Location and Unemployment

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Abstract

Are people receiving unemployment-related income support more likely to exit from income support if they live in a stronger labour market? This paper examines this question using data from the Australian Department of Family and Community Services Longitudinal Data Set (LDS). We find that, controlling for other observed characteristics, living in an area with a one percentage point lower unemployment rate is associated with a 5 per cent increase in the probability of exit. This implies a 9 per cent decrease in the mean duration of benefit receipt. This should be considered an upper bound for the impact of regional labour market characteristics as it partly reflects the fact that people with low skill levels can only afford to live in high unemployment regions. To control for unobserved characteristics (such as skill levels) that are constant over time we look at changes in income support among people who move location. This suggests a much lower, but still significant, impact of local labour market conditions on unemployment benefit receipt.

1. Introduction

Access to the social and economic benefits of employment varies widely across the regions of Australia. This reflects both the inability of people with poor labour market prospects to afford to live close to available jobs, and the direct impact of local labour market conditions. In this paper we seek to shed light on the latter mechanism, using administrative data on receipt of income support. What impact do local labour market conditions have on the likelihood of exit from (or receipt of) unemployment benefit payments?

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In Australia, it is well recognised that unemployed (or non-employed) people tend to be concentrated in particular regions, and there is some evidence that this association has increased over time in Australia (Gregory and Hunter 1995). However, it is equally well recognised that it is difficult to separate out the effects of local labour markets from the characteristics of people that tend to live in different regions (McDonald, 1995).

The high unemployment rates that are observed in the outer suburbs of the major cities may be due to regional characteristics that make it difficult to find work, such as poor public transport and an inadequate supply of child-care. Additionally, the concentration of disadvantaged people in these regions may lead to further social problems, which further disadvantages those living there. Both of these impacts we describe as *locational impacts*. (In this study we focus on labour market conditions as our key locational indicator – other social factors are only considered to the extent to which they are associated with labour market conditions).

However, it is also possible that the high unemployment regions in the outer suburbs of the major cities may have high unemployment rates because these are the only areas in which individuals that are disadvantaged in the labour market (such as the long-term unemployed and long-term low wage workers) can afford to live. That is, the outcomes are a reflection of the *individual characteristics* of the people that can afford to live there.

The policy implications of these two sets of explanations are quite different. For some targeting purposes, it may not matter whether it is locational impacts or individual characteristics that lead to an association between high unemployment regions and low exit rates from benefit. For example, if we are trying to identify which people are most likely to have a long spell of income support receipt.

However, for many policy purposes the direct impact of location is important. For example, in Australia, unemployment payment recipients are penalised if they move to an area of higher unemployment, because it is assumed that this will reduce their employment prospects. This 'Move to an Area of Lower Employment Prospects' (MALEP) exclusion rule means that people who move to an area of higher unemployment may be excluded from benefit receipt for a period of 26 weeks.[1] Such a policy may be defensible if location does indeed matter for employment prospects. However, if people with low levels of labour market skills will remain unemployed wherever they live, then such a policy has little merit.

Indeed, if location has a direct impact on individual labour market outcomes, this has implications for both labour market and housing policies. Whether or not this arises from direct labour market effects or broader neighbourhood effects, it suggests a greater need for regionally-specific labour market policies and for housing policies that encourage unemployed people to move to better labour markets. The latter might include policies to increase the supply of affordable housing in strong labour markets, or policies to increase rental assistance to people in higher housing cost regions.[2]

In this paper we estimate the impact of local labour market conditions on unemployment related income support receipt using data from the Australian Department of Family and Community Services (FaCS) Longitudinal Data Set 1 per cent sample (LDS). This contains information on the income support payments received for all fortnights between January 1995 and June 2001 for a 1 per cent sample of recipients. The data set includes information on the postcode of residence, which is matched to 1996 Census Statistical Local Area (SLA) characteristics. We consider two indicators of local labour market characteristics, the size of the labour market (measured by the number of jobs located within 20km) and the 'travel region unemployment rate' for the location. The latter is an average of unemployment rates in the surrounding regions, weighted on the basis of journey to work patterns.

In the next section, we briefly review previous work in this area. The data and definitions of key variables are described in Section 3. We use two different methods to estimate the impact of local labour market conditions on the likelihood of receiving unemployment income support payments. In Section 4 we estimate the probability of exiting a spell of unemployment payment as a function of labour and housing market characteristics and observed personal characteristics. We find that people in lower unemployment regions do have higher rates of exit from benefit.

However, this is partly due to the different (unobserved) characteristics of people in those regions. In Section 5 we control for fixed unobserved characteristics by examining the income support receipt patterns of people who move between regions. Though there are potential selection biases associated with this technique, our view is that these are not likely to be serious. Using this approach we find that a move to a low unemployment region is still associated with a fall in benefit receipt, but the effect is not so large.

2. Background

There are several strands of pre-existing research on the relationship between geographic location, mobility and employment outcomes. Some of the literature looks primarily at the impact of mobility *per se*. In the housing literature, Oswald (1996) has argued that higher rates of home ownership reduce mobility and hence lead to higher rates of national (or intranational) unemployment. Labour economists have similarly hypothesised that higher rates of geographic mobility can reduce aggregate unemployment rates by facilitating better matching of job seekers to jobs.[3]

There is evidence that unemployed people generally move between regions for reasons other than to improve their job search prospects (Gregg, Machin and Manning, 2003, Bradbury and Chalmers, 2003). Nonetheless, this does not preclude the possibility that moves made for housing or family-related reasons have implications for future employment outcomes.

A recent example of research looking at the impact of mobility is that of Pekkala and Tervo (2002), who examine the relationship between geographic mobility and employment in Finland. They find that those unemployed who are more geographically mobile are also more likely to find work. However, using housing tenure, housing prices and family status as statistical 'instruments', they conclude that this pattern is due to a selection effect. That is, those who are more employable are also more likely to move location.

Our interest here, however, is about the impact of *where* people move to rather than mobility in general. This question is more relevant to policies such as the MALEP rule and differential housing rent subsidies discussed above. In particular, does moving to an area with different labour market conditions affect an individual's labour market outcomes?

In the USA there has been considerable debate over the impact of the movement of jobs away from the inner areas of large cities such as Chicago. Kain (1968) proposed that racial segregation together with a spatial mismatch between residential and employment locations may be partly responsible for low employment and poverty among black Americans. Other writers such as Ellwood (1983) have argued that the geographic distribution of jobs is of limited importance, with black neighbourhoods with low employment rates often being located quite close to white neighbourhoods with high employment rates. More recently, Wilson (1996) has argued that neighbourhood characteristics (not just distance to jobs) may be inherently important. For example, he points to the successful outcomes of those people involved in the Gautreaux program, which provided subsidies to relocate people out of ghetto areas. Over a fifteen year period, research shows that people who moved had better outcomes than those who remained in the origin regions (Keels et al, 2003).

Participation in the Gautreaux program was voluntary, so it is possible that participants might have differed systematically from those who did not wish to move in terms of their labour market skills. More robust evidence comes from research methods that involve random assignment. Ludwig, Duncan and Hirschfield (2001) examine the "Moving to Opportunity" experiment in the US. In this experiment, families in high poverty suburbs were randomly assigned to a program of assistance to help them re-locate to higher income suburbs. Youth in the families that moved were significantly less likely to be involved in criminal activities. Experimental evidence such as this provides strong evidence that location does matter for a range of socio-economic outcomes.

However, given the very different urban structures of the US and Australia, we should be very reluctant to generalise these types of conclusions to Australia. In particular, Australia has no significant equivalent to the inner-urban ghettos of the large cities in the US.

One way of controlling for differences in employability in the population is to consider sub-groups of the population that are similar in terms of their labour market skills but live in locations with different employment opportunities. A simple analysis of this type is shown in Table 1, based on data from the 1996 Census 1% Household Sample File. This shows the employment patterns for lone parents who were living in public rental housing in both capital city and non- capital city regions of Australia.

Table 1. Employment Patterns of Lone Parents Living in Public Housing in and outside Capital Cities in Australia, 1996

Labour Force Status	Capital City (%)	Non Capital City (%)
Employed	23.9	20.8
Unemployed	11.5	12.5
Not in Labour Force	64.5	66.8
Total	100.0	100.0
Sample Size	485	313

Source: 1996 Census, Household 1% sample file. Tasmania, Northern Territory and the ACT are excluded, as their capital city areas are not separately identified.

Public housing authorities generally attempt to provide entry to the most disadvantaged in the community, and so the variation in skills among lone parents in public housing is likely to be lower than among lone parents generally.

Table 1 shows that lone parents living outside capital cities were less likely to be employed and more likely to be unemployed than those in the capital cities. This is suggestive of a role for labour market conditions. However, this difference is not statistically significant, and despite the use of a highly selected population, we cannot rule out the existence of selection effects. For example, lone parents with little labour market attachment may be more likely to seek residence outside capital cities.

Isolating the impact of location on employment outcomes is difficult, and it is not surprising that this is the first attempt (to our knowledge) using Australian data. The key identification problem is that both an individual's location and his/her employment outcomes will be influenced by fixed unobserved factors such as underlying 'ability'. Individuals with higher skill levels will be both more likely to find a job, and also more likely to have a higher wage when they start work. The financial incentive to move to a region of relatively high labour demand will thus increase with wage level and so the skill level of the jobseeker may be positively linked to the region's job opportunities. Hence an observation that residents of locations with relatively high labour demand experience relatively favourable employment outcomes might reflect the skill level of the jobseekers living in the area, rather than the effect of the relatively high labour demand (or other favourable labour market features such as good transport). Similarly, individuals with higher (anticipated) long-term incomes may be more likely to move to higher housing cost regions, which are likely to have lower unemployment rates.

In this study, we attempt to control for such fixed unobserved heterogeneity by following the circumstances of individuals as they move from one region to another. Data limitations mean that our estimates are far from perfect, but we feel that they do help shed light on the importance of location.

An additional complication is that there may be changes in unobserved factors that affect both employment status and location. For example, someone may be offered a job in a different location and then move to take up the job. Since our data only allows us to consider moves where a person is receiving benefit both before and after the move, we probably exclude most of those who move to take up work. Furthermore, we control for changes in job effort associated with changes in observed characteristics (such as the birth of a child or a marital split) in the spell duration model below by allowing the observed explanatory variables to vary with time. However it is still possible that some of the association we observe between location and outcomes is due to these types of unobserved time-varying factors.

3. Data and Methods

Most results in this paper are derived from analysis of the Department of Family and Community Services (FaCS) Longitudinal Data Set (LDS). The version we use includes information on a one per cent random sample of income support recipients. For this sample we have information on their income support status (and other characteristics when they are receiving income support) for every fortnight between January 1995 and June 2001. The LDS contains basic demographic information for each recipient, including their age, sex, country of birth, marital status, age and number of dependent children, home-ownership and rent status. It also contains information on their earned and unearned income and the amount of private rent paid. No information is available for fortnights when the person is not receiving income support.

We restrict attention to the people receiving unemployment payments[4] in the fortnight under consideration. We only consider unemployment payment recipients for two reasons. First, this is the population group for whom labour market factors are likely to be of most importance in influencing spell exit. Second, this analysis requires information on the spell duration, which for spells that were in progress at the start of the observation window is only available for unemployment payment recipients.

The LDS does not contain any information about recipients' names or addresses. However, it does contain information on the recorded postcode of residence[5] as at each fortnightly payment. We match this information to 1996 Census Statistical Local Areas (SLAs) on a 'best match' basis. That is, people are assumed to reside in the SLA in which the largest proportion of people in their postcode resides. Since we are examining moves over the 1995 to 2001 period, this unavoidably introduces a small number of classification errors due to changes over this period in the postcodes for different regions.

The characteristics of different locations are defined using data from the 1996 Census, as we do not have sufficiently detailed (and reliable) data to calculate trends in characteristics such as unemployment rates at the small area level.

In general, it is not straightforward to ascertain the employment opportunities associated with a particular location. For many people living in one of Australia's large cities, the best indicator of their employment opportunities is the unemployment (or employment) rate of the city as a whole. The variations in employment rates *within* cities are likely to reflect, in part at least, variations in housing costs and hence the ability of unemployed people to afford to live in different regions. (The employment rate for a given location is defined as the number of employed people who live in that location, divided by the total number of people living in the location). However, to use the city-wide employment or unemployment rate implies an unduly even pattern of labour market opportunities. It does not take into account the significant transport costs that effectively confine individuals to work in sub-sections of their urban region.

In this paper we use an indicator of labour market size together with a 'travel region unemployment rate', an indicator of the extent of competition for jobs faced by unemployed people, to summarise the labour market opportunities available in different parts of Australia.

Labour market size is an approximation of the number of jobs located within 20km of an individual's place of residence. This is estimated using 1996 Census journey to work data. This data provides information on the number of jobs located in each SLA in Australia (for SLAs outside the journey to work study areas, ie rural areas, we assume that people work and live in the same SLA). We assume that all the jobs in each SLA are located at the geographic centroid of the SLA and for each SLA we calculate the number of jobs that are located within 20km of the SLA centroid.

The calculation details for the *travel region unemployment rate* are detailed in Bradbury and Chalmers (2003). In summary, we start with the Census unemployment rate for people living in each residential SLA. The journey to work data contains information on the number of people in each residential SLA who work in each employment region in Australia. We use this to first estimate an 'excess labour supply index' in each employment region. This is a weighted average of the unemployment rates across all residential SLAs where greater weight is given to those residential SLAs that supply most people to the employment region's workforce. For each residential SLA the travel region unemployment rate is then calculated as an average of this excess labour supply index over all employment regions where the weights are the proportion of workers who go to work in each region.[6] The effect of the calculation process is to calculate an index where the value for a given SLA is based on an average across all SLAs but with greater weight given to those SLAs where people tend to work in the same areas.

For example, some inner urban areas have high unemployment rates. But the employed people in those areas tend to work in the city centre. The city centre, in turn, draws most of its workforce from regions with low unemployment rates, and hence effectively faces quite a tight labour market. Hence the access to employment for a person with average skill level, but living in a low-employment inner urban area will be quite good – and this will be shown in the travel region unemployment rate.

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The reason why the conventional unemployment rate is so high in the inner urban areas is not because the area has poor access to employment, but rather because of cheaper housing, which permits people with poor labour market opportunities to live there.

Following Dockery (2000), we estimate the relative price of housing in different regions by using the information on rents paid by private renters in the LDS (for all recipients, including the aged). Across all observations in the LDS, we estimate an OLS regression of the rent paid as a function of demographic characteristics and date of observation. The residual from this regression thus indicates the extent to which a person pays a higher rent than the average person with the same family characteristics (at the same date of observation). We then average this residual within SLAs to obtain an estimate of the rent differential applicable to that location. For SLAs with fewer than 20 people in the LDS, the average value over the corresponding Statistical Sub-division (SSD) is used. If the SSD has fewer than 20 people, the average is taken over the Statistical Division (SD). Our measure of housing costs is thus an estimate of the extent to which a particular location has a higher than average rental (controlling for household composition and date of observation).

4. The Impact of Location on Exit from Unemployment Payments

What is the association between the probability of exit from unemployment payments and regional and other characteristics? We address this question in this section using a 'spell duration' model.

Spell duration models are a method for estimating the impact of observed characteristics on the length of time that individuals spend in some particular situation. In the biomedical literature, they are referred to as 'survival models' because they are often used to describe the impact of different treatments on the time to death of subjects. Here, we look at the duration of receipt of unemployment payments.

Once an individual starts receiving an unemployment payment, the length of time that they continue to receive payment will depend upon the probability that they leave payment in each subsequent period. The probability that a person who is receiving payment will stop receiving payment in the next period is called the 'hazard of exit'. A higher hazard implies a shorter duration and we can describe the impact of particular characteristics as either being associated with a higher hazard or with a shorter duration – the two formulations are equivalent. In reporting our results, we mainly report the relationship between locational characteristics and the hazard of exit.

As noted above, individuals with characteristics that are associated with relatively high probabilities of finding employment may tend to live in more favourable labour markets. We can observe some of these characteristics and control for them. However, to the extent to which there are unobserved and/or unmeasurable factors influencing employment chances, then the relationship that we estimate in this section between regional labour market characteristics and spell duration will be an overestimate of the causal impact of location on benefit exit. Nonetheless, one of the strongest predictors of employability is duration of benefit receipt (included as a controlling variable in the model), and so the bias may not be too great.

To maximise sample size, we pool data from the *stock*, people receiving unemployment payment recipients at the commencement of the observation period (6 January 1995), together with the *flow* sample of those people who commenced an unemployment spell between January 1995 and May 2000. Our modelling procedure (the discrete-time hazard model of Jenkins, 1995) takes account of this sample structure. An unemployment spell is considered to end if the recipient does not receive income support for two payments. A single fortnight break is counted as a continuation of payment. If the person transfers to another income support payment (or is no longer of workforce age) we do not follow them further (in the terminology of duration models, the spell is considered as 'censored' at this point).

We estimate the hazard of a particular person leaving unemployment benefit as a function of their duration of unemployment payment receipt up to that point, the characteristics of their current location and their demographic characteristics. We use a 'proportional hazard model' with a flexible baseline hazard function.[7] The baseline hazard is the hazard for the (hypothetical) person in our sample for whom all the explanatory variables are set at zero. We allow the baseline hazard to vary with duration by breaking the time-line measuring spell duration into a number of intervals with a different coefficient attached to each of those intervals; with the intervals chosen so as to have sufficient sample size in each interval. The estimated hazard function for the reference person (though with a 10% travel region unemployment rate) is shown in Figure 1. The proportional hazard model assumes that duration has the same impact on the hazard of exit for all people but with the hazard curve shifted up or down depending upon the values of their explanatory variables.

Our estimates are obtained using logistic regression software with person-fortnights as the unit of analysis.[8] These are coded as 1 if an exit occurs and zero otherwise. Cases that are censored are not included after the censoring point. Time-varying covariates can then be defined for their relevant fortnight in a straightforward way. We exclude person-fortnights where the postcode of residence is not found in our postcode/SLA concordance (<1% of cases). Most of these cases were probably cases where the person did not have a fixed address and was using a postal box.

The sample size for the analysis is 1,213,437 person fortnights in 76,085 spells. These spells represent the experiences of 31,188 people. For computational simplicity we treat each spell as independent, ignoring the fact that some people have more than one spell.[9] This probably means that the standard errors reported here are too small, though we would not expect a large bias, given the variability in outcomes between spells for the same person.

Table 2. Sample of unemployment payment spells

	All spells	Stock spells	Flow spells
Duration (fortnights)	19.0	50.2	15.5
Women	32.8	30.7	33.1
Overseas born	21.7	24.4	21.4
Overseas born in English speaking country	5.0	5.5	4.9
Aboriginal or Torres Straight Islander	3.3	3.1	3.4
Repeat spells	59.1	0	65.7
Exited from unemployment payments	82.4	84.3	82.2
Exited and returned to income support	59.7	70.1	58.6
Censored			
Transferred to another payment	9.9	13.7	9.5
Spell still underway at end of observation window	7.5	1.7	8.1
No labour market information on last person fortnight in spell	0.2	0.2	0.2
Spells	76,085	7,599	68,486

Table 2 provides summary statistics for the unemployment payment spells and some of the key fixed covariates. The first column summarises all spells. The average spell duration was 19 fortnights, or nearly three-quarters of a year. Men accounted for nearly 67 per cent of the spells, overseas born people accounted for 22 per cent of the spells, and those who identified as Aboriginal or Torres Straight Islander accounted for 3.3 per cent of the spells.

Ten percent of the spells were stock spells. Stock spells were in progress on 6 January 1995, the first fortnight in the observation window.

The average duration of the stock spells was 50.2 fortnights, or nearly two years, while the average duration of the flow spells was only 15.5 fortnights.[10] The maximum duration for the flow sample was 50 fortnights or nearly two years, and for the stock sample was 588 fortnights or a little over 22.5 years.

Eight-two per cent of the spells ended in exit from unemployment payments, although nearly three-quarters of those exits were followed by a return to income support within the observation window. Similarly, where we have data, we know that nearly 60 per cent of the spells were repeat spells. Ten percent of the spells ended when the recipient transferred to another payment and 7.5 per cent of spells were running at the end of the observation window. In only 0.2 per cent of the spells was the last spell fortnight missing because of the lack of matching labour market data.

In the first column of Table 3 the means of the variables across all person fortnights are shown. Table 3 also reports the maximum likelihood estimates of three logistic regression models of fortnightly exit from unemployment payment receipt. Exit includes exit to employment but also exit due to other factors such as breaching (administrative penalties) or spouse employment. Model 1 includes demographic characteristics as the predictors plus the housing cost indicator variable. The second model adds the travel region unemployment rate to the list of predictors and the third adds indicator variables describing the number of jobs within 20 km.

Base-line hazard

Figure 1 shows the base line hazard rate for Model 3 (the other models are similar). The hazard is the probability of exit in the next fortnight for those people who have remained on benefit up until the time of estimation. This is shown for the base case of an unmarried man without dependent child aged 15-19, non-ATSI Australian born without earned and unearned income, renting privately, living in locations with 500,000+ jobs within 20 km and with a travel region unemployment rate of 10 per cent. His spell of unemployment payment receipt was not underway at the commencement of the observation period.

Figure 1. Baseline hazard rate for Model 3

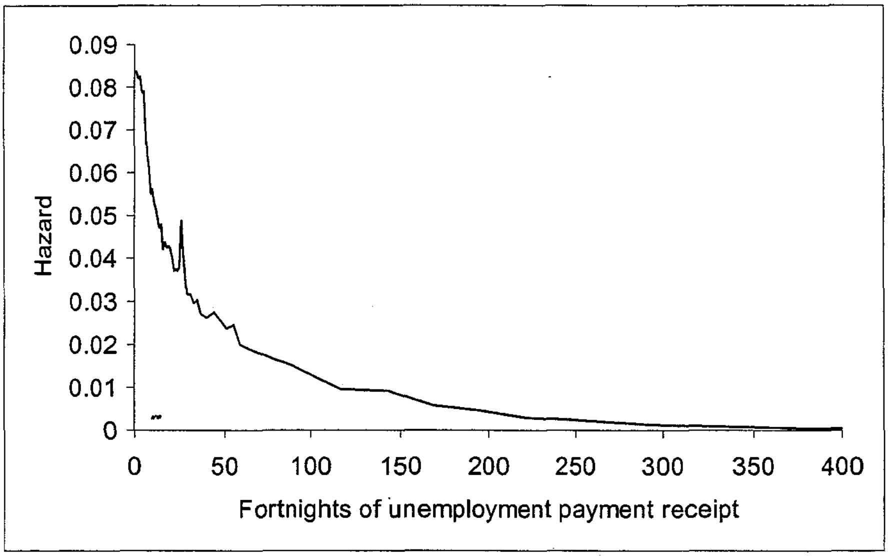
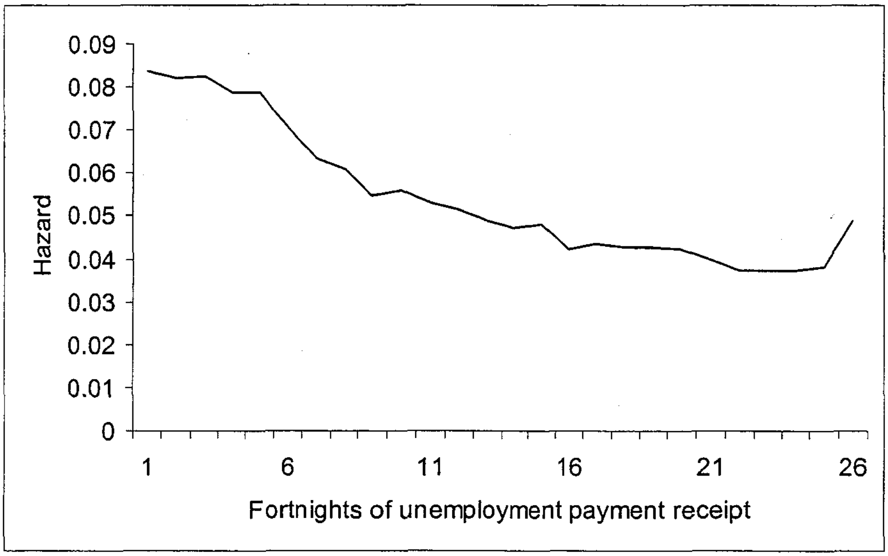


Figure 2. Baseline hazard rate for Model 3 for spells of one year or less in length



The hazard of exit declines gradually with time in receipt of unemployment payments, although that decline slows with time, and there is a spike at 26 fortnights,. suggesting that there may be an administrative reason for leaving unemployment payments after a year on payment. As Figure 2 (the base-line hazard for spells of one year or less in length) shows, the steepest decline occurs for durations of 6-9 fortnights.

Observed individual characteristics

In interpreting the parameter estimates (β) in Table 3, it is convenient to use the result that $e^{\beta}-1$ is approximately equal to the proportionate increase in the hazard associated with a one-unit increase in the variable. This approximation derives from the fact that the hazard of exit in any given time period is small.[11] When β itself is small, this simplifies further to $e^{\beta}-1 \approx \beta$. That is, the parameter estimate is approximately equal to the proportionate increase in the hazard associated with a one-unit increase in the variable.

The parameter estimates show that women's hazard of exiting unemployment payment was between 9.5 and 16.5 per cent lower than men's (ie calculated by inserting -0.10 and -0.18 into the expression given above). Because of the interaction terms in the model, this difference refers to that between single men and women. The gender differential is wider when the regional unemployment rate is added to the list of explanatory variables (Models 2 and 3). Since the hazard of exit was related negatively to the regional unemployment rate this suggests that single men in receipt of unemployment payments tend to live in areas with higher regional unemployment rates than do similar single women.

Family structure was important for both men and women, however there were clear gender differences. Married men had a significantly higher hazard of exit than unmarried men, whereas women's hazard of exit did not differ with marital status. For those exits associated with finding employment, this might be attributable to positive correlations between factors favouring marriage and employability for men, not measured by other explanatory variables, or to the greater pressure to find work experienced by married men. The hazard of exit decreased with the number of dependent children, for both men and women. Among women the presence of a child younger than 13 impacted negatively on their hazard of exit illustrating the difficulty associated with combining work with being the primary carer for young children.

To control for the fact that the duration of unemployment prior to the beginning of the observation window was measured differently than

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subsequent unemployment,[12] we include an explanatory variable that is set equal to the duration of the spell at the beginning of the observation period. The estimated coefficient on this variable is positive and significant, representing the fact that spell durations for members of the stock sample are (relatively) overestimated.

The highest hazard of exit was experienced by those aged in their 20s. From 30 onwards the hazard decreases with age, with the decrease accelerating at the age of 50. In model 1, recipients aged 55 or more had hazards 57 per cent lower than did recipients aged 16 to 19 years ($-0.57 = e^{-0.85} - 1$).

Compared to Australian born recipients, those born overseas in non-English speaking countries experienced a lower hazard of exit, while those born overseas in English speaking countries had a higher hazard of exit. When the regional unemployment rate was controlled for, the size of these relationships increased. This suggests that, in comparison to Australian born recipients, the first group of overseas born tend to live in regions with relatively low unemployment rates and the latter in regions with relatively high unemployment rates.

Indigenous Australians had significantly lower hazards of exit than other recipients. The size of that relationship increased with the inclusion of the unemployment rate, suggesting that indigenous recipients tended to live in areas of relatively low unemployment rates. This may be due to the fact that a substantial number of the indigenous Australians living in more isolated regions tend to qualify for CDEP rather than unemployment payments (and are hence not included in our study).

Those who received earned income while in receipt of income support had a significantly higher hazard of exit, as did those who were in receipt of unearned income. The level of earnings (both earned and unearned) was also significantly and positively related to the hazard of exit, although the hazard increased at a decreasing rate in both instances. The earned income effect was larger than the unearned income effect.

Compared with private renters, non rent-paying homeowners (ie outright owners and purchasers) experienced a higher hazard of exit. Non rent-paying non-homeowners also experienced a higher hazard of exit. In contrast public renters who paid rent exhibited a hazard of exit significantly lower than did rent paying private renters. One explanation for these findings is that an individual's housing arrangement acts as a useful proxy for past attachment to the labour market. We would expect homeowners to have spent more of their working lives in employment than non-home owners, and among renters we would expect public renters to be more disadvantaged in the labour market than private renters.

Table 3. Logistic hazard regression models of probability of exit from unemployment payment receipt

	Sample Means	Model 1	Model 2	Model 3
		Coefficient Estimates		
Women	0.315	-0.10#	-0.18#	-0.18#
Married	0.272	0.10#	0.11#	0.11#
Youngest child aged less than 13	0.136	0.03	0.03	0.03
Youngest child aged 13 to 15	0.014	0.08*	0.08*	0.08*
Number of dependent children	0.318	-0.03#	-0.03#	-0.03#
Women				
Married	0.057	-0.09#	-0.08#	-0.08#
Youngest child aged less than 13	0.015	-0.18**	-0.19**	-0.19**
Youngest child aged 13 to 15	0.002	-0.16	-0.15	-0.16
Number of dependent children	0.033	-8.9E-03	-9.4E-04	-1.5E-03
Age in years (relative to age 15-19)				
20-24	0.209	0.02*	0.01	0.02
25-29	0.153	0.02**	0.02	0.02
30-34	0.115	-0.10#	-0.11#	-0.11#
35-39	0.100	-0.16#	-0.17#	-0.17#
40-44	0.089	-0.26#	-0.26#	-0.26#
45-49	0.081	-0.34#	-0.35#	-0.35#
50-54	0.070	-0.54#	-0.55#	-0.55#
55 plus	0.072	-0.85#	-0.87#	-0.87#
Born overseas	0.236	-0.06#	-0.11#	-0.10#
Born overseas in English speaking country	0.049	0.14#	0.17#	0.16#
ATSI	0.040	-0.17#	-0.23#	-0.24#
Received earned income	0.140	0.23#	0.23#	0.23#
Earned income per fortnight ($/100)	0.347	0.17#	0.17#	0.17#
Earned income squared ($/10,000)		-2.9E-03#	-2.9E-03#	-2.9E-03#
Received unearned income	0.147	0.18#	0.19#	0.19#
Unearned income (pf) ($/100)	0.054	0.05#	0.05#	0.05#
Unearned income squared ($/10000)		-2.3E-04#	-2.2E-04#	-2.3E-04#
Housing cost index ($pw deviation from pred.)	-3.82	1.6E-03#	1.3E-03#	1.6E-03#
Housing (relative to private renter)				
Home-owner, pays no rent	0.169	0.17#	0.18#	0.18#
Pays rent and public renter	0.042	-0.26#	-0.26#	-0.25#
Pays no rent, not owner	0.216	0.11#	0.11#	0.11#
Duration of spell at January 1995 (days)	126.87	7.7E-04#	7.6E-04#	7.6E-04#
Unemployment rate	10.05		-0.05#	-0.05#
Number of jobs within 20 km (relative to 500,000+)				
<5000	0.110			0.05#
5-49,999	0.302			0.07#
50,000-399,999	0.225			-6.5E-03
300,000-499,999	0.168			0.06#
Intercept		-2.35#	-1.88#	-1.89#
Sample size (person-fortnights)	1,213,437	1,213,437	1,213,437	1,213,437
-2 Log L		467,080	466,445	466,392

1 per cent level of significance
** 5 per cent level of significance
* 10 per cent level of significance

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There is a positive and significant relationship between the housing cost measure and the hazard of exit. We interpret this to reflect the fact that those with higher levels of unobserved human capital tend to be congregated in relatively higher cost regions.

In Model 2, the unemployment rate is added to the list of explanatory variables. The estimates suggest that a one-percentage point increase in the unemployment rate is associated with a 4.9 per cent drop in the hazard of exit (95% confidence interval of 4.6 per cent to 5.2 per cent). As noted above, this measure of association should be considered an upper bound estimate of the direct impact of regional labour market conditions.

Model 3 adds a set of dummy variables describing the number of jobs within 20 km of the location. The size of the relationship between the unemployment rate and the hazard of exit was unchanged by the addition of these variables. The estimated coefficients for the set of labour market size dummies do not reveal a consistent pattern. Relative to the residents of the most densely populated locations in terms of jobs (at least 500,000 jobs within 20 km), residents of locations with less than 50,000 jobs within 20 km and locations with 300,000–499,999 jobs within 20 km had significantly larger hazards (holding unemployment rates constant). We can offer no explanation for this result.

The proportional hazard model assumes that all the predictor variables have the same proportional impact on exit hazard, irrespective of the duration of unemployment. However, it is possible that that the impact of regional characteristics may change as the length of unemployment spell lengthens. To test this, we also estimated the probability of exiting for those recipients whose duration on unemployment payments was 365 days or more.

Table 4 reports the coefficient estimates from this analysis for model 3. We find that the size of the relationship between the housing cost indicator and the hazard of exit is almost identical for exits from unemployment payment receipt and long-term unemployment receipt. Similarly the estimated relationship between the hazard of exit and the unemployment rate is much the same. However the relationship between the number of jobs within 20 km and the hazard of exit is different, although still difficult to explain. Those living in areas with 50,000 to 399,999 jobs within 20 km had a lower hazard of exit than all others.

What does the estimated impact of the impact of regional unemployment rates imply for expected durations of unemployment benefit receipt? For the reference person (at mean unemployment rate) a one percentage point increase in unemployment is associated with a 5 per cent fall in the hazard of exit. This implies a corresponding 6.6 per cent increase in the median duration of benefit receipt, and a 9.2 per cent increase in the mean duration.[13]

Table 4. Logistic hazard regression model of probability of exit from long-term unemployment payment receipt

	Sample Means	Model 3 Coefficient Estimates
Women	0.295	-0.18#
Married	0.293	-0.02
Youngest child aged less than 13	0.151	0.03
Youngest child aged 13 to 15	0.017	0.11
Number of dependent children	0.364	-0.03
Women		
Married	0.054	0.01
Youngest child aged less than 13	0.016	-0.25
Youngest child aged 13 to 15	0.003	-0.47
Number of dependent children	0.038	5.6E-03
Age in years		
20-24	0.177	-0.02
25-29	0.148	-0.12#
30-34	0.117	-0.23#
35-39	0.108	-0.37#
40-44	0.105	-0.51#
45-49	0.100	-0.64#
50-54	0.096	-0.88#
55 plus	0.092	-1.10#
Born overseas	0.251	-3.9E-03
Born overseas in English speaking country	0.049	0.11**
ATSI	0.043	-0.17**
Received earned income	0.129	-0.29#
Earned income ($/100)	0.277	0.45#
Earned income squared ($/10000)		-0.02#
Received unearned income	0.140	-6.2E-03
Unearned income ($/100)	0.051	0.12**
Unearned income squared ($/10000)		-2.3E-03
Housing cost indicator ($)	-4.86	2.6E-03#
Housing		
Home-owner, pays no rent	0.177	0.09**
Pays rent and public renter	0.061	-0.19#
Pays no rent, not owner	0.182	0.06**
Duration at January 1995 (days)	326.61	7.3E-04#
Unemployment rate	10.23	-0.04#
No. of jobs within 20 km		
<5000	0.115	-0.04
5-49,999	0.298	-0.03
50,000-399,999	0.223	-0.08#
300,000-499,999	0.160	-0.03
Intercept		-2.77#
Sample size	458, 753	
-2 Log L		102,974

1 per cent level of significance
** 5 per cent level of significance
* 10 per cent level of significance

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5. Impact of Mobility on Fortnights on Benefit

The spell duration model described above cannot control for unobserved differences between individuals in their ability to find work. As discussed above, there are reasons to believe that this may produce an upwards bias to our estimate of the impact of locational characteristics on benefit exit. In this section we use an alternative estimation approach which controls for fixed differences between people even when they are unobserved. The methodology does however, have other limitations that we discuss below.

The population for this estimation is people who changed postcode while receiving unemployment payments between January 1996 and June 2000 (and who were aged less than 64, if men, and less than 59 through 61, if women – depending on their date of birth). For those people who moved more than once, we examine only one of the moves. The dependent variable (the 'income support receipt gap') is the number of fortnights for which they received unemployment payment in the 12 months after the move, minus the number of benefit receipt fortnights in the 12 months prior to the move. An OLS regression is estimated with this difference as the dependent variable and with the change in the regional characteristics as independent variables. We ignore any information about multiple moves during the period – treating this as additional random noise in the estimation.

This differencing approach controls for the linear impact of any person-specific fixed effects and any endogeneity of the move decision that is determined by these fixed effects. For example, an unemployed person with relatively high skill levels will be able to find employment faster, irrespective of where they live. Their long-term history of labour market success also allows them to live in a good labour market. In the analysis presented in Section 4, we attempted to control for this using observable characteristics of the person (and their local housing market). However, to the extent to which these variables are incomplete in their description of their underlying personal job seeking ability, some of their success in searching for work is attributed to the state of the labour market. Nonetheless, such a person will have a lower likelihood of receiving income support both before and after their move. There is no particular reason to expect that their higher skill level will have an impact on the *change* in their likelihood of benefit receipt when they change locations.

Nonetheless there are aspects of this estimation strategy that could conceivably bias the results. First, is the fact that we cannot take account of multiple moves. This introduces error into the measurement of regional characteristics and means that the estimates of the impact of regional characteristics will be attenuated. Of the first-move sample (defined below), 43 per cent moved again in the 12 months following the first move, though nearly 60 per cent of this group moved only once more. Very few moved more than twice in the ensuing 12 months, although one person moved 11 times.

The second issue is a potential selection bias. We only examine people who move. To apply these results to the whole population requires an assumption that non-movers would respond in the same way to changes in regional characteristics. Given, however, that most moves are for non-labour market related reasons (see Section 2), this generalisation seems plausible.

In addition, a second potential selection bias arises from the fact that we can only observe moves that take place when people are receiving income support, and we only choose one of these moves. The potential impact of this is best understood if we consider people who only have a single spell of unemployment benefit receipt. If we choose their first move then people with longer spells will tend to have higher values for the 'income support receipt gap' dependent variable. These people will also tend to have lower skills and live in poorer labour market regions. Nonetheless, constrained by the need to minimise housing costs, such people will tend to live in poor labour market regions both before and after their move, and so this will not necessarily bias the estimates of the effect of changes in location on outcomes.

In order to provide some degree of robustness with respect to this type of selection effect we undertake two analyses. In the first regression we select the *first* move that each person has during the observation window and calculate the associated change in dependent and independent variables. In the second regression, we select the *last* move that each person made. For people who only have a single spell of benefit receipt but multiple moves, choosing the last move will lead to a lower value for the dependent variable, and this will be particularly lower for those with long spells (ie the opposite pattern to that described in the previous paragraph).[14]

The fourth issue is one that we cannot resolve with the available data. It is possible that there are unobserved factors that are not fixed and influence both the change in location and the change in employment status. They include job offers that encourage movement. More subtle interactions may occur via the dynamics of the job search process. For example, an unsuccessful jobseeker may, with time, lose some motivation for job search. At some point they may concurrently decide to move to a region with a better housing cost/amenity trade-off and reduce their job search effort. In our analysis we assume that the individual's intensity of job search does not change with the move, so any difference in the time spent in income support receipt is attributed to changed labour market conditions.

In general, we believe that these potential biases are probably not very important. This is primarily because, as discussed in Section 2, labour market and housing cost factors are only a minor part of the decision-making process that drives moves between postcodes. Though there is some association with labour market conditions, most moves appear to occur for other reasons.

For each of the two dependent variables, we estimate three models. The first includes fixed demographic characteristics, the distance moved and the unemployment rate gap attached to the move, as explanatory variables. The second model adds the change in the number of jobs within 20 km to the list of explanatory variables and the third adds the move type. Table 5 shows the estimates when we use the first move of each person and Table 6 the estimates obtained from the last move.

The fixed variables in the regression (ie the constant and the demographic variables) reflect the fact that the mean of the dependent variable is not zero but varies depending on the propensity to relocate at different points during the unemployment spell. Thus in Table 5 the mean of the income support receipt gap is 3.7 fortnights because the first move generally takes place towards the beginning of a spell of income support receipt (though the analysis also includes people with multiple spells). In Table 6 the mean is -0.1 fortnights because the last move tends to take place towards the end of the spell. The parameter estimates for the fixed demographic variables indicate how these patterns vary between demographic groups and are not of particular interest here.

For both dependent variables, and all models, the change in labour market conditions associated with the move has a significant impact. Moving to an area with a one percentage point higher travel region unemployment rate leads to an increase in income support receipt of about one-third of a fortnight (95% confidence interval of 0.22 to 0.42 for Model 3 for the first move calculations). This increase is about 2 per cent of the average number of fortnights of income support receipt per annum. There is also some indication that moving to a larger labour market is associated with a decrease in benefit receipt, though this relationship is only significant for the last move.

Moving more than 40km is associated with a reduction in the time spent in receipt of benefit of around 0.6 to 0.75 fortnights per annum. The distance moved is related to the type of move, and so not significant in model 3. One explanation for this is that the shortest moves are motivated more by the desire to find cheaper accommodation than to improve employment opportunities.

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Table 5. OLS Regression Estimates of the Income Support Receipt Gap for Unemployment Payment Recipients Who Move – First Move

	Sample means	Model 1	Model 2	Model 3
		Coefficient Estimates		
Income support receipt gap (fortnights)	3.660			
Locational variables				
Distance moved (km/10^4)	0.033	-1.67	-1.70	-2.13
Moved more than 40 km	0.435	-0.63**	-0.61**	-0.40
Unemployment rate gap (percentage points)	-0.146	0.33#	0.31#	0.32#
Change in no. of jobs within 20 km / 10^6	0.110		-0.07	-0.08
Move Type (relative to between capital cities)				
Within capital of same state/territory	0.442			-0.02
Non capital to capital	0.115			-0.16
Within non-capital	0.302			-0.60
Capital to non-capital	0.091			-0.40
Fixed variables				
Women	0.369	0.65**	0.65**	0.63**
Married	0.181	0.40	0.40	0.42
Married women	0.050	0.41	0.41	0.43
Youngest child aged less than 13	0.082	-0.98	-0.98	-0.97
Youngest child aged 13 to 15	0.006	-1.83	-1.83	-1.90
Number of dependent children	0.177	0.07	0.07	0.07
Age in years				
20-24	0.260	-3.71#	-3.71#	-3.74#
25-29	0.169	-4.07#	-4.08#	-4.12#
30-34	0.109	-3.56#	-3.58#	-3.62#
35-39	0.081	-2.38#	-2.39#	-2.41#
40-44	0.061	-3.44#	-3.45#	-3.46#
45-49	0.051	-3.39#	-3.42#	-3.45#
50-54	0.036	-1.74**	-1.77#	-1.78#
55 plus	0.030	-0.42	-0.46	-0.47
Born overseas	0.205	0.32	0.32	0.20
Born overseas in English speaking country	0.040	-1.09	-1.09*	-1.02
ATSI	0.045	0.30	0.29	0.38
Received earned income	0.094	-2.32#	-2.32#	-2.34#
Earned income per fortnight ($/100)	0.201	-0.43	-0.43	-0.41
Earned income squared ($/10000)	0.707	0.01	0.01	0.01
Received unearned income	0.090	0.09	0.10	0.09
Unearned income per fortnight ($/100)	0.028	0.76	0.78	0.87
Unearned income squared ($/10000)	0.041	5.2E-04	-0.01	-0.04
Intercept		6.70#	6.70#	6.91#
Sample size	8,203			
Adjusted R squared		0.0364	0.0366	0.0366

1 per cent level of significance
** 5 per cent level of significance
* 10 per cent level of significance

Table 6. OLS Regression Estimates of Income Support Receipt Gap for Unemployment Payment Recipients Who Move – Last Move

	Sample means	Model 1	Model 2	Model 3
		Coefficient Estimates		
Income support receipt gap (fortnights)	-0.146			
Location variables				
Distance moved (km/10^4)	0.030	-1.71	-1.68	-1.05
Moved more than 40 km	0.417	-0.77#	-0.75#	-0.36
Unemployment rate gap	-0.120	0.37#	0.33#	0.33#
Change in no. of jobs within 20 km / 10^6	0.059		-0.13#	-0.13#
Move Type				
Within capital of same state/territory	0.459			0.71
Non capital to capital	0.100			-0.02
Within non-capital	0.304			0.32
Capital to non-capital	0.091			0.05
Fixed variables				
Women	0.370	0.92#	0.92#	0.92#
Married	0.185	0.66	0.65	0.65
Married women	0.054	0.21	0.21	0.20
Youngest child aged less than 13	0.085	0.45	0.39	0.42
Youngest child aged 13 to 15	0.006	2.47	2.45	2.44
Number of dependent children	0.182	-0.28	-0.27	-0.27
Age in years				
20-24	0.274	-2.49#	-2.49#	-2.50#
25-29	0.184	-2.71#	-2.72#	-2.73#
30-34	0.118	-2.05#	-2.08#	-2.09#
35-39	0.083	-0.90*	-0.90*	-0.90*
40-44	0.064	-1.86#	-1.91#	-1.91#
45-49	0.054	-1.45**	-1.49#	-1.52#
50-54	0.038	0.98	0.94	0.93
55 plus	0.032	3.13#	3.05#	3.07#
Born overseas	0.205	0.21	0.23	0.18
Born overseas in English speaking country	0.040	-0.25	-0.25	-0.21
ATSI	0.047	-0.25	-0.27	-0.28
Received earned income	0.101	-2.34	-2.38#	-2.37#
Earned income ($/100)	0.233	-0.32	-0.30	-0.30
Earned income squared ($/10000)	1.300	0.01	0.01	0.01
Received unearned income	0.090	0.38	0.39	0.39
Unearned income ($/100)	0.027	1.44	1.47	1.49
Unearned income squared ($/10000)	0.037	-0.16	-0.17	-0.18
Intercept		1.57#	1.58#	0.99
Sample size	8189			
Adjusted R squared		0.0386	0.0396	0.0395

1 per cent level of significance
** 5 per cent level of significance
* 10 per cent level of significance

6. Summary and Conclusions

Considering the results in both Section 4 and in Section 5, we conclude that regional labour market conditions do have an impact upon the probability of receipt of unemployment payments.

In Section 4 we found that people living in areas with a one-percentage point higher travel region unemployment rate had a 5 per cent lower likelihood of exit from benefit in any given week, and a 9 per cent increase in their mean duration of benefit. In the long run, and assuming a steady inflow rate, this would translate to an increase in the stock of unemployment payment recipients of the same percentage.

However, we believe that this is an over-estimate of the impact of regional labour market conditions, as part of this association is due to the fact that people with low skill levels can only afford to live in high unemployment regions. This is likely to be the case even though we control for regional housing costs.

In Section 5 we employed an alternative method that looked at the change in benefit receipt patterns when individuals moved location. Here, an increase of one percentage point in the travel region unemployment rate is associated with a 2 per cent increase in the likelihood of unemployment payment receipt. Though this method is subject to a number of potential biases, this lower estimate is our best estimate of the independent impact of locational labour market characteristics on unemployment benefit receipt. In future work we plan to explore alternative statistical models that are less sensitive to the potential biases associated with the simple differencing approach used here.

There is also some suggestion that moving to a larger labour market helps (independent of the change in unemployment rate), but this is not always statistically significant.

Overall, the estimation results of this paper suggest that regional labour market conditions do matter, though the effect is not very large. Unemployment payment recipients themselves appear to believe this – they do tend to move towards areas of better labour market opportunities, though this is by no means the main factor influencing mobility (Bradbury and Chalmers, 2003).

This paper therefore provides some support for policies that seek to influence the movement decisions of unemployment payment recipients and for regionally-specific labour market policies. The former set of policies include both income support policies (such as exclusion rules for people who move to high unemployment regions and possible regional variations in rent assistance) as well as housing policies that can influence the geographic distribution of affordable housing in Australia. Decisions about the implementation of such policies, however, should be based upon a consideration of a much wider range of costs and benefits than are considered here.

Notes

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1 We understand that this rule may be applied if the unemployment rate in the region the person is moving to is more than two percentage points higher than the rate in the region they are leaving. However, discretion can be used and some moves for family reasons are permitted.

2 As Hulse (2002) notes, the level of rent assistance paid to income support recipients varies little between high and low rent regions.

3 For surveys see Herzog, Schlottmann and Boehm (1993) and Dockery (2000).

4 Unemployment payments are Newstart Allowance, Jobsearch Allowance and Youth Allowance when the recipient is looking for work.

5 The LDS documentation states that where postcode of residence is not known (eg the person does not have a fixed residence) the postcode of payment address is used. We have no information on the extent to which this is the case, but believe it to apply to only a small percentage of cases. We exclude cases where their postcode is not found in our postcode to SLA concordance. This excludes many of the (non-residential) postal box postcodes.

6 For people living outside the journey to work study areas, we simply use the unemployment rate for their own SLA as their travel region unemployment rate.

7 See Jenkins (2004) for a discussion of the advantages in using flexible baseline hazards.

8 We do not include person-fortnights prior to the beginning of the observation window. Jenkins (1995) shows that this is the appropriate way to deal with a mixed stock/flow sample.

9 Within each spell, the benefit status across each person-fortnight is obviously not independent. However, this is accounted for in the estimation process. See Allison (1982) and Jenkins (1995).

10 This difference arises because longer spells are more likely to be captured in a sample taken at any one point in time, a stock sample.

11 The logistic regression model fits the hazard as $h = 1/(1+e^{-X\beta})$. If h is small, $h \approx 1/e^{-X\beta} = e^{X\beta}$. This implies that $\Delta h/h = e^{\beta_0} - 1$ when X_0 increases by one unit (Jenkins and Garcia-Serrano, 2000).

12 For spells that were under way at the beginning of the observation window, spell length is measured by a Centrelink-generated variable recording the length of time that the unemployment payment recipient has been continuously in the Centrelink system. If the income support recipient finds new work

he/she is removed from the Centrelink system, unless he/she does not expect the job to last for more than 12 weeks (6 pays) and chooses to stay in the system without receiving income support. By choosing to stay in the system the recipient keeps a Healthcare card and does not need to re-apply for unemployment payments. Furthermore, in the first 12 months of unemployment, breaks of up to six weeks in payments were ignored and after 12 months of unemployment, breaks of up to 13 weeks were ignored. For subsequent duration and for spells that commence in the observation window, we measure duration as time in receipt of income support, with exit defined as two fortnights without receiving income support. This means that some people in the stock sample may be recorded as having longer spell durations than if they had been measured in the same way as for the flow sample.

13 We calculated mean duration for those people with spells of up to 400 fortnights. Only 1 per cent of cases had spells that were longer than this.

14 Comparing these two regressions also addresses another potential bias. It is possible that people with low skills are more mobile and also tend to continue to move towards areas of poorer labour market opportunity. These people will have high values of the dependent variable in the first regression, but low values in the second regression.

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