(0.127)	(0.090)	(0.099)	(0.116)	(0.089)	(0.094)
Homeless as child	-0.074	0.027	-0.140	-0.034	0.022	-0.135
	(0.129)	(0.094)	(0.106)	(0.117)	(0.090)	(0.101)
Hist. of incarceration before JH	-0.324**	0.431***	-0.149	-0.320**	0.400***	-0.144
	(0.142)	(0.099)	(0.108)	(0.130)	(0.095)	(0.103)
Age at interview	-0.060	-0.020	-0.074***	-0.027	-0.040	-0.070**
	(0.038)	(0.029)	(0.029)	(0.037)	(0.029)	(0.027)
Age squared / 100	0.011	0.052	0.067	-0.016	0.072*	0.064
	(0.054)	(0.042)	(0.042)	(0.052)	(0.041)	(0.040)

Completed Year 10 or 11	0.301*	-0.103	0.451***	0.153	-0.016	0.439***
	(0.164)	(0.141)	(0.125)	(0.150)	(0.135)	(0.121)
Completed Year 12 or more (no degree)	0.844***	-0.446***	0.798***	0.592***	-0.294**	0.759***
	(0.174)	(0.144)	(0.134)	(0.157)	(0.138)	(0.130)
Completed university degree	1.253***	-0.735***	1.059***	0.952***	-0.500**	0.990***
	(0.351)	(0.254)	(0.277)	(0.317)	(0.242)	(0.265)
Avg. Local unemployment rate (6m)	-0.016	0.051**		-0.020	0.051**	
	(0.029)	(0.023)		(0.028)	(0.022)	
Lagged endogenous controls						
Married or de-facto t-1				-0.058	0.158*	
				(0.110)	(0.087)	
Number of dep. Children t-1				-0.093	0.047	
				(0.057)	(0.051)	
Disability t-1				-0.181*	0.308***	
				(0.098)	(0.076)	
Small city t-1				-0.031	0.131	
				(0.128)	(0.098)	
Rural or boundary area t-1				-0.021	-0.383**	
				(0.201)	(0.178)	
Self-reported poor health t-1				-0.277**	0.165	
				(0.130)	(0.133)	
Diagnosed with psych. Condition t-1				0.056	0.116	
				(0.117)	(0.085)	
Times 5+ drinks/day in a month t-1				-0.000	0.006	
				(0.007)	(0.006)	
Marijuana use 1 or more days/month t-1				-0.133	0.125	
				(0.107)	(0.083)	
Registered with any job agency to help find job t-1				0.714***	0.110	
				(0.091)	(0.075)	
Any employed friends t-1				0.186**	-0.288***	
				(0.085)	(0.074)	
λ_E	1.000		0.501***	1.000		0.522***
	(0.000)		(0.105)	(0.000)		(0.122)
λ_L		1.000	-0.349**		1.000	-0.496**
		(0.000)	(0.168)		(0.000)	(0.201)
cov (η_{Ei}, η_{Li})		(-)0.4454**			-0.1937	
var (η_{Ei})		1.5135			0.9549	
var (η_{Li})		0.5589			0.4152	
Log likelihood		-3310.5506			-3198.7956	

Note: Unweighted longitudinal data from the JH survey for 560 persons (2,344 obs.). In addition to the listed coefficients, the models include intercepts and controls for missing responses for the childhood sexual abuse, long-term disability, psychological diagnosis, and drinking behaviour. Standard errors in parentheses. * Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level.

A7b. Regressions results for the effect of homelessness on labour force entry and exit from the main model

	Model with full set of controls and with the equation for homelessness			
VARIABLES	Transition into Labour force t-1 to t	Transition out of labour force t-1 to t	Homeless at t	Initially employed
Homeless *t-1*	0.151	-0.046		
	(0.123)	(0.104)		
<u>Demographic/background controls</u>				
Gender (female=1)	-0.740***	0.421***	-0.396***	-0.456***
	(0.126)	(0.076)	(0.096)	(0.080)
Abor. or Torres St. islander	0.094	0.077	0.259**	-0.073
	(0.128)	(0.091)	(0.111)	(0.098)
Immigrant from non-English country	0.239	0.111	-0.083	-0.023
	(0.202)	(0.132)	(0.178)	(0.151)
Bi/gay/lesbian	0.212	-0.240**	0.019	0.474***
	(0.189)	(0.120)	(0.159)	(0.143)
Childhood physical or sexual violence	-0.080	-0.081	0.050	-0.053
	(0.109)	(0.075)	(0.095)	(0.081)
Homeless as child	-0.048	0.004	0.089	-0.114
	(0.109)	(0.076)	(0.097)	(0.086)
Hist. of incarceration before JH	-0.220*	0.362***	0.113	-0.124
	(0.120)	(0.080)	(0.099)	(0.088)
Age at interview	-0.034	-0.049**	0.008	-0.060***
	(0.034)	(0.024)	(0.027)	(0.023)
Age squared / 100	0.001	0.074**	0.014	0.056*
	(0.049)	(0.035)	(0.038)	(0.034)
Completed Year 10 or 11	0.123	0.036	-0.198*	0.405***
	(0.141)	(0.114)	(0.114)	(0.104)
Completed Year 12 or more (no degree)	0.459***	-0.161	-0.410***	0.656***
	(0.147)	(0.114)	(0.117)	(0.109)
Completed university degree	0.810***	-0.299	-0.691***	0.862***
	(0.298)	(0.202)	(0.254)	(0.226)
Avg. Local unemployment rate (6m)	-0.018	0.036*	-0.021	
	(0.027)	(0.020)	(0.020)	
<u>Lagged endogenous controls</u>				
Married or de-facto t-1	-0.053	0.099		
	(0.107)	(0.076)		
Number of dep. Children t-1	-0.069	0.020		
	(0.055)	(0.044)		
Disability t-1	-0.196**	0.292***		
	(0.095)	(0.068)		
Small city t-1	-0.053	0.108		
	(0.123)	(0.084)		
Rural or boundary area t-1	-0.099	-0.336**		
	(0.197)	(0.158)		
Self-reported poor health t-1	-0.256**	0.160		
	(0.126)	(0.121)		
Diagnosed with psych. Condition t-1	0.092	0.100		
	(0.112)	(0.072)		
Times 5+ drinks/day in a month t-1	-0.001	0.006		

	(0.007)	(0.005)		
Marijuana use 1 or more days/month t-1	-0.120	0.099		
	(0.103)	(0.073)		
Registered with any job agency to help find job t-1	0.767***	0.119*		
	(0.088)	(0.067)		
Any employed friends t-1	0.167**	-0.253***		
	(0.083)	(0.066)		
<u>Contemporaneous variables in homelessness eq.</u>				
Married or de-facto			-0.627***	
			(0.081)	
Number of children			-0.248***	
			(0.048)	
Disability			0.135**	
			(0.065)	
Small city			0.157	
			(0.100)	
Rural or boundary area			0.279**	
			(0.126)	
Self-reported poor health			0.109	
			(0.084)	
Diagnosed with psych. cond.			-0.108	
			(0.086)	
Times 5+ drinks/day in a month			0.003	
			(0.004)	
Marijuana use 1 or more days/month			0.161**	
			(0.068)	
Registered with any job agency to help find job			0.229***	
			(0.061)	
Any employed friends			-0.218***	
			(0.058)	
Log SA4 area apartment/flat rental price			0.881***	
			(0.191)	
λ_E , λ^*_E	1.000		-2.245**	0.516***
	(0.000)		(1.007)	(0.168)
λ_L , λ^*_L		1.000	5.699***	-0.653*
		(0.000)	(1.809)	(0.334)
cov (η_{Ei}, η_{Li})		0.2829***		
var (η_{Ei})		0.7353		
var (η_{Li})		0.1491		
Log likelihood		-5870.9772		

Note: Unweighted longitudinal data from the JH survey for 560 persons (2,344 obs.). In addition to the listed coefficients, the models include intercepts and controls for missing responses for the childhood sexual abuse, long-term disability, psychological diagnosis, and drinking behaviour. Standard errors in parentheses. * Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level.

A8. Regressions results for the effect of homelessness on employment entry and exit with added interaction between gender and homelessness status

	Model with full set of controls and with the equation for homelessness			
VARIABLES	Transition into emp. t-1 to t	Transition out of emp. t-1 to t	Homeless at t	Initially employed
Homeless *t-1*	0.048	0.160		
	(0.118)	(0.174)		
Homeless t-1 X gender (female=1)	0.087	-0.254		
	(0.178)	(0.292)		
<u>Demographic/background controls</u>				
Gender (female=1)	-0.386***	0.031	-0.411***	-0.165*
	(0.092)	(0.113)	(0.096)	(0.088)
Abor. or Torres St. islander	-0.158	0.156	0.261**	-0.271**
	(0.103)	(0.152)	(0.111)	(0.117)
Immigrant from non-English country	0.132	0.196	-0.091	-0.185
	(0.149)	(0.185)	(0.179)	(0.168)
Bi/gay/lesbian	0.127	0.070	0.018	0.261*
	(0.134)	(0.167)	(0.160)	(0.145)
Childhood physical or sexual violence	0.076	-0.172	0.048	-0.100
	(0.084)	(0.108)	(0.095)	(0.089)
Homeless as child	-0.152*	0.057	0.089	-0.144
	(0.085)	(0.112)	(0.097)	(0.097)
Hist. of incarceration before JH	-0.214**	0.198	0.114	-0.224**
	(0.090)	(0.123)	(0.099)	(0.101)
Age at interview	-0.036	-0.056	0.007	-0.039
	(0.028)	(0.036)	(0.027)	(0.026)
Age squared / 100	0.021	0.079	0.014	0.053
	(0.039)	(0.052)	(0.038)	(0.038)
Completed Year 10 or 11	0.111	0.189	-0.198*	0.262**
	(0.127)	(0.204)	(0.114)	(0.126)
Completed Year 12 or more (no degree)	0.554***	0.045	-0.400***	0.559***
	(0.128)	(0.198)	(0.117)	(0.128)
Completed university degree	0.926***	0.214	-0.653***	0.693***
	(0.221)	(0.278)	(0.252)	(0.235)
Avg. Local unemployment rate (6m)	-0.058***	0.058**	-0.021	
	(0.022)	(0.028)	(0.020)	
<u>Lagged endogenous controls</u>				
Married or de-facto t-1	0.040	0.120		
	(0.083)	(0.109)		
Number of dep. Children t-1	-0.073	-0.051		
	(0.048)	(0.061)		
Disability t-1	-0.284***	0.304***		
	(0.076)	(0.100)		
Small city t-1	-0.141	0.087		
	(0.096)	(0.133)		
Rural or boundary area t-1	0.183	-0.198		
	(0.151)	(0.197)		
Self-reported poor health t-1	-0.167	0.194		
	(0.123)	(0.178)		

Diagnosed with psych. Condition t-1	-0.034	0.062		
	(0.082)	(0.103)		
Times 5+ drinks/day in a month t-1	-0.002	0.016**		
	(0.006)	(0.007)		
Marijuana use 1 or more days/month t-1	-0.124	0.037		
	(0.081)	(0.110)		
Registered with any job agency to help find job t-1	0.471***	0.436***		
	(0.073)	(0.088)		
Any employed friends t-1	0.267***	-0.148		
	(0.070)	(0.101)		
<u>Contemporaneous variables in homelessness eq.</u>				
Married or de-facto			-0.634***	
			(0.082)	
Number of children			-0.247***	
			(0.048)	
Disability			0.144**	
			(0.065)	
Small city			0.157	
			(0.100)	
Rural or boundary area			0.301**	
			(0.126)	
Self-reported poor health			0.117	
			(0.084)	
Diagnosed with psych. cond.			-0.102	
			(0.086)	
Times 5+ drinks/day in a month			0.004	
			(0.004)	
Marijuana use 1 or more days/month			0.155**	
			(0.068)	
Registered with any job agency to help find job			0.181***	
			(0.060)	
Any employed friends			-0.219***	
			(0.058)	
Log SA4 area apartment/flat rental price			0.932***	
			(0.191)	
λ_E , λ^*_E	1.000		-4.970**	1.086**
	(0.000)		(2.037)	(0.442)
λ_L , λ^*_L		1.000	5.167***	-0.946**
		(0.000)	(1.859)	(0.426)
cov (η_{Ei}, η_{Li})			0.3264***	
var (η_{Ei})			0.3622	
var (η_{Li})			0.3417	
Log likelihood			-5373.7704	

Note: Unweighted longitudinal data from the JH survey for 560 persons (2,344 obs.). In addition to the listed coefficients, the models include intercepts and controls for missing responses for the childhood sexual abuse, long term disability, psychological diagnosis, and drinking behaviour. Standard errors in parentheses. * Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level.

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