Final Report

Housing, location and employment

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CONTENTS

FIGURES

TABLES

EXECUTIVE SUMMARY

What determines the choice of residential location for workforce-age income support recipients? Does location matter for employment outcomes? This report examines these two questions using data from the Department of Family and Community Services Longitudinal Data Set (LDS).

Answers to these questions are important for housing, income support and other policies designed to help those most disadvantaged in the labour market, as well as for policies that seek to ensure a smoothly functioning labour market. Does cheap housing (public or private) attract people to areas where they have little chance of finding employment? Should housing and income support policies attempt to discourage this?

Current social security legislation does assume that location matters. People can be excluded from unemployment benefits if they move to areas of higher unemployment.

These questions are also relevant to housing policy decisions about where to site affordable housing and how to structure rent assistance programs to take account of regional variations in housing costs and labour markets.

In addressing these questions, this report deals with two main methodological issues. The first question is how to best measure the labour market characteristics of the different regions of Australia. In particular, how do we take account of the patterns of commuting between the regions of our cities? Often the local unemployment rate of an area will be more a reflection of the characteristics of the people that live there, than it will be of the labour market opportunities available to people in this location. To address this question, the report calculates a *travel region unemployment rate*, which summarises the balance of labour demand and supply facing individuals living in each postcode area.

The second (related) issue concerns the estimation of the impact of labour market conditions on individuals' employment outcomes. It is well known that some rural, regional and outer urban areas have higher unemployment and lower employment than other areas in Australia. It is possible that this reflects the disadvantages associated with these regions (eg lack of economic growth, transport problems). If this is the case, then there may be a policy case for measures to encourage unemployed people to either not move to, or to move out of these regions. On the other hand, this association might simply be a reflection of the fact that these locations are the only regions where people with low income earning potential can afford to live. If this is the case, then a policy that encouraged an unemployed person to move to a region of greater employment opportunity (or discouraged them from doing the opposite) might not have any impact on their labour market prospects. To address this issue it is necessary to control for those difficult-to-observe factors that influence both location and employment outcomes. We do this by examining the *change* in the labour market outcomes of individuals as they move between locations.

Previous research: The determinants of mobility

Research in the US and UK has found that housing affordability has a strong role in influencing the patterns of geographic mobility of low-income families. Some studies have found evidence that labour market conditions matter. US research on the impact of variations in levels of welfare provision across regions has found that this has little impact.

In Australia, the main focus of research has been on migration into and out of the major cities, with a substantial movement of low-income people away from the cities being documented. Greater housing affordability has been proposed as the main reason for this. However these Census-based studies are limited. They cannot tell whether it is unemployment that leads to exit from the city, or movement out of the city that leads to unemployment.

Studies that collect information on the same individuals at two or more points in time (longitudinal data) can help disentangle these causal relationships. Two recent studies by Morrow (2000) and Dockery (2000) use the FaCS LDS to examine the impact of housing costs and labour market conditions on mobility of income support clients. In contrast to the Census-based results, Morrow finds that unemployed people tend to move toward the cities rather than away from them. Dockery, on the other hand finds that locational decisions do not seem to respond to labour market opportunities. However, it is possible that Dockery's results stem from a too-small definition of labour market regions that do not take into account the commuting possibilities within large cities.

Previous research: The impact of location

Though there is ample evidence that labour market conditions (such as unemployment rates) vary substantially across Australia, there is very little research that attempts to ascertain the causal impact of locational characteristics on individual outcomes. Such research needs to control for the characteristics of the people that live in different regions.

One way of doing this is by examining sub-populations that are relatively homogeneous with respect to their labour market opportunities. Data from the 1996 Census suggest that lone parents in public housing in non-metropolitan regions have slightly lower employment rates than lone parents in metropolitan regions (though the difference is not statistically significant). Even for this highly selected sub-population, however, there may be some self-selection, with those parents with little labour market attachment more likely to live in non-urban environments.

Social experiments in the US do suggest that location may be important for a range of social outcomes such as youth crime rates.

Behavioural theory

A simple model of residential mobility and job search effort suggests the following factors may influence the locational choice of people receiving income support payments.

- For people with low probabilities of employment or with low potential wages, the relative costs and amenities of different regions will be the main economic determinants of locational choice.
- Regional labour market conditions will have the greatest locational choice relevance for those people who expect the highest returns from working.
- Over time, changes in locational amenities and expectations of returns to labour market participation or home production will influence decisions to move or not.
- The probability of gaining employment will tend to be higher in larger labour markets and higher when unemployment is low.

When examining the impact of location on employment outcomes, we need to take account of the fact that individuals with higher skills and motivation will be both more likely to find employment and also more likely to live in low unemployment regions. The association between location and employment on its own, therefore, cannot be used as an estimate of the impact of location.

If these unobserved personal characteristics are fixed over time, we can control for them by observing the changes in labour market outcomes as people move between regions. However, there are some circumstances where the unobserved factors may themselves change. For example, when the youngest child of a lone mother is about to start school, it is quite possible that she may both increase her job search effort and consider moving to a region with higher labour market demand. If we therefore observe that lone mothers who move to lower unemployment regions tend to find employment, we can ascribe only part of this association to the direct effect of location on employment.

Similar reasoning applies to people who move to take up a job offer. We exclude many of these people in the analysis of Section 6 by only considering people who receive income support before and after the move. Nonetheless, these possible changes in unobserved circumstances remain a caveat to the results that we show there.

Data

The results in this report are based on the FaCS LDS 1 per cent sample file. This includes (anonymous) data for a 1 per cent sample of FaCS income support clients. The file includes information on the income support payments received for every fortnight between January 1995 and June 2001. No information is available for fortnights when the customer did not receive income support (other than the fact that no income support was received). In this report we restrict our analysis to people of workforce age.

The LDS contains information on the postcode of residence at the time of payment receipt. The 1996 Census postcode concordance is used to match these postcodes to 1996 Census Statistical Local Areas (SLAs).

The LDS data on rent paid is used to estimate the relative housing prices in each region. The measure of housing costs is thus an estimate of the extent to which a particular location has a higher than average rental (controlling for family size).

Using the 1996 Census Journey to Work data, we estimate the number of jobs located in each SLA in Australia. To calculate the number of jobs within 10, 20 and 50km, it is assumed that these jobs are all located at the centroid of the SLA.

The *travel region unemployment rate* is estimated using Journey to Work data. For any target SLA, this is a weighted average of the unemployment rates in all SLAs with the weights higher for those SLAs where people tend to work in the same area as the target SLA. Details of this calculation are in Appendix A.

The determinants of mobility

Two sets of questions are examined.

- *Gross flows*: What are the characteristics of people who move? Are some population groups more mobile than others? Do some people move further?
- *Net flows:* What impact does residential relocation have on the geographic distribution of income support recipients? Is the stock of recipients tending to move towards low-rent, high unemployment regions?

The units of analysis are pairs of consecutive fortnights in which an individual is in receipt of payment ('person fortnight pairs'). For each person fortnight pair, we compare the postcode of residence in the first fortnight with that in the second fortnight.

Unemployment payment recipients were more likely to move than those people receiving other payments. Women were slightly more likely than men to move.

Forty five per cent of moves were within a state capital city, four per cent between capitals, ten per cent non-capital to capital, ten per cent capital to non-capital and 31 per cent within non-capital regions. Unemployment payment recipients tended to move further than people receiving other payments.

Logistic regressions of the probability of moving were estimated. The regressions estimated the probability of moving, the probability of moving more than 10 km and the probability of moving more than 100 km. People living in high housing cost regions were more likely to move postcode, though this relationship was insignificant for longer moves. Those in both the smallest and largest labour markets were most likely to move postcode. For moves over 10 or 100 km, however, those in the largest labour markets were least likely to move.

We find that people living in low unemployment regions were *more* likely to move than those in high unemployment regions. This counter-intuitive result has also been found in other research in Australia and other countries. However, this result tells us nothing about the locations that people move *to*. It is conceivable, for example that the people in low unemployment regions are moving to other low unemployment regions, while the movers from high unemployment regions are also moving to low unemployment regions.

In general, between any two regions, significant numbers of people are always moving in both directions. Our main interest, however, is in the *net impact* of this re-location. From this perspective, there is a tendency for unemployment payment recipients to move away from the regions with the poorest labour markets.

On balance, about 4,200 unemployment payment recipients per annum are leaving the regions with the highest unemployment rates (that is rates over 12% in 1996). This is 4.3 per cent of the average total number of unemployment payment recipients in those regions, or 17.1 per cent of gross flows (average of those moving in and out of the region). Associated with this, there is a tendency for people to move towards the larger labour markets, and towards higher housing cost areas.

For non-unemployment payment recipients, the patterns of movement, if anything, were in the opposite direction.

A weighted least squares regression analysis using net inflows as the dependent variable, and postcodes as the unit of analysis was undertaken. For unemployment payment recipients, an increase in the travel region unemployment rate of a region by one percentage point is associated with an increase in the net outflow per annum of around one per cent of the recipients in the region. A similar relationship exists for both short and long duration unemployment payment recipients. The size of the labour market also has an impact on net movements, though only for the short duration unemployed.

For non-unemployment payment recipients, there is no significant relationship between labour market conditions and net flows.

The impact of mobility

How much impact do regional labour market conditions have on the likelihood that a person will be employed or not receiving income support? We employ two estimation methods to address this question. The first is an estimation of the impact of location on probability of leaving benefit. The second is an estimate of the change in benefit receipt between two consecutive years when people move location. In both cases, we restrict our attention to unemployment payment recipients, both for data availability reasons and also because this is the group for whom labour market factors are likely to be of most importance in influencing spell exit.

We first estimate an unemployment payment spell duration model using demographic characteristics plus time-varying regional characteristics as the explanatory variables. The combined stock and flow sample discrete-time hazard model of Jenkins (1995) is used, in conjunction with a flexible base-line hazard function. The sample consists of the stock of unemployment payment recipients at the commencement of the observation period (6 January 1995) together with those that commenced an unemployment spell before the end of May 2000. An unemployment spell is considered to end if the recipient does not receive income support for two payments. This could include exit to employment, breaching or spouse employment.

A one-percentage point increase in the unemployment rate was associated with a 5 per cent drop in the probability of exit from benefit. This should be considered an upper bound for the impact of regional characteristics as it partly reflects the fact that people with low skill levels can only afford to live in high unemployment regions.

There was no clear pattern of exit with respect to labour market size. Patterns for long-duration unemployed were similar to the overall pattern.

In the second estimation, we use an alternative approach. The population for this estimation is people who changed postcode while receiving unemployment payment between January 1996 and June 2000. 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 that they received 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.

Though this differencing approach controls for fixed differences between people even when they are unobserved, it has other potential limitations.

- Multiple moves are ignored. This measurement error means that the estimates of regional effects will be under-estimated.
- We only examine people who move. Possibly, the non-movers would respond differently to changes in labour market conditions.

- We only examine movers who move when receiving benefit. For people experiencing single spells of unemployment, this may introduce a bias because of the interaction of movement behaviour with spell duration. In order to control for this, we estimate the impact of both the first move made by the person, and also their last move. The comparison of estimates suggests that this bias is not important.
- It is possible that some unobserved factors may change over time and create an association between change in location and change in benefit receipt which is not causal. They include changes in family status, or job offers that encourage movement. We believe that these influences are not likely to be very important because labour market factors are only a minor part of the decision-making process that drives moves between postcodes.

The change in labour market conditions associated with moving 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. This increase is about 2 per cent of the average number of fortnights of income support receipt per annum. As expected, this impact is less than found using the first estimation method, and we believe, a better measure of the true impact of location.

Conclusion

Overall, the results of this paper suggest that regional labour market conditions do matter. Unemployment payment recipients themselves appear to believe this – they tend to move towards areas of better labour market opportunities (though this is by no means the main factor influencing mobility). The estimation results also support this view, even though they are not conclusive.

This report therefore provides support for policies that seek to influence the movement decisions of income support recipients (and unemployment payment recipients in particular). These 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 other policies that might influence the geographic distribution of affordable housing in Australia.

1 INTRODUCTION AND RESEARCH QUESTIONS

Do housing markets and housing policies provide incentives for economically disadvantaged people to live in areas of low employment opportunities? Does living in such an area actually impede their employment prospects? This report examines these questions focusing on working age income support recipients in Australia.

The project has the following two objectives:

- To describe the role of employment and housing in influencing the locational choice and geographic mobility of income support recipients and other low-income groups.
- To estimate the direct effect of housing location on employment outcomes.

These questions are important both for effective operation of the labour market and for the well being of individuals. It is often argued that high levels of geographic mobility among job seekers will reduce labour market friction and lead to a more efficient labour market and lower levels of unemployment (see Dockery, 2000). This mobility will be most effective if job seekers respond to labour market conditions and move to areas where they are more likely to find employment.

If, on the other hand, low incomes together with the operation of housing markets and housing policies lead people to move to regions where they are less likely to find employment, then labour market efficiency and individual welfare may be detrimentally affected. However, there is little evidence available to show whether location is in fact an important influence on labour market outcomes.

The current Social Security legislation in Australia does assume that location matters. For people receiving unemployment benefits Centrelink applies a *Move to an Area of Lower Employment Prospects* (MALEP) exclusion rule. Under this rule, people who move to an area of higher unemployment may be excluded from benefit receipt for a period of 26 weeks.[1]

Similarly, the recent Welfare Reform Review considered the characteristics of location, and the factors that encourage people to move to unfavourable employment regions, to be important impediments to full social participation.

> Cheaper housing (including public and community housing) in [the most disadvantaged] regions may tend to attract unemployed and underemployed people with lower education and skill levels, including many in receipt of income support, adding locational disadvantage to their existing barriers to accessing employment (Reference Group on Welfare Reform, 2000, p65).

The answers to the questions posed above are also relevant to a range of housing policy questions. These include

- To what extent is the location of public housing an impediment to employment?
- Similarly, does the location of other forms of affordable housing (both private rental and private ownership) in our cities and regions reinforce the prospect of poor employment outcomes for disadvantaged groups?
- Should policies such as rent assistance be adjusted to encourage people to move to higher employment regions? As Hulse (2002) notes, the level of rent assistance varies little between those areas with high (eg Sydney) and low rents (eg Tasmania). This might provide an incentive for people to move to cheaper areas. However, these areas also tend to have the poorest labour markets.

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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, there is administrative discretion possible, and we have been unable to ascertain the extent to which this rule leads to loss of benefits.

- What policy options are available to improve the characteristics of location to enhance employment outcomes?

The answers to these policy questions depend both on the impact of policy on locational choice, but also on whether location has an impact on employment outcomes. Hence, it is important to address both sets of research questions raised above.

In the next section of the report, we review previous research in Australia, the US and the UK that has addressed these questions. Australian studies on the determinants of mobility have produced mixed conclusions, arising from the limitations in the data and methods used. In particular, point-in-time Census data on the movement patterns of unemployed people can arise from several different causal mechanisms. The use of panel data in this report allows us to distinguish between these factors more clearly. Another issue concerns the best way to describe the labour market conditions of different regions, given the commuting possibilities available to workers.

With respect to the impact of location on employment outcomes, the geographic patterns of unemployment in Australia are well known. However, no research has been able to ascertain the strength of the causal impact of location on employment. It is possible, for example, that the higher unemployment in some regions simply reflects the fact that these locations are the only regions where people with low income earning potential can afford to live. If this is the case, then a policy that encouraged an unemployed person to move to a region of greater employment opportunity might not have any impact on their labour market prospects.

In Section 3 of the report these issues are elaborated within a simple economic model of locational choice and employment outcomes.

Section 4 introduces the primary data source for this study, the FaCS 1% Longitudinal Data Set (LDS). This contains information on the income support payments received by a sample of recipients for all fortnights between January 1995 and June 2001. This includes the postcode of residence, which is matched to 1996 Census Statistical Local Area (SLA) characteristics. An appendix describes the calculation of a ‘travel region unemployment rate’ designed to measure the labour market opportunities available within each of the SLAs of Australia.

Section 5 then provides evidence on the determinants of mobility among income support recipients. Both gross and net flows are examined. In net terms, we find that unemployment payment recipients do tend to move towards areas of greater labour market opportunities. However, this is the result of large gross flows in both directions.

Section 6 then examines the role of location on unemployment payment benefit receipt. People in lower unemployment regions do have higher rates of exit from benefit. However, this is probably partly due to the different (unobserved) characteristics of people in those regions. We can control for this by examining people who move between regions. In this case 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 PREVIOUS RESEARCH

2.1 The Determinants of Mobility

Substantial research has been undertaken in Australia and other countries on the determinants of geographic mobility. One of the most important themes of this research is the importance of housing costs. This has been found to be of particular importance for low-income groups.

US research on the mobility of low-income families has focussed on three key factors, housing affordability, labour market conditions, and variations in welfare benefits across regions (‘welfare magnets’). State variations in welfare generosity do not seem to have any significant impact on cross-state migration (Torrecilha and Sandefur, 1990, Clark, 1995). Labour market conditions also seem to have little impact, but there is strong evidence that people with low incomes tend to move to areas of lower housing prices (Fitchen, 1995). In the United Kingdom, there have been mixed findings with respect to the role of labour market conditions on inter-regional migration. Some studies have suggested that out-migration is encouraged by high unemployment (Pissarides and Wadsworth, 1989; Jackman and Savouri, 1992). However, Henley (2000) and Hughes and McCormick (1994) conclude that migration flows are largely unresponsive to demand for labour.

In Australia, the main focus of research has been on migration into and out of the major cities (see Hugo and Bell, 1999 and Burnley and Murphy, forthcoming, for overviews). Research over the last decade has documented a substantial movement of low-income people away from the cities (Bell 1995, Flood, 1992, Bell and Maher 1995, Wulff and Bell, 1997). Greater housing affordability has been proposed as the main reason for this (Hugo and Bell, 1998). Marshall et al (2003) find that housing affordability features prominently as a mobility driver among low-income people moving out of Sydney and Adelaide.

These estimates of the volume of movement out of the cities are mainly based on cross-sectional census data and need to be interpreted cautiously. For example, census data can tell us whether people who are currently unemployed have migrated into a region within the last year. However, we do not know whether they were unemployed and then moved, or moved and then became unemployed.

Studies that collect information on the same individuals at two or more points in time (longitudinal data) can help disentangle these causal relationships. Two important recent studies are those by Morrow (2000) and Dockery (2000). These both use data from the FaCS longitudinal data set (LDS) of administrative data on income support payments. The main determinants of mobility that both authors examine are housing costs and labour market opportunities.

Morrow (2000) looks at the mobility of workforce-age FaCS clients over a twelve-month period in 1996 and 1997. He finds that clients receiving unemployment benefits tend to move towards regions with greater employment opportunities. In particular, he finds positive net migration towards the major cities accompanied by migration away from the industrial towns and coastal regions of northern New South Wales and southeast Queensland. When statistical sub-divisions are categorised on the basis of their unemployment rates, he finds that unemployed clients have a net movement out of those regions with the highest unemployment rates and a movement into the regions with the lowest unemployment rates. At the same time, the housing rent of those who move goes up faster than the rent of those who do not move. He concludes “This pattern suggests that jobseekers are willing to incur the extra costs of housing in the capital cities in exchange for greater access to employment opportunities and important services available in the capital city regions.” Morrow (2000, p.27)

In contrast to the unemployed, he finds that Sole Parent and Disability Pension clients were more likely to move out of the cities.

Dockery (2000) uses similar data to model the determinants of mobility.[2] Consistent with Morrow's results, he finds that those unemployment benefit recipients who moved tended on average to be slightly more likely to move to an area with a lower unemployment rate. On the other hand, he finds that the male unemployed tended to move to areas with *lower* rents.

These housing and labour market variables, together with personal characteristics, are then included in a multivariate model predicting the probability that a person will move out of a particular local labour market (LLM). When controlling for other variables, the apparent impact of labour market conditions on mobility changes. He finds that the unemployed are *less* likely to move out of regions with higher unemployment rates (though the difference is not significant for men).[3] They continue to be more likely to move out of regions with higher rents. He concludes that "although the unemployed are generally more mobile than persons on other forms of income support, their locational decisions do not seem responsive to regional employment opportunity" (Dockery, 2000, p 419).

This recent research raises new questions and areas for further research. First, the regional patterns of mobility identified by Morrow appear to conflict with the conclusions of the earlier research noted above which suggested that the unemployed were leaving the capital cities and moving to coastal areas and other non-metropolitan regions. It is possible that these different conclusions are due to methodological limitations in the earlier studies. The LDS results are for people who are receiving unemployment benefits both before and after their move. The earlier, Census-based, results categorise people according to their status after they move. It is therefore possible that these earlier results arose from people becoming unemployed *after* they moved out of the metropolitan regions.

That is, the apparent patterns of counter-urbanisation among the unemployed found in the earlier studies might be due to the impact of location on employment rather than employment status influencing location.

Though the research of Morrow and Dockery appear at first glance to offer differing conclusions as to the role of housing costs, these results are not necessarily inconsistent. Morrow finds that unemployed people who move face an increase in housing costs. Dockery finds that they tend to move to regions with cheaper housing. The two phenomena can occur simultaneously if the attraction of cheaper housing is one reason for relocation, but people who move initially face higher rents as they move into unfamiliar rental markets[4].

However, the different conclusions about the impact of labour market conditions are puzzling. These results probably stem from limitations in the specification of the labour market environment in both studies. In particular, the level of regional aggregation used to describe labour market conditions in these studies leads to indicators that are not accurate measures of the employment opportunities available to people living in different regions.

To describe the labour market characteristics of the regions in which people live, Dockery uses the "Local Labour Market" concept as defined in the DEETYA publication *Small Area Labour Markets*.[5] These regions were defined by DEETYA as "the geographical area in which individuals residing in a particular region typically commute to work or search for jobs". However, this is not really an accurate description of these regions. In particular, the large cities are generally disaggregated into several regions, despite the fact that many people commute from one part of the city to another.[6] In Dockery's study, around 35 per

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2 He uses the 1% sample from the LDS between April 1997 and April 1998. Morrow's results appear to be based on the full LDS population.

3 He also observes an association with the employment growth of the region (in absolute numbers). However, this may reflect the size of the region, and so is difficult to interpret.

4 Other possible reasons for this anomaly include changes in family composition associated with moves and people moving to areas of cheaper rent so as to live in a bigger house.

5 The current DEWSRB publication *Small Area Labour Markets* no longer uses this geographical grouping. Morrow uses the ABS 'statistical sub-division' geographic unit. The comments in the text with respect to LLMs apply equally to this geographic unit.

6 O'Connor and Healy (2002) divide the Melbourne labour market into 10 regions. For regions other than the core region, between 28 and 57 per cent of workers were employed in their own region (the core was 76%).

cent of all residential re-locations of people on unemployment benefits were between different regions of the same city. To the extent to which movements between these regions determine the results he found, it is debateable whether they are a reflection of the impact of employment opportunities.

For example, consider an unemployed person who moves from, say, the North shore of Sydney to the inner West region. Though unemployment rates are much higher in the latter region, geographic access to employment is very similar. In the model estimated by Dockery (and in Morrow's data), this person will contribute to the finding that unemployed people tend to move to higher unemployment regions. At least in this example, we cannot interpret this to mean that people are necessarily moving away from employment opportunities.

In general, it is not straightforward to ascertain the employment opportunities associated with a particular location. For many people, the best indicator for the employment opportunities facing a person living in one of Australia's large cities will be the unemployment (or employment) rate of the city as a whole. The variations in employment 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. At the same time, however, there may be other people for whom the local labour market is most important. Travel may be expensive or inconvenient for those with caring responsibilities (particularly sole parents) and for those with disabilities.

At present, therefore, many of the key research questions about the mobility of low-income Australians remain unanswered. Most importantly, there is conflicting evidence about the mobility patterns of the unemployed. Some research suggests that they are tending to move away from labour market opportunities, while other research suggests the opposite.

In this report we develop a *travel region unemployment rate* in order to better indicate the labour market opportunities available in different parts of Australia. We also employ longitudinal data to examine the patterns of movement of people who are income support recipients before their move, and develop statistical approaches that allow us to more clearly estimate the net impact of movement on the labour market opportunities facing income support clients.

2.2 The Impact of Location on Employment Outcomes

It is generally accepted in the labour market literature that higher rates of geographic mobility can reduce unemployment rates by facilitating better matching of job seekers to jobs (See Dockery, 2000 for a survey). 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 sub-national) unemployment.[7]

These conclusions, however, are about the impact of mobility per se. The focus here is on the impact of particular types of mobility. In particular, does moving to an area with a higher unemployment rate affect an individual's labour market outcomes?

It is well recognised that low-income families tend to be concentrated in regions with low levels of employment, and there is evidence that this association has increased over time (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 (eg McDonald, 1995). For example, 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. Alternatively, these regions 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. The policy implications of these two sets of explanations are quite different.

One way of controlling for unobserved heterogeneity in the population is to select sub-groups of the population that are reasonably homogeneous but live in locations with different employment opportunities. An analysis of this type is shown in Table 2.1, based on

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7 Indirect effects via land-use restrictions may also be important.

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 metropolitan and non-metropolitan regions of Australia. Metropolitan is defined as living in a state capital city. Tasmania, the Northern Territory and the ACT are excluded from the table.

Table 2.1 Employment Patterns of Lone Parents Living in Public Housing in Metropolitan and Non-Metropolitan Regions of Australia, 1996

Labour Force Status	Metropolitan (%)	Non-Metropolitan (%)
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.

Public housing authorities generally attempt to provide entry to the most disadvantaged in the community, and so within each demographic category the variation in skills among public housing tenants is likely to be lower than among the overall income support population.

Table 2.1 shows that lone parents living in non-metropolitan regions 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 in non-urban environments.

Identifying the distinct impact of location on employment is difficult, and it is not surprising that this has not been attempted in the Australian literature (to our knowledge). As noted above, there are two identification problems. First, both location and employment outcomes will be influenced by unobserved factors such as underlying 'ability' (which influences past income and hence ability to afford to live in certain areas). Second, there may be direct effects of changes in employment status on location (eg moving in expectation of getting a job, moving after taking up a new job).

Research methods that involve random assignment are the ideal method to address both these issues. Some experimental evidence from the US suggests that location does matter for a range of socio-economic outcomes. 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. 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.

In summary, we do not really know whether moving to an area of better labour market opportunities is likely to improve the employment prospects of any particular individual. There are good reasons to think that this might be the case, but also reasons why we might expect any such effect to minimal at best. The newly available panel data in the LDS allows us to begin to address these issues.

3 BEHAVIOURAL THEORY

It is useful to summarise these different relationships within a formal model. This allows a clear presentation of the key issues involved in estimating the determinants and outcomes of locational choices. Dockery (2000) presents a simple additive welfare model to describe the determinants of locational mobility. We extend this here to include job search effort as a choice variable and employment as an outcome variable. In this project, we do not attempt to estimate this theoretical model directly. Rather, it is presented to illustrate the impact of some variables that we cannot observe (such as job search effort) on the relationship between the variables that we can observe (employment status and location).

Consider a non-employed person who is currently living in region r^0. They are facing two decisions. Which region, r, should they choose to live in during the next period, and how much effort they put into searching for employment.[8] They make choices so as to maximise their expected income in the next period. Using a broad concept of income, this is defined as

$$\begin{aligned} E(y) &= j(w-t_r)+(1-j)b+a_r+H(-j)-k_r-m_{r^0r} \\ &= b+\left(w-t_r-b\right)j+a_r+H(-j)-k_r-m_{r^0r} \end{aligned} \tag{1}$$

where

$$j = J\left(s,p,d_r\right)$$

In this equation, *E(y)* is expected income, j is the probability of finding a job, which depends on the person's job search effort, s, their skill level or marginal productivity, p, and the level of labour demand in the region that they move to, d_r. We assume a positive relationship with all three variables. The increase in employment probability with skill level can be derived from a simple non-wage clearing labour market model, and is in accord with extensive data on the skill levels of the unemployed.

Given this probability of employment, a person expects to receive a monetary income of $j(w-t_r)+(1-j)b$ where w is the wage level, t_r is the transport cost associated with employment when living in region r, and b is the benefit level. For simplicity, we assume the wage and benefit level to be fixed irrespective of the location.9

In addition to the expected income to flow from wages or benefits, individuals are assumed to place a value on the geographic amenities of the region, a_r, and their expected level of home production or leisure $H(-j)$. The latter is negatively related to the probability of finding a job.

Each region also has a particular set of costs, k_r. For example, some regions will have higher housing prices. Finally, in order to move from region r^0 to r the person must incur some (positive) moving costs, m_{r^0r} (we define $m_{r^0r^0}=0$). These costs of relocation provide an incentive for the person to remain in their current region unless some alternative region is particularly attractive for either monetary or amenity reasons. Though this model is described in terms of single individuals, many of the effects of marital joint decision making can be incorporated as an additional cost of moving (i.e. the relocation of the employment of the spouse).

8 The model is easily adapted to consider part-time employed people searching for full-time employment.

9 Both these conditions could be relaxed. In particular, this model could be generalised to include the possibility that a person might be excluded from benefit if they move to a region with a poorer labour market. Generalisations to multiple periods are also possible. In this case we might expect labour market factors to have less impact on older workers who have a shorter expected future time in the labour market.

A number of relationships can be illustrated with this simple model. In this project we are particularly interested in the factors that drive the choice of region (r) and the importance of the choice of r on the probability of employment (j).

3.1 Choice of location

Many of the issues associated with location choice can be considered under the assumption that an individual's job search effort is fixed. In this case they chose their location to maximise their expected income. This will generally mean choosing regions with high employment prospects,[10] good locational amenity and low costs. However, there are generally trade-offs between these characteristics, with regions of high labour demand also having high housing costs.

From equation (1), it can be seen that for people with a low probability of employment (eg those with disabilities) the relative costs and amenities of regions will be the key determinants of location. For these people, the choice between regions will be determined mainly by differentials in amenities and costs (and constrained by the cost of moving).

For those with a greater chance of finding employment, the impact of the different levels of labour demand in different regions will vary depending on the net return to working. If wages (after deducting working costs) are not much higher than benefits, the impact of regional employment probability differentials on locational choice will be small. Indeed, given the negative impact of employment on home production/leisure, it is possible that people with strong preferences for home production or leisure might choose to move to an area of lower employment prospects in order to reduce their likelihood of finding employment (this potential behaviour is what the MALEP policy is designed to discourage).

When net wages are higher than benefits, regional employment probabilities will influence expected incomes, and so will be expected to have some influence on the choice of residential location.

For newly non-employed people, the factors described in this model may encourage them to move location – either to higher employment or higher amenity regions depending on their expectations and values. For long-term non-employed people (or people experiencing multiple spells of non-employment) these factors will have influenced their locational decisions in previous periods. Movement in the next period will be determined by *changes* in the factors described above. Thus individuals may move because new job opportunities arise, the value of locational amenities or costs change, or their moving costs fall (eg they reach the end of their rental lease).

More generally, changing information about all these factors, and their future values, will influence behaviour. For example, if an unemployed person continues to fail to find work, they may adjust downwards their expected likelihood of employment (and possibly their expected wages). As this happens, the non-employment related components of (1) will become more important in deciding whether to move or not (and where to move). In this case we might expect a tendency for them to move to a region with a better balance of amenities and costs.

On the other hand, some people may commence their job search with an expectation of finding a job in their own area. An extended spell of unemployment may then lead to a lowering of their expectation of finding work in this region. If they remain hopeful of finding work elsewhere, they may then decide to move to an area with stronger labour demand.

Labour demand in this model is a broad concept designed to reflect the number of job offers that a person is likely to receive (for some given level of job search effort). We would expect it to be higher in larger labour markets (eg large cities), and higher when job growth is high and unemployment is low (i.e. there are fewer competitors for jobs).

In cities, the locations where labour is demanded and where people live may be quite different. Nonetheless, for simplicity we denote demand in terms of the region where the person lives. The variable d_r should thus be considered as an average index of the labour

10 Unless they have strong preferences for home production/leisure (see text below).

demand within feasible commuting distances from region r, and $t_{r'}$ defined as the average transport costs to these regions.

3.2 Employment Outcomes

In this model, employment outcomes depend on labour demand in the region in which the person lives (or moves to), the person's job search effort, and their desirability to employers. If a person has a fixed skill level and maintains a constant job search effort, then a move to a region with greater labour demand will increase the likelihood that they will find employment.

However, skill and job search effort vary across individuals, and individuals can change their job search effort (and skills to a lesser extent) over time. Hence we cannot assume that an observed correlation between location and employment outcomes is a direct result of the effect of location on employment.

First, we may note that 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. As discussed above, the latter implies that they will be more likely to move to a region of high labour demand because the returns to working are greater. Hence we may observe an association between regions of high employment and locations with high labour demand that is actually due to variations in personal characteristics rather than a direct causal link. A similar association might arise via income effects, with individuals with higher expected incomes more likely to choose an area with greater amenities and lower travel time (the latter is not explicitly included in this simple model).

By observing *changes* in individual circumstances we can control for such fixed person effects (represented by p in equation (1)). However, it is more difficult to control for the impact of changes in job search effort. If job search effort increases at the same time as a person moves to high employment region, it will be difficult to separate the two effects.

The model suggests that one circumstance where these might move together is when household circumstances change. For example, when the youngest child of a lone parent starts school. A mother in this situation may both increase her job search effort and consider moving to a region with higher labour market demand. This is because the marginal value of non-work time $\partial H / \partial(-j)$ has fallen, implying a higher marginal value of employment and a higher optimal level of employment.[11]

In order to increase her chance of finding employment, it is quite possible that she will increase both job search effort and move to a higher employment region at the same time. If we therefore observe that lone mothers who move location tend to find employment, we can ascribe only part of this association to the direct effect of location on employment.

A similar problem arises when the level of labour demand in a region contains time-varying person-level components. In particular, consider the example of a person living in the western suburbs of Sydney, who is offered a job in the eastern suburbs. Because their travel costs will be much lower, they may thus decide to move to the eastern suburbs. We will thus observe a movement from a region with relatively low labour demand, to one with higher levels of labour demand, and also observe the person starting work. However, in this case the causality is from employment to location rather than the other way round.

In the empirical analysis below we partly control for this relationship by restricting our attention to those people who do not immediately change employment status when they move.

While these two examples provide caveats to the extent to which we can infer causal impacts of location on employment, there are many other causes of re-location that are not so problematic. As discussed above, change of region can occur for many different reasons, which do not have any direct effect on employment outcomes. For example, people may move because their costs of moving have fallen (eg at the end of a lease), because of personal preferences about the value of amenities in each region and changing regional differences in costs.

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11 Applying the standard labour supply assumption of diminishing marginal returns to home production.

4 DATA

4.1 The FaCS LDS

Most results in this report are derived from the Department of Family and Community Services (FaCS) Longitudinal Data Set (LDS). The data is drawn from the 1 per cent random sample of the LDS. The random sample is itself drawn from a framework of fortnightly extracts of all Centrelink customer records, and the version we use consists of data extracted from January 1995 to June 2001. To generate this sample FaCS firstly selected a group comprising every 100th record from the list of income support recipients for the second payment date in June 1995. Each subsequent fortnight every 100th customer who had not previously been a customer for the life of the survey was added to the sample. A similar process added customers from preceding fortnights. Each customer has only one chance of being selected. Once the sample was selected, information on every fortnight of payment receipt during the observation window was collected. The LDS contains basic demographic information for each customer, 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.

In all the analysis presented in this report we restrict attention to people in receipt of income support who are of workforce age (men aged 16 to 64 and women aged 16 to 60 through 62 depending on their date of birth).

4.2 Location

The LDS does not contain any information about recipients' names or addresses. However, it does contain information on the recorded postcode of residence[12] 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.

4.3 Housing Costs

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 (and date). 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 (averaged over the full period of the LDS).

4.4 Labour Market Size

Using the 1996 Census Journey to Work data, we estimate the number of jobs located in each SLA in Australia. For SLAs outside the Journey to Work study areas, we assume that people work in the same SLA that they live in. 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

[12] The LDS documentation states that where postcode of residence is not known (eg the person does not have a fixed residence), then 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 (1996) postcode to SLA concordance. This excludes many of the (non-residential) postal box postcodes.

jobs that are located within 10km, 20km and 50 km. We mainly focus on the number of jobs within 20km of the respondent.

4.5 Travel Region Unemployment Rate

As discussed above, the specification of the labour market conditions facing people in different regions is not straightforward. For urban dwellers, labour market measures based solely on the local environment may be misleading as they do not take account of the employment opportunities available in other regions which are within commuting distance.

One solution to this is to use metropolitan-wide indicators of labour market conditions. However, this implies an unduly even pattern of labour market opportunities. It does not take into account the significant costs that effectively confine individuals to work in sub-sections of the urban labour market.

In addition to the indicator of labour market size described above, we also calculate a *travel region unemployment rate*. For large regions, the unemployment rate is a good indicator of the balance of labour demand and supply, and of the relative difficulty of finding a job. However, the unemployment rate of the person's SLA (for example) is not necessarily a good indicator of the balance of labour supply and demand in those regions where they might feasibly find a job. The objective of the travel region unemployment rate is to calculate an index that indicates this broader balance of demand and supply.

The details of the calculation method are shown in Appendix A. In brief, the indicator is calculated by first estimating an *excess labour supply index* in each employment region. This is a weighted average of the unemployment rate in all regions of the journey to work study area, where greater weight is given to those residential regions that supply most people to the employment region's workforce. The travel region unemployment rate is then calculated as an average of this index over all employment regions where the weights are the proportion of workers who go to work in each region.

The effect of this averaging process is to calculate an index where the rate for a given region will be based on an average across all regions but with greater weight on those regions 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 employment prospects 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*. 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 prospects to live there.

5 ESTIMATION 1: THE DETERMINANTS OF MOBILITY

The model presented in Section 3 implies that people will move location when the costs of moving are low and when there are other locations which offer a better balance of costs and benefits. We address two sets of questions in this section.

- What are the characteristics of people who move? Are some population groups more mobile than others? Do some people move further?
- What impact does residential relocation have on the geographic distribution of income support recipients? Is the stock of recipients tending to move towards low-rent, high unemployment regions?

The first set concerns the *gross flows* of geographic location, while the second set focuses on the *net impact* of relocation. Our unit of analysis is pairs of consecutive fortnights for which an individual is in receipt of income support, or 'person fortnight pairs'. For each person fortnight pair, we compare the postcode of residence in the first fortnight with that in the second fortnight. The results of this analysis are thus representative of the mobility patterns among the stock of income support recipients.[13]

In the sample of income support recipients of work-force age there were 3,675,469 person fortnight pairs for which we have matched geographic information. In 1.3 per cent of those person-fortnight pairs the income support recipient moved postcode. For the first set of questions, we compare those who move with those who do not move. For the second set of questions, where we examine the net impact of movement on the geographic characteristics of income support recipients, we only consider the 48,071 person-fortnight pairs where a postcode move occurs.

Table 5.1 summarises the person fortnight pairs by the sex of the income support recipient and the payment received in the first fortnight. Non-unemployment payment recipients accounted for around 70 per cent of the person fortnight pairs. Nearly one half of the person fortnight pairs were those of non-unemployed women, almost one quarter were those of non-unemployed men, one-fifth were associated with unemployed men and 10 per cent with unemployed women.

Unemployment payment recipients were more likely to move than other recipients. There was little difference in the tendency to move between men and women. If anything, women seem more likely to move than men.

Table 5.1 Person Fortnight Pairs by Payment Type Received by and Sex of Work-force Age Income Support Recipient

	Person fortnight pairs (%)	Proportion involving move (%)
	Unemployment payment recipients	
Men	20.9	2.3
Women	9.7	2.6
	Other recipients	
Men	24.2	0.8
Women	45.3	0.9
Sample Size	3,625,464	1.3

Table 5.2 summarises each of the moves described in Table 5.1 in terms of the recipients' type of move. It shows that overall, 45 per cent of the moves were within a capital city and four percent of the moves were between capital cities. The moves of male unemployment payment recipients were less likely than those of similar women and other recipients to be within a capital city. Unemployment payment recipients were slightly more likely than other

13 Since long-duration income support recipients are over-represented in the stock, this will not be representative of the mobility patterns associated with a typical *spell* of income support receipt.

recipients to move between capital cities. While close to 30 per cent of the moves were made outside capital cities, regardless of gender and payment type received, nearly ten percent were from a capital city to an area outside capital cities and a further ten percent from areas outside capital cities into a capital city. These findings do not match up with the census analyses findings that low income Australians were moving to regional Australia. As noted in Section 2.1, this could be because of the inability of the census data to identify those people who were unemployed *prior to* their move.

While the patterns of moves for unemployed recipients and other recipients were remarkably similar, the unemployed were more likely to move between capital cities and slightly more likely to move into capital cities from outside capital cities. In general it would be easier to find work in capital cities than outside capital cities. A cursory analysis, using cross-tabulations, suggests that most of the ‘between capital city moves’ are towards Sydney and Melbourne[14]. However, this could also be illustrative of the tendency for young people to move towards big cities, remembering that the young are over-represented amongst unemployment payment recipients.

Table 5.2 Type of Move By Payment Type and Sex

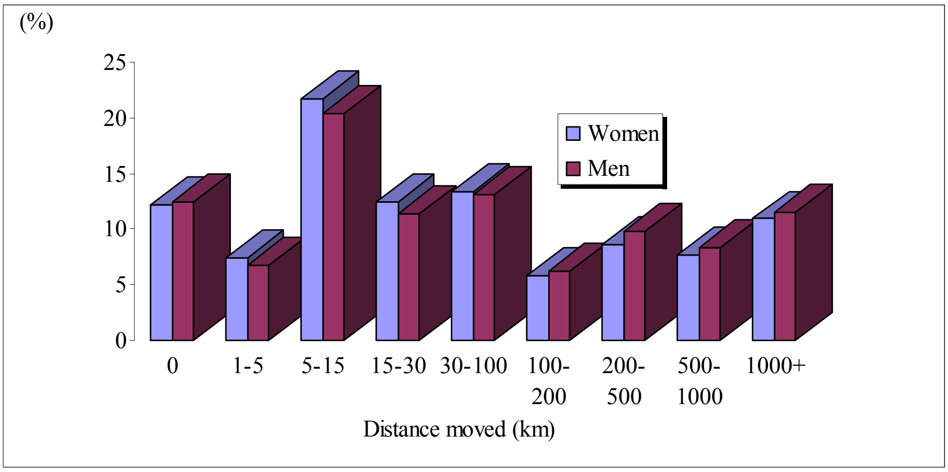
	Within capital city of same state/territory	Between capital cities	Non capital to capital	Within non capital	Capital to non capital	Number of Moves
	Unemployment payment recipients					
Men	42.3	4.9	10.8	31.9	10.2	17,513
Women	46.0	5.2	10.5	29.6	8.7	9,201
	Other recipients					
Men	46.6	3.1	9.5	29.7	11.2	6,527
Women	47.0	3.2	9.0	31.5	9.4	14,830
All moves	45.0	4.2	10.0	31.0	9.8	48,071

Figures 5.1 and 5.2 are histograms of the distances moved. Distance is calculated as the difference between the centres of the SLAs containing the before and after postcodes[15]. Hence the distance will be zero for postcodes within the same SLA. One disadvantage of this methodology for measuring distance moved is that movements from one side of an SLA to another are associated with a zero distance moved, whereas movements between postcodes attached to bordering SLAs, even if the move is from one end of a street to another end, will be associated with a distance moved described as the distance between the centres of the adjoining SLAs. The figures show that upwards of 15 per cent of moves were within an SLA. Unemployment payment recipients were more likely to move between SLAs. Furthermore, they were more likely to move distances of 200 km or more.

[14] Amongst those who move capitals, residents of Perth, Hobart and Adelaide were most likely to move to Melbourne, regardless of whether they were unemployment payment recipients. Similarly, residents of the ACT and Brisbane tended to move to Sydney.

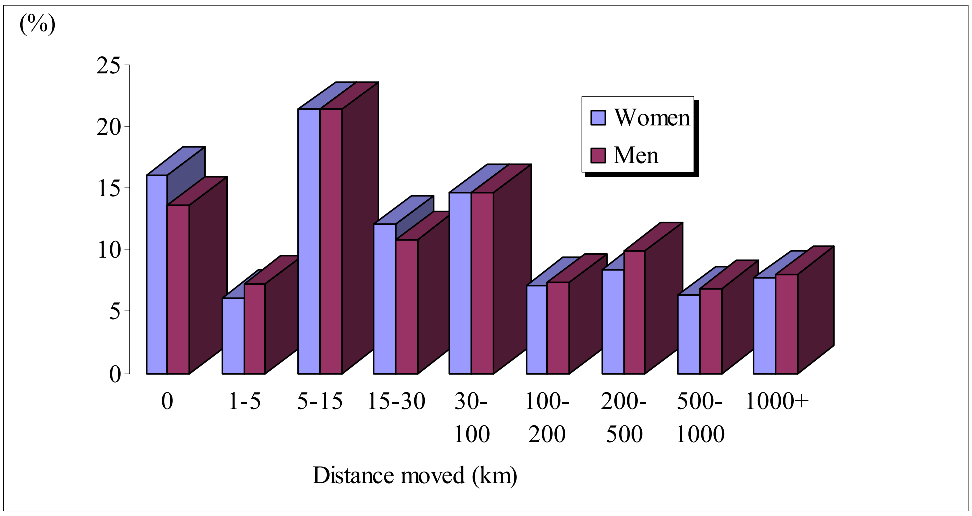
[15] Distances were calculated using an Australia-based spheroidal calculation model available from Geoscience Australia (http://www.auslig.gov.au/geodesy/datums/distance.htm).

Figure 5.1 Distance Moved (Unemployment payment recipients)



Note: People who changed postcodes, but who were still located within the same SLA are coded as moving zero distance.

Figure 5.2 Distance Moved (Non unemployment payment recipients)



Note: People who changed postcodes, but who where still located within the same SLA are coded as moving zero distance.

5.1 Factors associated with the decision to move

Which personal and locational characteristics were associated with the decision to move? Using the sample of person fortnight pairs we model three processes, the process of moving postcode, the process of moving more than ten km (medium distance) and the process of moving more than 100 km (long distance). We use three different distance categorisations because of previous research that has suggested different motivations for short and long-distance moves. For example, Owen and Green (1992) found in the UK that intra-urban moves were primarily housing related while interregional moves were primarily job related. The explanatory variables include basic demographic characteristics, income support type (unemployment payment recipients compared with others), housing tenure (before move) and housing cost and regional labour market indicators (separately for unemployment payment recipients and other recipients).

We certainly do not claim that these factors are the only, or even the main factors that influence the decision to move. The costs of moving will vary between individuals because of many factors that we do not observe. For example, Millington (1994) reminds us that the psychic costs of migration increase with the length of residence in the origin region and the extent to which family and friends are concentrated there. For others, changes in personal housing conditions will be the primary impetus for the decision to move house – for example increased rent levels, or the end of a housing lease.

Nonetheless, many of the personal and environmental variables described above prove to be empirically associated with re-location. Appendix Table B.1 presents estimates from logit regressions of the probability of moving postcode, moving more than ten km and moving more than 100km. Overall, there was a postcode move in 1.3 per cent of the person fortnight pairs, a medium distance move in 0.9 per cent of the cases and a long distance move in 0.4 per cent of the cases. The unemployment payment fortnight pairs were more likely to be associated with a move than other fortnight pairs, regardless of distance moved.

Indeed the estimated coefficients from the logit regressions confirm that unemployment payment recipients were substantially more likely to make all three moves, and the odds gap increased slightly in size with distance moved. This finding is consistent with Dockery (2000).

Personal and Demographic Characteristics

In terms of marital status and gender (for those without children), we see a similar pattern for postcode moves and medium distance moves. Unmarried people were most likely to move. Married men were less likely to move than were unmarried people, and married women were least likely to move. In terms of long distance moves, unmarried men were most likely to move. Unmarried women and married men were less likely to move and married women were least likely to move.

The presence and age of dependent children increases the complexity of the story. For example, if we compare married income support recipients, with one dependent child younger than 13, with their childless counterparts the mothers are most likely to move and the fathers are least likely to move. The tendencies to move of childless married men and women sit between the two extremes.

Reflecting the increased housing stability associated with age, regardless of housing tenure, we find that the tendency to move decreases with age. Nonetheless, the size of the age effect is substantially smaller for long distance moves than for shorter moves. Furthermore, while the youngest recipients are most likely to move postcode and medium distances, recipients in their early twenties are more likely to move longer distances than those aged 16-19 years.

Recipients born overseas in countries where English is the primary language spoken (Canada, Ireland, USA, and the United Kingdom) were no more or less likely to move than Australian born recipients, although those born overseas in other countries were significantly less likely to move and the odds gap was larger the further the move.

Recipients who self identified as Aboriginal or Torres Straight Islander (ATSI)[16] were more likely to move, regardless of distance moved and the odds gap was largest for the longest moves.

The presence of both earned income and unearned income[17] was related negatively to the tendency to move, although the size of the earned income effect increased with distance moved while the size of the unearned income effect decreased with distance moved. The tendency to move was unrelated to the level of unearned income but was related negatively to the level of earned income. Income, both unearned and earned, does provide a sense of financial security to income support recipients. One interpretation of these findings is that there is less pressure on more financially secure recipients to move. They may be less likely to fall behind with rent payments or mortgage repayments. Furthermore, the amount of earned income may be indicative of security of employment and/or likelihood of part-time or casual employment to lead to full-time permanent employment.

Another aspect of financial security is the cost and security of housing. Housing tenure is described relative to rent-payers living in private rental accommodation. Non-rent paying home-owners (outright owners and purchasers combined) were least likely to move. While public housing is also reasonably secure, rent-payers living in public rental accommodation were more likely to move than owners, followed by those who do not pay rent and do not own a home. Rent-paying private renters were most likely to move, since they would tend to

16 Note that filling in the indigenous identifier on social security forms is not compulsory. Recipients who self-identify as Aboriginal or Torres Straight Islander, may not be representative of all indigenous unemployment payment recipients.

17 Following Barrett (2002), we inflate earned and unearned income to June quarter 2001 price levels, using the ABS quarterly CPI for eight capital cities averaged.

have least control over their housing costs and the repercussions of falling behind with rental payments can, initially at least, be more severe than those attached to say falling behind with mortgage repayments. Non-rent paying non home owners might be relying on the, often short-lived, hospitality of family and friends.

The effect of location

Like Dockery (2000) we found that the tendency to move postcode was positively associated with our indicator of housing costs in the region of origin[18]. In other words, people in high cost regions are more likely to move postcodes than people in low cost regions. However, this relationship was insignificant for longer moves. This pattern is consistent with the research noted above, that short distance moves are predominantly determined by housing factors whereas other factors influence longer moves.

The estimated relationship between the number of jobs within a 20 km radius and the probability of moving postcode proved to be quite complicated. While the tendency to move medium and long distances decreased with the size of the labour market, the group least likely to move postcode included those living in the smallest and largest labour markets (labour markets with less than 5000 jobs and labour markets with at least 500,000 jobs). Amongst the other sizes, the tendency to move increased with the number of jobs. These findings can also be interpreted in terms of opportunities for re-location.

Finally, this analysis adds weight to Dockery's conclusion that the moves of unemployed Australians do not seem to be responsive to regional employment opportunity. Both unemployed and non-unemployed recipients were *less* likely to move the higher their regional unemployment rate. This effect was strongest for the long-distance moves, however the size of the effect is modest. For unemployment payment recipients, an increase in the unemployment rate of one percentage point was associated with a drop in the probability of moving of around 0.04 per cent.[19] This is about 5 per cent of the mean probability of 0.8 per cent. The corresponding numbers for non-unemployed were similar at 0.02 per cent, 7 per cent and 0.3 per cent).

This counterintuitive finding for unemployment payment recipients, which was also found in Dockery’s (2000) research, is not without precedent in overseas analysis either (see, for example Antolin and Bover, 1997[20]). In interpreting this result, however, we need to remember that the analysis here provides estimates of the impact on the probability of moving of the labour market (and other) characteristics of the region of origin. It does not contain any information on the labour market characteristics of the locations that people move *to*.

In particular, even though we observe more movement out of low unemployment regions, this does not necessarily mean that residential re-location tends to move income support recipients away from these regions. It is possible that people in these regions are moving to areas of similar (or even better) labour market prospects. Similarly, the smaller proportion of people in high unemployment regions who move may nonetheless be moving to better labour markets.

In order to ascertain the overall impact of movement on the labour market opportunities of income support recipients, it is necessary to consider both the source and origin of moves. In the next section, therefore we examine the changes in the regional characteristics that are associated with residential re-location.

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18 Note that the mean of housing cost indicator is negative. It was calculated over all income support recipients with rent recorded, so those with rent recorded tend to live in the more expensive regions.

19 Evaluated at the mean probability, the marginal increase in probability associated with a one-unit increase in an independent variable is approximately $\overline{p}(1-\overline{p})\beta_k$ where $\overline{p}$ is the mean probability of the event occurring and β_k is the associated parameter estimate. (This result obtained by differentiating the logit function). For binary (dummy) variables, the approximation is valid as long as β_k is not too large.

20 Like we do, Antolin and Bover (1997) use micro-level data to analyse the determinants of the individual probability of migration.

5.2 Changes in the Regional Characteristics of Movers

When people change residential location, do they tend to move towards areas with lower housing costs and/or better labour market opportunities?

Figure 5.3 Change in Travel Region Unemployment Rate (Unemployment payment recipients)

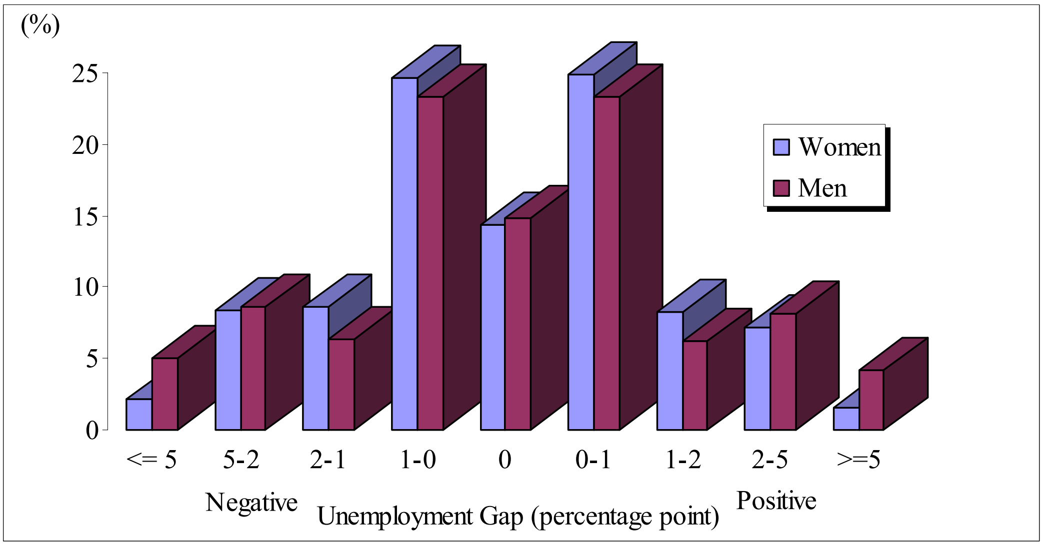
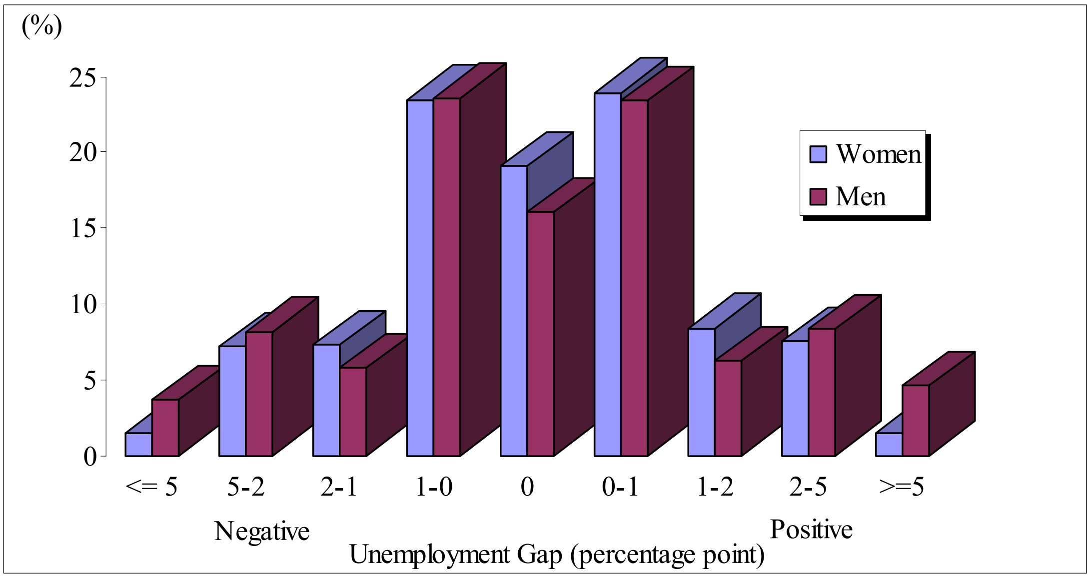


Figure 5.4 Change in Travel Region Unemployment Rate (Non-unemployment payment recipients)



In Figure 5.3 and Figure 5.4 we show the distribution of the increase in regional unemployment rates associated with each move (for unemployment payment recipients and other recipients respectively). It is clear that movement towards labour market opportunities cannot be the main reason for residential re-location. Regardless of payment received, a similar number of recipients move to areas of higher unemployment rates than to areas of lower unemployment rates, and most moves involve a negligible change in the unemployment rate. The patterns for men and women are much the same, although men's moves are slightly more likely to be associated with more extreme changes in unemployment rates.

Figure 5.5 and Figure 5.6 present equivalent information on the changes in the regional rent levels, as measured by the housing cost indicator, associated with each move. As for regional employment conditions, it is clear that regional housing costs are not the main reason for moves. Most people don't move far enough to count as a change in housing cost levels,[21] and of those who move, roughly similar numbers move to regions with higher as opposed to lower housing prices.

Figure 5.5 Change in Regional Rent Level (Unemployment payment recipients)

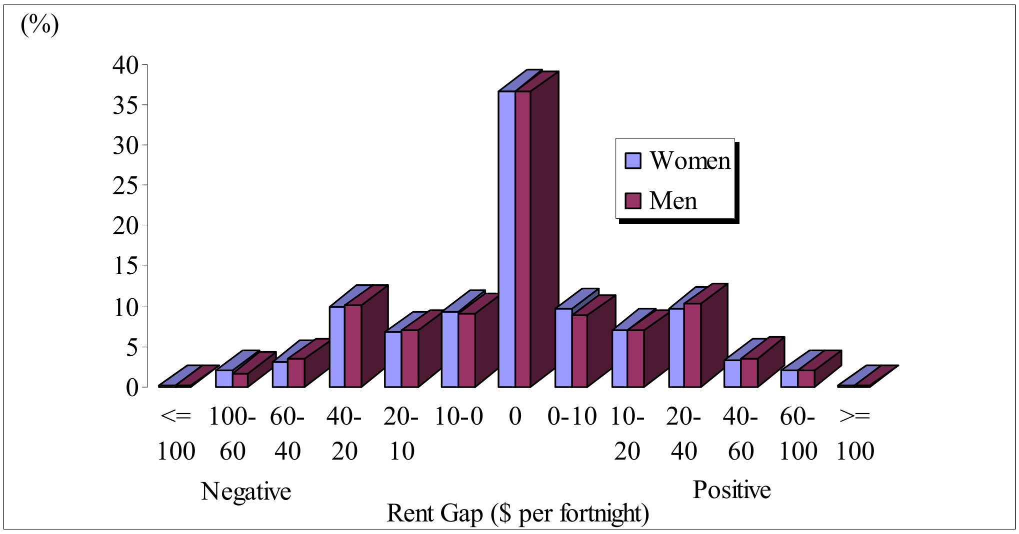
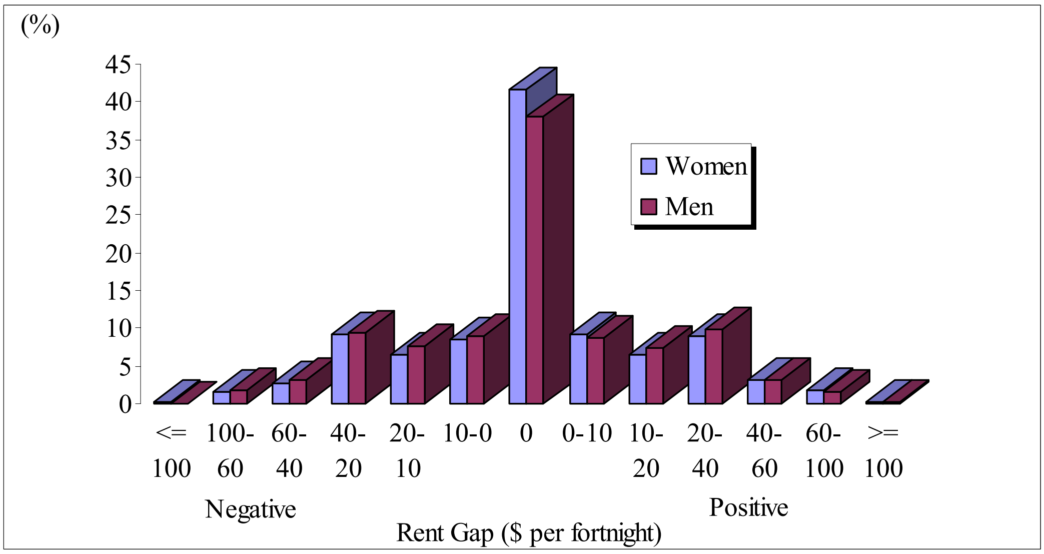


Figure 5.6 Change in Regional Rent Level (Non-unemployment payment recipients)



However, we should not be surprised that there is such wide variation in the labour and housing market outcomes associated with moves. As noted earlier, there are many factors influencing the destinations of people who move. These include the need to be near family, friends and services together with the personal labour and housing market opportunities available to individuals. Even though some regions might have higher housing costs on average, an individual might find housing available during the period that they are searching which has a particularly good cost/amenity trade-off for them. Similarly, even in high unemployment regions, some individuals may have (or think they have) favourable labour market prospects.

Though systematic differences between regions might explain some part of the patterns of mobility, we should not expect them to explain most or even a large part of the variation in movement decisions. Nonetheless, given that most of the other sources of variation are stochastic in nature (or at least not amenable to policy manipulation), it is important to consider whether these locational changes are associated to any extent with regional labour and housing market characteristics.

One way to consider this is to examine the average change in regional characteristics associated with moves. In Table 5.3 we show the average change in the mean travel region

[21] Recall that housing costs are averaged over areas large enough to contain 20 income support recipients in the 1% LDS sample file.

unemployment rate associated with each move. That is, for each move we subtract the travel region unemployment rate in the region of origin from that for the destination region, and average this value across all moves. Table 5.4 presents the corresponding calculation for the housing price estimates in each region.

We see, in general, that the moves of unemployment payment recipients were associated with slight, but statistically significant, falls in the regional unemployment rate, and moves of other recipients were associated with slight increases in the regional unemployment rate. The increase was statistically significant for men only. Recall that in Section 5.1 we found that both sets of recipients were less likely to move the higher the unemployment rate in the region of origin. The fall in average unemployment rate for the unemployment payment recipients thus reflects the lower average unemployment rate in the regions that they move *into*.

Not surprisingly, we find that those who move to the capital cities experience the strongest falls in unemployment rates, and those who move out of the capitals experience increases. For all recipients making these moves the change in the unemployment rate was statistically significant.

There was little change in the unemployment rate for moves within capital cities (remember that the travel region unemployment rate averages small area rates to take commuting to other sub-regions into account). Nonetheless, the slight increase for other recipients was statistically significant. However, consideration of the housing cost changes reported in Table 5.4, suggests that these moves tend to be towards areas of cheaper housing, although not significantly so. This is most apparent for non-unemployed women. Parenting Payment recipients would comprise a large proportion of this group of women. A significant number of their moves may be into public housing, with such housing tending to be located in areas with relatively low housing costs.

Regional unemployment rates tend to fall slightly for unemployment payment recipients moving within non-capitals (within and between states), while they increase for other recipients. Intriguingly the regional rent changes are of the same sign as the unemployment rate changes.

Moves between capital cities tend to be associated with small statistically insignificant falls in unemployment rates and increases in regional rent levels, statistically significant only for men in receipt of unemployment payments. The majority of these moves may be towards more expensive capitals, or from low cost areas within a capital city to relatively high cost regions within the new capital city.

We observe the largest changes in regional housing costs and unemployment rates in moves between capital cities and non-capital cities. All changes are statistically significant. As one would imagine, regional rent levels increase substantially for moves from non-capitals to capitals. The comparable fall for capital to non-capital moves is smaller for unemployment payment recipients and other recipients who are women. Indeed, the unemployment rate decrease associated with the former move for unemployment payment recipients, was larger in size than the increase associated with the latter move. At the very least this suggests that movements from capitals to non-capitals do not mirror movements from non-capitals to capitals. If unemployment payment recipients move out of capital cities in search of cheaper housing this observation implies that the corresponding rise in their travel region unemployment rate could be larger than it is.

Table 5.3 Unemployment rate change by type of move

	Within capital city of same state	Capital to capital between state	Non capital to capital	Within non-capital	Capital to non-capital	All
	(Percentage point change in mean travel region unemployment rate)					
	Unemployment payment recipients					
Men	0.01	-0.08	-2.14	-0.07	1.69**	-0.08**
Women	-0.01	-0.07	-1.87	-0.10*	1.73**	-0.08**
	Other recipients*					
Men	0.02*	-0.05	-1.82**	0.07	2.07*	0.08*
Women	0.03	-0.11	-1.49**	0.02	1.53**	0.02

* significant at 5% level

** significant at 1% level

Table 5.4 Regional rent change by type of move

	Within capital city of same state	Capital to capital between state	Non capital to capital	Within non-capital	Capital to non-capital	All
	(Change in regional rent level, $ per fortnight)					
	Unemployment payment recipients					
Men	-0.12	3.13*	6.69**	-0.04	-5.30**	0.27
Women	-0.08	3.76	6.29**	-0.40	-5.51**	0.22
	Other recipients					
Men	-0.06	4.06	5.54**	0.54	-7.33**	-0.03
Women	-0.25	2.59	7.06**	0.80*	-5.63**	0.32

* significant at 5% level

** significant at 1% level

Appendix Table B.2 summarises some key demographic characteristics of movers in terms of the unemployment rate gap associated with their move, to see whether we can distinguish which recipients were most likely to improve their chances of finding work by moving. For example, the first row in the unemployment payment recipients section shows the proportion of female unemployment payment recipients whose move was associated with a decrease in their regional unemployment rate of 2 percentage points or more, between –2 and –1 percentage points, from –1 to 1 percentage points and so on. Compared to men, women are under-represented in the most extreme unemployment rate change moves. However, comparison of the two outside columns suggests that unemployed women are no more or less likely than men to make moves that substantially lower their regional unemployment rate. In fact, none of the listed characteristics proved to be associated with such a move, at least in this bi-variate analysis.

The results for non-unemployment payment recipients highlight some interesting differences. The more financially secure groups in terms of asset ownership, home-owners (purchasers and outright owners combined) not paying rent, do seem more likely to make moves that were associated with increases in the unemployment rate of two percentage points or more. Consistent with this the oldest recipients tend also to make such moves. In contrast, private rent payers tend to make moves associated with large falls in the regional unemployment rate. In all cases there was a statistically significant difference (at the five per cent level at least) between the proportions in the two extreme groups, that is, the groups for which the unemployment rate gap is the most positive and most negative.

5.3 The Net Impact of Re-location

Another way to examine these issues is to look at the net impact of the geographic mobility of income support recipients. Do moves to low housing cost regions outweigh moves to high cost areas? Does movement lead to a net improvement or deterioration in labour market opportunities? These patterns are shown in Table 5.5 for unemployment payment recipients, and in Table 5.6 for other income support recipients.

For the former group, the net movement is generally towards regions with lower unemployment, larger job markets but higher housing prices.

On balance, about 4,200 unemployment payment recipients per annum are leaving the regions with the highest unemployment rates (that is rates over 12% in 1996). This is 4.3 per cent of the average total number of unemployment payment recipients in those regions, or 17.1 per cent of the average of the gross flows into and out of the region.

Though not all individual cells are statistically significant (absolute z above 1.96), there is a clear trend (among unemployment payment recipients) of movement out of the higher unemployment regions and into the lower unemployment regions. Similarly, people were tending to move towards larger labour markets. Associated with this, unemployment payment recipients were, on balance, moving towards higher housing cost regions.

In most cases, however, the net flow is only a small proportion of the gross flow. That is, many people are moving in both directions, with slightly more moving in the directions described above. As noted in the previous section, this reflects the multitude of factors that influence residential location decisions.

Across the states, the only statistically significant movement was a substantial *inflow* of unemployment recipients to the Northern Territory. The main components of this net flow were from NSW and SA (a net inflow of 300 from each). We have no explanation for this and cannot discount the possibility of postcode re-classification or the result being due to sampling error.

No clear pattern was found of movements in or out of regions when grouped by the ARIA remoteness index.

For the non-unemployment payment recipients, the picture is somewhat different. If anything, people were tending to move towards the high unemployment regions and away from the larger labour markets (though the unemployment patterns were not statistically significant). This difference from the unemployment payment recipients has been noted above, and reflects the lower degree of workforce attachment for these groups. Again, there is no particular pattern of movement with respect to the States or ARIA categories.

Table 5.5 Net Movement into Regions (Unemployment Payment Recipients)

	Net Inflows Per Annum	z	Net Inflows as % of Population	Net Inflows as % of Gross Inflows
Travel Region Unemployment Rate				
<7%	1,307	1.9	4.1	7.9
7 - <8%	1,938	1.9	2.0	5.7
8 - <9%	2,230	1.9	1.4	4.7
9 - <10%	-138	-0.1	-0.1	-0.3
10 - <12%	-1,108	-1.0	-0.7	-2.8
>12%	-4,231	-4.7	-4.3	-17.1
Number of Jobs Within 20km				
<5,000	-477	-0.5	-0.7	-1.7
5-50,000	-2,754	-2.2	-1.4	-5.3
50-300,000	-954	-0.8	-0.7	-2.1
300-500,000	1,723	1.7	1.6	4.9
500,000+	2,461	2.9	1.9	10.2
Quintile of Regional Housing Cost Indicator				
Lowest	-384	-0.4	-0.3	-1.0
2nd	-600	-0.6	-0.5	-1.7
Middle	-862	-0.7	-0.6	-1.8
4th	770	0.7	0.7	2.2
Highest	1,077	1.0	0.8	3.0
State				
ACT	-15	-0.1	-0.2	-0.7
NSW	-170	-0.2	-0.1	-0.9
NT	846	2.6	8.1	21.7
QLD	-107	-0.1	-0.1	-0.6
SA	-123	-0.3	-0.2	-1.8
TAS	-354	-1.2	-1.6	-14.0
VIC	-61	-0.1	0.0	-0.4
WA	-15	0.0	0.0	-0.3
Aria Remoteness Index				
Highly Accessible	631	0.6	0.1	1.7
Accessible	-1,523	-1.5	-1.6	-4.7
Moderately Accessible	462	0.7	1.6	3.1
Remote	-308	-0.7	-3.3	-5.2
Very Remote	738	1.7	6.2	11.0

Notes *Net Inflows Per Annum* is calculated as the number of people moving to regions with the given characteristics (eg with an unemployment rate under 7%) minus the number of people moving out of these regions, with the result multiplied by 100 (because the the LDS is a 1% sample) and then divided by 6.5 to take account of the fact that we observe all movements within a 6½ year window. Note that within each classification, the net flows sum to zero by definition.

The z score is the net flow estimate divided by its standard error. The standard error calculation assumes moves are independent and is calculated as $\sqrt{V(inflow)+V(outflow)}$ with $V(inflow) = p_i(1-p_i)N_i$, $V(outflow) = p_o(1-p_o)N_o$, p_i the proportion of people not in the region who enter it, N_i the sample size of people not in the region, p_o the proportion of people in the region who leave it, N_o the sample size of people in the region.

To calculate the *net inflows as % of population*, the population of recipients is estimated as 100 times the total number observed in all fortnight-pairs in the observation window, divided by (6.5x26), since the observation window covers 6.5 years with 26 fortnight pairs per annum.

Table 5.6 Net Movement into Regions (Non-Unemployment Payment Recipients)

	Net Inflows Per Annum	z	Net Inflows as % of Population	Net Inflows as % of Gross Inflows
Travel Region Unemployment Rate				
<7%	-770	-1.3	-1.0	-6.6
7 - <8%	-1,723	-1.9	-0.8	-7.0
8 - <9%	954	0.9	0.3	2.7
9 - <10%	-262	-0.3	-0.1	-0.9
10 - <12%	862	0.9	0.2	2.9
>12%	938	1.2	0.5	4.9
Number of Jobs Within 20km				
<5,000	-61	-0.1	0.0	-0.3
5-50,000	2,908	2.5	0.7	6.6
50-300,000	954	0.9	0.3	2.5
300-500,000	-1,600	-1.8	-0.7	-6.1
500,000+	-2,200	-3.1	-0.8	-14.4
Quintile of Regional Housing Cost Indicator				
Lowest	-2,800	-3.0	-1.0	-10.3
2nd	707	0.8	0.2	2.6
Middle	1,584	1.5	0.5	4.5
4th	369	0.4	0.1	1.4
Highest	138	0.2	0.1	0.6
State				
ACT	-185	-0.8	-1.2	-12.0
NSW	-892	-1.4	-0.2	-7.2
NT	77	0.3	0.6	4.3
QLD	1,647	2.7	0.6	13.0
SA	-569	-1.6	-0.4	-14.2
TAS	-277	-1.2	-0.5	-16.5
VIC	338	0.7	0.1	4.2
WA	-138	-0.5	-0.1	-5.3
Aria Remoteness Index				
Highly Accessible	-816	-0.9	-0.1	-3.0
Accessible	1,370	1.5	0.6	5.2
Moderately Accessible	-292	-0.5	-0.4	-2.6
Remote	-185	-0.5	-0.9	-4.9
Very Remote	-77	-0.2	-0.4	-1.8

Notes See notes to Table 5.5 for definitions.

5.4 Modelling Net Mobility among Unemployment Payment Recipients

The above evidence suggests that unemployment payment recipients tend to move, on balance, towards areas of greater labour market opportunity and higher housing costs.

The most plausible explanation for the relationship with housing costs is that this also reflects labour market factors; housing costs are higher in areas with stronger labour markets. If this is the case, we might expect that when we compare areas of similar labour market opportunities, we would find that unemployed people tend to move to areas of *lower* housing costs. Moreover, if indeed regional housing costs do influence location, then they may be masking a stronger relationship between labour market conditions and movement than that observed here. That is, within areas of similar housing costs, we might expect to find a greater tendency to move to areas with stronger labour markets. For policy purposes, these *ceteris paribus* questions are often of more value than the descriptive results shown in the previous section. For example, how would movement change if some policy were introduced that reduced the housing costs of unemployment payment recipients living in strong labour market areas? To evaluate these hypotheses it is necessary to undertake a multivariate analysis.

The question addressed by this analysis is whether people tend, on balance, to be moving towards regions with particular characteristics. Since both the movement and the characteristics are a feature of regions, it is natural to model this at the regional level. (Indeed, we are unaware of computationally feasible methods for modelling this at the level of individual people). Because postcode areas vary widely in size, it is of greater interest to model net flows as a proportion of the population in the area, rather than the number of net flows directly (we would expect larger areas to have a greater number of both gross and net flows by virtue of their size alone). We therefore estimate the following equation

$$c_i / n_i = \alpha + \beta' x_i + e_i$$

where c_i is the net inflow for postcode *i* , n_i is the corresponding population size, x_i is a vector describing the regional characteristics of postcode *i* and e_i is a random error term. The vector x_i contains characteristics of the postcode such as the travel region unemployment rates, as well as variables summarising the demographic characteristics of the postcode.

In estimating this equation, it is necessary to take account of the widely differing sizes of the postcode areas. This issue is partly addressed by examining net flows as a proportion of the population of the area, rather than net flows directly. However, even with this adjustment, the error term e_{ik} is still heteroskedastic (the variance is not constant), and ordinary least squares estimates of the parameters will be inefficient. In relatively small postcode regions the estimate of net flows (and net flows as a proportion of population) is based on fewer cases and thus subject to more sampling error. The estimation process should thus give more weight to the larger postcode regions.

One approach is to undertake a weighted regression, weighting each postcode by the population size of that postcode, n_i . This is equivalent to assuming that the variance of the error term is proportional to $1/n_i$. Using this weighting method, weighted least squares estimates of the impact of the variables considered one at a time yield identical estimates to those shown in Table 5.5 and Table 5.6.[22] However, visual inspection of the initial estimates using this method showed substantial residual heteroskedasticity.

An alternative approach is to model the variance patterns directly. It is common in mobility studies to model the number of people moving between any two regions as a Poisson random variable. Assuming that these moves are independent (eg a move in one direction does not lead to a move in the opposite direction later on), this implies that the net flows into a given region are a random variable with an estimate of the variance given by the total gross flows into and out of the region.[23] If we then ignore the fact that the estimate of the population of each region is itself a random variable,[24] this implies that the variance of the net flows as a proportion of the population will be proportional to g_i / n_i^2 where g_i is the total gross flow into and out of region *i.* Note that if gross flows are proportional to population, this simplifies to the population size weighting given in the previous paragraph. However, visual inspection of residuals using this approach (i.e. weighting by n_i^2 / g_i) showed less heteroskedasticity than for the population size weighting, and so this weighting

22 To see this, note that OLS parameter estimates of the impact of a single set of dummy variables are simply the mean value of the dependent variable within each category. If the set of postcodes with a given characteristic is denoted by S, this weighted mean is given by $\left(\sum_{i \in S} n_i (c_i / n_i)\right) / \left(\sum_{i \in S} n_i\right) = \left(\sum_{i \in S} c_i\right) / \left(\sum_{i \in S} n_i\right)$ – which is how the estimates of the net inflow as a proportion of the population in Table 5.5 and Table 5.6 are calculated.

23 The expected number of people moving between any two regions can be estimated by the actual number moving. For Poisson random variables, the variance is equal to this expected value. The variance of the sum or difference of a set of independent random variables is equal to the sum of the variances, which is the total of the gross flows.

24 This is justified on the basis that the net flows are much smaller than the population, and so variation in the estimate of the latter will contribute only a small component to the variation of net flows as a proportion of population.

method is used for the WLS estimates shown here.[25] We have also calculated estimates using the population size weighting; these results are very similar to those given here.

The results of these estimates for unemployment payment recipients and for recipients of other payments are shown in Table 5.7. The net inflow of unemployment payment recipients to postcode regions is significantly associated with both the travel region unemployment rate as well as the size of the labour market. An increase in the unemployment rate of a region by one percentage point is associated with an increase in the net outflow per annum of one per cent of the number of unemployment payment recipients in the postcode. In addition, the size of the labour market also has a direct impact. Compared to the large cities, postcodes in very sparse labour markets are losing about 4 per cent of their unemployment recipient population per annum.

Thus, even though it remains the case that many unemployment payment recipients move to areas of poorer employment prospects (eg as shown in Figure 5.3), the net effect of all movements is to increase the numbers living in stronger labour markets.

No such pattern is found for the non-unemployment payment recipients, for whom there is no significant relationship with unemployment rate or labour market size.

There is some tendency for both groups to move to higher rent regions, but this is not statistically significant at the 5% level (almost significant for the non-unemployment payment group). The latter group also have some tendency to move away from remote areas and towards Victoria, but both these results are only just statistically significant.

Finally, Table 5.7 also contains variables describing the demographic characteristics of the postcode. Unemployment payment recipients tend to leave postcodes where many recipients have children and tend to move towards areas where many are homeowners or have long durations of payment receipt. It is difficult to interpret these results, as they could be a proxy for many other regional characteristics.

25 If there are zero gross flows, we set $g_i = 1$ for this weighting. We ignore the fact that the equation errors are correlated as a result of the adding up constraint that $\sum_i c_i = 0$. Because the number of regions is very large, this will have minimal impact on the results.

Table 5.7 The Impact of Regional Characteristics on the Net Inflow Rate

	Unemployment Payment Recipients		Non-Unemployment Payment Recipients	
	Estimate	t	Estimate	t
Intercept	8.85	2.8	-2.14	-1.1
Travel Region Unemployment Rate (%)	-1.00	-5.4	0.07	1.0
Number of Jobs Within 20km (relative to 500,000+)				
<5,000	-4.34	-2.4	1.20	1.6
5-50,000	-3.20	-2.2	0.84	1.4
50-300,000	-2.81	-2.1	0.66	1.2
300-500,000	0.16	0.1	-0.06	-0.1
Rent level in region ($pf deviation from average)	0.03	1.4	0.02	1.9
State (relative to NSW)				
Vic	-0.08	-0.1	0.94	2.0
Qld	1.48	1.3	0.65	1.4
NT	5.05	1.4	1.69	0.8
SA	1.52	0.9	1.04	1.6
WA	-1.06	-0.6	0.88	1.3
Tas	2.48	1.2	-0.46	-0.6
ACT	0.32	0.1	-1.52	-0.9
Aria Remoteness Index (relative to highly accessible)				
Accessible	1.10	0.9	-0.04	-0.1
Moderately Accessible	1.54	0.8	-0.65	-0.9
Remote/Very Remote	-0.97	-0.4	-1.91	-2.0
Fraction of People in Postcode Who…				
Are Female	-2.16	-0.9	-0.98	-0.9
Have Children in Household	-7.12	-2.2	2.33	1.8
Are Aged 25 to 39	0.06	0.0	0.13	0.1
Are Aged 40+	-1.01	-0.3	1.27	0.6
Are Overseas Born	-3.43	-1.4	-0.55	-0.5
Are Home Owners	5.59	1.9	-0.80	-0.8
with >12 Months on Unemployment Payments	8.88	2.7		
Number of postcode areas	2,145		2,183	
R^2	0.033		0.014	

Notes: The dependent variable is the net inflow per annum for the postcode as a percentage of the population (i.e. defined as in Table 5.5 and Table 5.6). Postcodes with no recipients in fortnight 1 or 2 of all fortnight pairs are excluded. Estimation is with weighted least squares as described in the text.

The relationship with duration is more clearly presented in Table 5.8, which separates the unemployment payment recipients into those with short and long durations (at the time of their move). The impact of unemployment is roughly the same for both groups (though here a bit weaker than in the previous table). However, the relationship with labour market size is now only apparent in the short duration group.

The net movement towards larger labour markets is thus a phenomenon that happens primarily in the first year of unemployment payment receipt. Nonetheless, holding labour market size constant, both long and short duration unemployed tend to move towards lower unemployment regions.

Note also that there is a slight (though non-significant) tendency for the long duration unemployed to move to cheaper housing cost regions – the opposite of the tendency found for short duration unemployed.

Table 5.8 The Impact of Regional Characteristics on the Net Inflow Rate for Short and Long-term Unemployment Payment Recipients

	Short Duration (<1 year)		Long Duration (1 yr+)	
	Estimate	t	Estimate	t
Intercept	8.15	1.7	6.36	1.8
Travel Region Unemployment Rate (%)	-0.82	-2.6	-0.72	-3.5
Number of Jobs Within 20km (relative to 500,000+)				
<5,000	-7.73	-2.5	0.87	0.5
5-50,000	-7.25	-2.9	1.15	0.7
50-300,000	-5.96	-2.7	1.19	0.8
300-500,000	-0.43	-0.2	1.31	0.8
Rent level in region ($pf deviation from average)	0.07	1.9	-0.02	-0.7
State (relative to NSW)				
Vic	0.55	0.3	-0.61	-0.5
Qld	0.87	0.5	0.89	0.7
NT	11.86	1.9	-1.95	-0.5
SA	1.78	0.7	-0.58	-0.3
WA	-0.68	-0.3	-2.07	-1.0
Tas	6.31	1.7	-2.13	-0.9
ACT	2.52	0.5	-2.57	-0.6
Aria Remoteness Index (relative to highly accessible)				
Accessible	2.78	1.3	-0.11	-0.1
Moderately Accessible	3.61	1.1	0.16	0.1
Remote/Very Remote	1.00	0.2	-0.59	-0.2
Fraction of People in Postcode Who…				
Are Female	4.86	1.1	-2.40	-1.1
Have Children in Household	-3.25	-0.5	-6.17	-2.2
Are Aged 25 to 39	4.18	0.8	2.17	0.7
Are Aged 40+	6.34	1.1	3.48	1.1
Are Overseas Born	-6.55	-1.5	-1.66	-0.8
Are Home Owners	2.48	0.4	-0.41	-0.2
N	2,108		1,876	
R^2	0.023		0.014	

Notes: Dependent variable is the net inflow per annum for the postcode as a percentage of the relevant population (short or long duration unemployment payment recipients). Postcodes with no recipients in fortnight 1 or 2 of all fortnight pairs are excluded. Estimation is with weighted least squares as described in the text.

5.5 Summary

Housing costs and labour market conditions are only two of the many factors that influence the decision of whether to move and where to move. Nonetheless, they are of particular policy-relevance and so it is important to understand their impact upon movement.

We find that people living in high cost regions are move likely to move than those in low cost regions (while controlling for other factors). Paradoxically, we also find that people living in low unemployment regions are more likely to move than those in high unemployment regions. This same result was found by Dockery (2000). However, this paradox is easily explained when we realise that this is an estimate of *whether* people move, not *where* they are moving to. People in low unemployment regions may be more likely to move, but this does not mean that they are moving to regions with poorer labour market prospects.

When we compare the characteristics of the origin and source regions for people who move, we find that there is a tendency for unemployment payment recipients to move to areas with lower travel region unemployment rates. More specifically, we find that on balance, about 4,200 unemployment payment recipients per annum are leaving the regions with the highest unemployment rates (that is rates over 12% in 1996). This is 4.3 per cent of the average total number of unemployment payment recipients in those regions, or 17.1 per cent of the average of the gross flows into and out of the region.

This association continues when controlling for changes in other factors (such as housing costs). An increase in the unemployment rate of a region by one percentage point is associated with an increase in the net outflow per annum of one per cent of the number of unemployment payment recipients in the postcode. In addition, the size of the labour market also has a direct impact. Compared to the large cities, postcodes in very sparse labour markets are losing about 4 per cent of their unemployment recipient population per annum. The net movement towards larger labour markets happens primarily in the first year of unemployment payment receipt.

For non-unemployment payment recipients, there is little association with labour market conditions, and controlling for other factors, regional rent levels appear to have little impact upon net mobility patterns (though the impact for non-unemployment recipients is almost statistically significant).

6 ESTIMATION 2: THE IMPACT OF MOBILITY

How much impact do regional labour market conditions have on the likelihood that a person will be employed or not receiving income support? A number of factors complicate the analysis of this question using the LDS.

First, some individuals may have unobserved (fixed) characteristics that influence their likelihood of finding employment or leaving income support. For example, as noted in Section 3.2, 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. Since the financial incentive to move to a region of relatively high labour demand will increase with wage level, the skill level of the jobseeker may be positively linked to the region's job opportunities. Hence an observed association between favourable employment outcomes and locations with relatively high labour demand might reflect the skill level of the jobseekers living in the area, rather than the effect of the relatively high labour demand. Similarly, individuals with higher expected long-term incomes may be more likely to move to higher housing cost regions, which may tend to be areas with lower unemployment rates.

To partly correct for the latter association, we include our regional housing cost indicator as a control variable. However, this is not a perfect measure of housing costs, and only controls for the heterogeneity that is associated with housing costs. A more comprehensive way of dealing with both observed and unobserved person-specific fixed effects is to examine the *changes* in outcomes for particular individuals when they move between regions.

However, in addition to unobserved person-specific fixed effects, there may also be relevant time-varying effects that we cannot observe. In Section 3.2, we considered some examples where job search effort might change at the same time that a person moved location. When the youngest child of a lone parent is about to start school, for example, she might both increase her job search effort and consider moving to an area of higher labour demand. Similarly, a person may move to a high employment region because they have received the offer of a job in that region (rather than receiving a job offer after moving to the high employment region).

Since our data only allows us to consider moves where a person is receiving benefit both before and after the move, we will probably exclude most of those who move to take up work. Furthermore, we control for changes in job effort associated with observed characteristics (such as family situation) 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 time-varying factors which are unobserved.

Finally, we must deal with selection issues. We only have data (including location) for the periods when people are receiving income support payments. For other periods within our 6½ -year observation window, we only know that they are not receiving payments.

In attempting to resolve these methodological issues, we employ two separate estimation approaches.

One approach focuses on the factors influencing the exit from a spell of benefit receipt. In particular, we focus on the way in which locational characteristics (entered as time-varying covariates) influence exit probabilities. This controls for personal heterogeneity only to the extent to which this is correlated with the observed covariates or with elapsed duration of the spell.[26]

The second approach is not restricted to single spells, but instead examines the characteristics of multiple spells over a period. We select people who move while receiving benefit and examine the difference between the number of weeks they received benefits in

[26] An extension to this, which could control for other person-level effects, would be to analyse multiple spells for the same individuals – preferably living in different locations during each spell. However, even if we had sufficient data to do this, we would need to deal with changes in unobserved personal characteristics between spells.

the 12 months before the move and the number of benefit weeks in the 12 months after 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 removes any person-specific fixed effects. However, we need consider the possible effects of selection bias (we only observe moves that take place when people are on benefit) and non-exogeneity (moves may be influenced by benefit status rather than the other way round). We discuss these issues further in Section 6.2 below.

6.1 Impact of Mobility on Exit from Unemployment Payments

Does movement to an area with better labour market prospects increase the probability that the individual will exit from income support? In this section, we address this question by estimating an unemployment payment spell duration model with regional characteristics as predictor variables.

As noted above, individuals with characteristics that give them high probabilities of finding employment may tend to live in more favourable labour markets. We can observe some of these factors and control for them. However, to the extent to which there are unobserved 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 in the model), and so the bias may not be too great.

We restrict attention to 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. To include other payment categories would substantially reduce the sample size.

The sample consists of the stock of unemployment payment recipients at the commencement of the observation period (6 January 1995) together with those that commenced an unemployment spell before the end of May 2000. Spells that were under way at the commencement of the observation window are known as stock spells and spells that commenced during the observation window are flow spells. An unemployment spell is considered to end if the recipient does not receive income support for two payments. Hence the fortnightly payment duration count continues even if the unemployment payment recipient leaves payment for one fortnight. If the person transfers to another income support payment we treat the spell as censored and do not follow them further.[27]

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. 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.

We use a proportional hazard model with a flexible baseline hazard function. The baseline hazard is the hazard for the (hypothetical) person in our sample for whom all the

[27] One problem with combining the stock with the flow is the difference in the way duration is measured. For spells that are under way at the beginning of the observation window we use a variable that describes the length of time that the unemployment payment recipient has been continuously in the Centrelink system to tell us how long the spell is. If the income support recipient finds new work he/she is removed from the Centrelink system, unless he/he 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 not 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. We control for this potential difference in the analysis.

explanatory variables are set at zero. We allow this to be a flexible function of duration by breaking the time-line measuring spell duration into a number of intervals with a different baseline hazard attached to each of those intervals (with the intervals chosen so as to have sufficient sample size in each interval). By not making parametric assumptions about the time dependency of the hazard we avoid inconsistent estimation of the coefficients due to a misspecification of the baseline hazard.[28] The estimated hazard function for the reference person (though in a region with the mean unemployment rate) is shown in Figure 6.1. The proportional hazard model that we use assumes that the hazard for other people will be proportional to this baseline hazard, with the constant of proportionality depending upon the values of their explanatory variables.

To take account of the fact that we have a mixture of stock and flow samples, we use the discrete-time hazard model described in Jenkins (1995). In this estimation procedure, a logistic regression model is estimated using person-fortnights as the unit of analysis. 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. Jenkins and Garcia-Serrano (2000) note that since the hazard of exit in any given time period is small, a convenient approximation can be used to interpret the logistic regression coefficients.[29] For both continuous and binary (dummy) variables $e^{\beta}-1$ is approximately equal to the proportionate increase in the hazard associated with a one-unit increase in the variable.

We use information from every payment period (fortnight) for which we observe the unemployment payment recipient to be receiving income support, that is every person fortnight. This allows for time-varying covariates.

The analysis commenced with 76,584 unemployment spells comprised of 1,224,380 person fortnights. In 83 per cent of those spells we observe an exit from income support. Ten percent of the spells ended with the individual transferring to another payment and eight per cent of the spells were still running at the end of the observation period. However, we then had to exclude those person fortnights for which we did not have labour market information. This occurred when the current postcode of residence was not found in our postcode/SLA concordance. Most of these cases were probably cases where the person did not have a fixed address and was using a postal box. Note that if the recipient moved from a postcode with labour market information to one without we only include the person fortnights relating to the postcode with labour market information. We ended up with 1,213,437 person fortnights and 76, 085 spells.

Table 6.1 provides summary statistics for the unemployment payment spells and some of the key fixed covariates. The first column summarises all spells. On average the 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.[30] The maximum duration for the flow was 50 fortnights or nearly two years, and for the stock was 588 fortnights or a little over 22.5 years. Men were over-represented among the stock spells, as were overseas born people. Recipients who self-reported as Aboriginal or Torres Straight Islander, were under-represented among the stock spells.

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28 See Jenkins (2002) for a discussion of the advantages in using flexible baseline hazards.

29 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. (This is also approximately equal to β_0 when β_0 is small).

30 This difference arises because longer spells are more likely to be captured in a sample taken at any one point in time (ie a stock sample).

82 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

Table 6.1 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

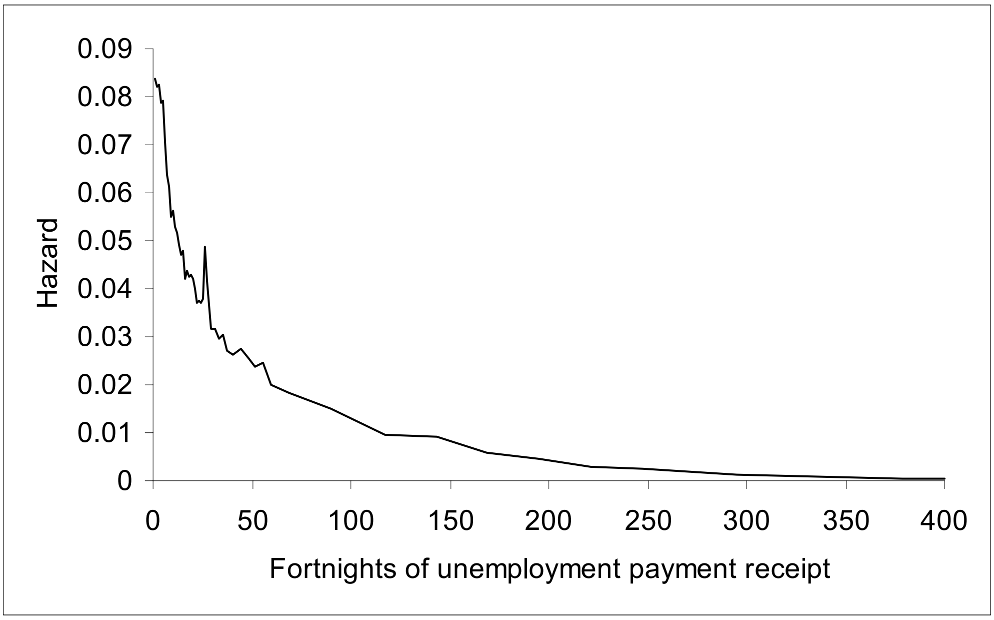
In the first column of Table 6.2 the mean of the variables across all person fortnights are shown. Table 6.2 also reports the maximum likelihood estimates of three logistic regression models of fortnightly exit from unemployment payment receipt. Exit includes exit to employment but also exit due to other factors such as breaching 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

To control for the fact that the duration of the unemployment prior to the beginning of the observation window was measured differently than subsequent unemployment, we include an explanatory variable that is set equal to the duration of the spell at the beginning of the observation period. For those whose spell commenced within the observation period, this variable is set equal to zero. The estimated coefficient on this variable is positive and significant, representing the fact that spell durations in stock sample are relatively overestimated and hence the actual hazard of exit is higher.

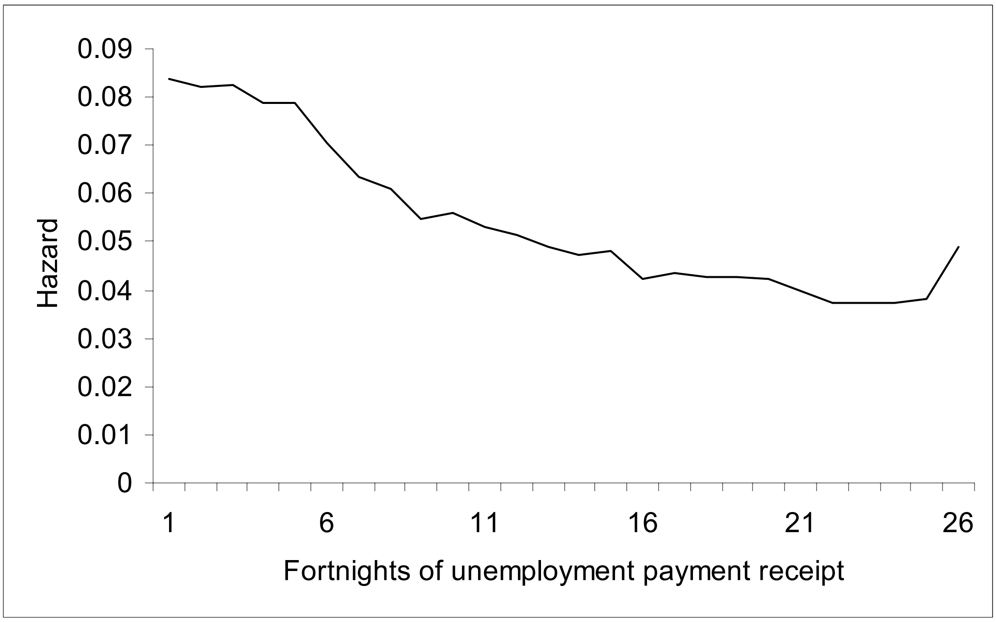
The base-line hazard represents 49 separate duration intervals. For durations of 1 to 26 fortnights each fortnight has a variable (1-26). For 27 to 38 fortnights there is a variable for each set of two fortnights (27-32). For 39 to 62 fortnights there is a variable for each set of four fortnights (33-38). For 63 to 76 fortnights there is a variable (39). For 77 to 104 fortnights there is a variable (40). For 105 to 260 fortnights there are variables for each set of 26 fortnights (41-46). There are variables for durations of: 261-330 fortnights (47), 331-428 fortnights (48), 429 + fortnights (49).

Figure 6.1 Baseline hazard rate for Model 3



Note: Base-line hazard rate for 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 6.2 Baseline hazard rate for Model 3 for spells of one year or less in length



Note: Base-line hazard rate for 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 the corresponding unemployment rate of 10 per cent. His spell of unemployment payment receipt was not underway at the commencement of the observation period.

There was little variation in the estimates of the baseline hazard parameters across the models. Figure 6.1 illustrates the base-line hazard for Model 3, showing that in general, 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 6.2 (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

The parameter estimates show that men's hazard of exiting unemployment payments was significantly higher than was women's. The gender differential was even wider when the regional unemployment rate was 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 unemployed men tend to live in areas with higher regional unemployment rates or fewer job opportunities than do 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. In contrast, the hazard of exit was significantly higher (for both men and women) if the youngest child was aged 13 to 15.

In general the exit hazard decreased with age. The highest hazard of exit was experienced by those aged in their 20s. From 30 onwards the hazard decreased 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 to19 years ($-0.57 = e^{-0.8348} - 1$).

In relation 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 former overseas born tend to live in regions with relatively low unemployment rates and the latter in regions with relatively high unemployment rates.

Those who self-represent as Aboriginal or Torres Straight Islander 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 live in more isolated regions, and 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 rent-paying private renters, non rent-paying homeowners (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. An explanation for these findings is that an individual's housing arrangement housing acts as a useful proxy for past (unobserved) 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 6.2 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				
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 ($/100)	0.347	0.17***	0.17***	0.17***
Earned income squared ($/10000)		-2.9E-03***	-2.9E-03***	-2.9E-03***
Received unearned income	0.147	0.18***	0.19***	0.19***
Unearned income ($/100)	0.054	0.05***	0.05***	0.05***
Unearned income squared ($/10000)		-2.3E-04***	-2.2E-04***	-2.3E-04***
Housing cost indicator ($)	-3.82	1.6E-03***	1.3E-03***	1.6E-03***
Housing				
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 at January 1995 (days)	126.87	7.7E-04***	7.6E-04***	7.6E-04***
Unemployment rate	10.05		-0.05***	-0.05***
No. of jobs within 20 km				
<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	1213437	1213437	1213437	1213437
-2 Log L		467080	466445	466392

***1 per cent level of significance

** 5 per cent level of significance

* 10 per cent level of significance

There was a positive and significant relationship between the housing cost measure and the hazard of exit. This variable was included in the hope that it might capture some of the unobserved differences in employability. In this context the estimated coefficient behaves as anticipated, since we expected those with higher levels of unobserved human capital to be congregated in relatively higher cost regions.

In Model 2, the unemployment rate was 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 should be considered an upper bound estimate of the 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 this variable. 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. We can offer no explanation for this observation.

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 (eg as was shown for locational choice in Section 5). To test this, we also estimated the probability of exiting from long-term unemployment payment receipt, by estimating the model for those recipients whose duration on unemployment payments was 365 days or more.

Table 6.3 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? We calculate that, for the reference person (at mean unemployment rate), the 5 per cent fall in the hazard of exit associated with a one percentage point increase in unemployment implies an 6.6 per cent increase in the median duration of benefit receipt, and a 9.2 per cent increase in the mean duration.[31]

[31] Mean duration is defined as the area under the survival function. We truncated the function at 400 fortnights, since very few members of the sample had unemployment benefit spells longer than this, and calculated mean duration as the area under the survival function up to 400 fortnights. At that duration the value of the survival function was about 0.01.

Table 6.3 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 ($/100)		0.12**
Unearned income squared ($/10000)	0.051	-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

6.2 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 payment between January 1996 and June 2000. For those people who moved more than once, we examine only one of the moves (as described below). The dependent variable (the 'income support receipt gap') is the number of fortnights that they received payment for 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, a person with relatively high skill levels will have an incentive to live in a good labour market (see Section 3), and also be more likely to find employment irrespective of where they live. However, 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, 43 per cent move again in the 12 months following the first move, though nearly 60 per cent of these move only once more. Very few move more than twice in the ensuing 12 months, although one person moves 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, this generalisation seems plausible.

In addition, a second selection bias arises from the fact that we can only observe moves that take place when people are receiving income support. The potential impact of this is best understood if we consider people who only have a single spell of unemployment benefit receipt. The LDS data suggest that moves are more likely to take place towards the beginning of each spell. This means that people with long 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, 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 (i.e. the opposite pattern to that described in the previous paragraph).[32]

[32] 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.

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. Some examples of this were discussed in Section 3.2. They include changes in family status, or job offers that encourage movement. More subtle interactions may occur via the dynamics of the job search process. For example, an unsuccessful jobseeker may eventually lose their motivation for job search. At this point they may both decide to move to a region with a better housing cost/amenity trade-off and reduce their job search effort. In our data their behaviour will be identified as part of the association between labour market conditions and income support receipt, but we cannot interpret this as a causal impact of the labour market conditions of the region.

In general, we believe that these potential biases are probably not very important. This is primarily because, as Section 5 showed, 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 variables, the distance moved and the unemployment rate gap attached to the move. 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 6.4 shows the estimates when we use the first move of each person and Table 6.5 the estimates obtained from the last move.

The fixed variables in the regression (i.e. 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 6.4 the mean of 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 6.5 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 drop in benefit receipt of around 0.6 to 0.75 fortnights per annum. This is collinear with 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.

Table 6.4 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	-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				
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 ($/100)	0.201	-0.43	-0.43	-0.41
Earned income squared ($/10000)	0.707	0.01	0.01	0.01
Received unearned income	0.090	0.09	0.10	0.09
Unearned income ($/100)	0.028	0.76	0.78	0.87
Unearned income squared ($/10000)	0.041	5.2E-04	-0.01	-0.04
Intercept		6.70***	6.70***	6.91***
Sample size	8203			
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 6.5 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

6.3 Summary

Considering the results in both Section 6.1 and in Section 6.2, we conclude that regional labour market conditions do have an impact upon the probability of receipt of unemployment payments.

In Section 6.1 we found that people living in areas with a one-percentage point higher value of the 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 info 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 will reflect the types of location that people with low employment probabilities can afford to live in. This is likely to be the case even though we endeavour to control for regional housing costs.

In Section 6.2 we employed an alternative method that looked at the change in benefit receipt patterns when individuals moved location. As noted above, 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.

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.

7 CONCLUSIONS

In this report we have examined two issues, the determinants of geographic mobility among workforce-age income support recipients and the impact of that mobility on the benefit receipt of unemployment payment recipients. This analysis has been based on the FaCS 1% LDS data file, together with geographic information derived from the 1996 ABS Census.

Compared to people receiving other payments, unemployment payment recipients were more likely to move, and likely to move further. Younger and unmarried people were more likely to move, as were those with some non-benefit income or renting privately. Those born in non English-speaking countries and those identifying as Aboriginal or Torres Straight Islander were less likely to move.

People in high housing cost regions were more likely to move, though there was little difference for long-distance moves. Those living in the largest and smallest labour markets were most likely to move between postcode areas. However, those in the largest labour markets were least likely to move long distances. People living in low unemployment regions were *more* likely to move. However, many of these moves were to other low unemployment regions.

Comparing the characteristics of the origin and source regions, we found large numbers of people moving both to more advantaged and to more disadvantaged labour markets. On balance, however, there was a tendency for unemployment payment recipients to move away from those regions with the poorest labour markets. For other payment recipients, the direction of move, if anything, was in the opposite direction.

Holding other factors such as regional housing costs constant, an increase in the travel region unemployment rate of one percentage point was associated with an increase in the net outflow per annum of around one per cent of the unemployment payment recipients in the region.

How much impact does this have on employment and benefit receipt outcomes? In this report we have employed several estimation strategies to estimate the impact of geographic mobility on employment outcomes. This issue is of most importance to unemployment payment recipients, and so the estimation focuses on this group. We find that living in area with a one percentage point higher unemployment rate is associated with a probability of exit from benefit which is five per cent lower. This translates into an increase in average benefit duration of around 9 per cent.

However, part of this association could be due to the fact that people with low skill levels can only afford to live in high unemployment regions (though the analysis does control for regional housing costs).

To address this issue, we estimated the impact on benefit receipt for individuals who move between different locations. The dependent variable is the number of fortnights in the year after the move, minus the number in the year before the move. Moving to an area with a one percentage point higher travel region unemployment rate leads to an increase in income support of about one third of a fortnight (2% of the average number of fortnights of income support per annum).

This estimation method is potentially affected by selection biases, as we can only consider people who move while receiving income support. Some sensitivity testing is undertaken which supports the conclusions found, and there do not seem to be strong reasons for expecting bias in any particular direction. Nonetheless this result should not be considered as definitive.

Overall, however, the estimation results of this paper suggest that regional labour market conditions do matter. 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). The evidence in this report also supports this view.

This report therefore provides support for policies that seek to influence the movement decisions of income support recipients (and unemployment payment recipients in particular). These 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, which can influence the geographic distribution of affordable housing in Australia.

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APPENDIX A: TRAVEL REGION UNEMPLOYMENT RATES

For isolated regions, the unemployment rate provides a useful indicator of the difficulty an individual is likely to find in searching for work. The higher the unemployment rate, the greater is the number of other jobseekers competing for each job.[33] In large cities, however, the average unemployment rate for the whole city is not an appropriate indicator of labour market tightness, as the cost (in time and money) of travelling can make some areas of employment effectively inaccessible for some people. At the same time, the unemployment rate of the local area will be misleading, as many people may be able to travel to neighbouring regions to find employment.

In this appendix we develop a methodology for deriving a *travel region unemployment rate* for each region within a large urban area that takes into account the possibility of travelling to other regions. We use ABS Journey to Work (JTW) data collected in the 1996 Census to calculate weighted regional unemployment rates. This method could also be used for other regional labour market characteristics such as employment growth rates.

The JTW data show statistical local area (SLA) of usual residence cross-tabulated by the SLA of main employment. They are available separately for 8 Journey to Work Study Areas,

1. Sydney/Wollongong/Newcastle
2. Melbourne/Geelong/Latrobe Valley/Bendigo/Ballarat
3. Brisbane/Gold Coast/Sunshine Coast
4. Adelaide
5. Perth
6. Hobart/Launceston
7. Darwin
8. Canberra/Queanbeyan

For people not covered by these study areas, we define their travel region unemployment rate as the unemployment rate for their Statistical Sub-Division.

Within each study area, we define the *excess labour supply index* for a given employment area *j* as the weighted average of the unemployment rates in each region, with the weights being the proportion of workers in area *j* who live in each region. That is,

$$E_j = \sum_i^I \left(N_{ij} / N_{+j}\right) U_i$$

where N_{ij} is the number of people who live in area i and work in area j, U_i is the unemployment rate in area i, and + denotes summation over the relevant subscript. In matrix notation, we can write this as $E = N_c' U$, where N_c' is the transpose of the matrix of column fractions of the matrix formed from the elements N_{ij}.

We then define the *travel region unemployment rate* for a region i as the weighted average of this across all employment regions, with the weights corresponding to the proportion of people from region i who work in each region. That is,

$$T_i = \sum_j^J \left(N_{ij} / N_{i+}\right) E_j = \sum_j^J \left(N_{ij} / N_{i+}\right) \sum_i^I \left(N_{ij} / N_{+j}\right) U_i$$

In matrix notation, this is $T = N_r N_c' U = CU$, where N_r is the corresponding matrix of row fractions, and C is an $I \times I$ similarity matrix.

This calculation approach is illustrated in Table A.1 for a hypothetical case with four residential regions (1,2,3,4) and three employment regions (a,b,c). The first panel shows the unemployment rate in each residential region (identical apart from area 1). The second

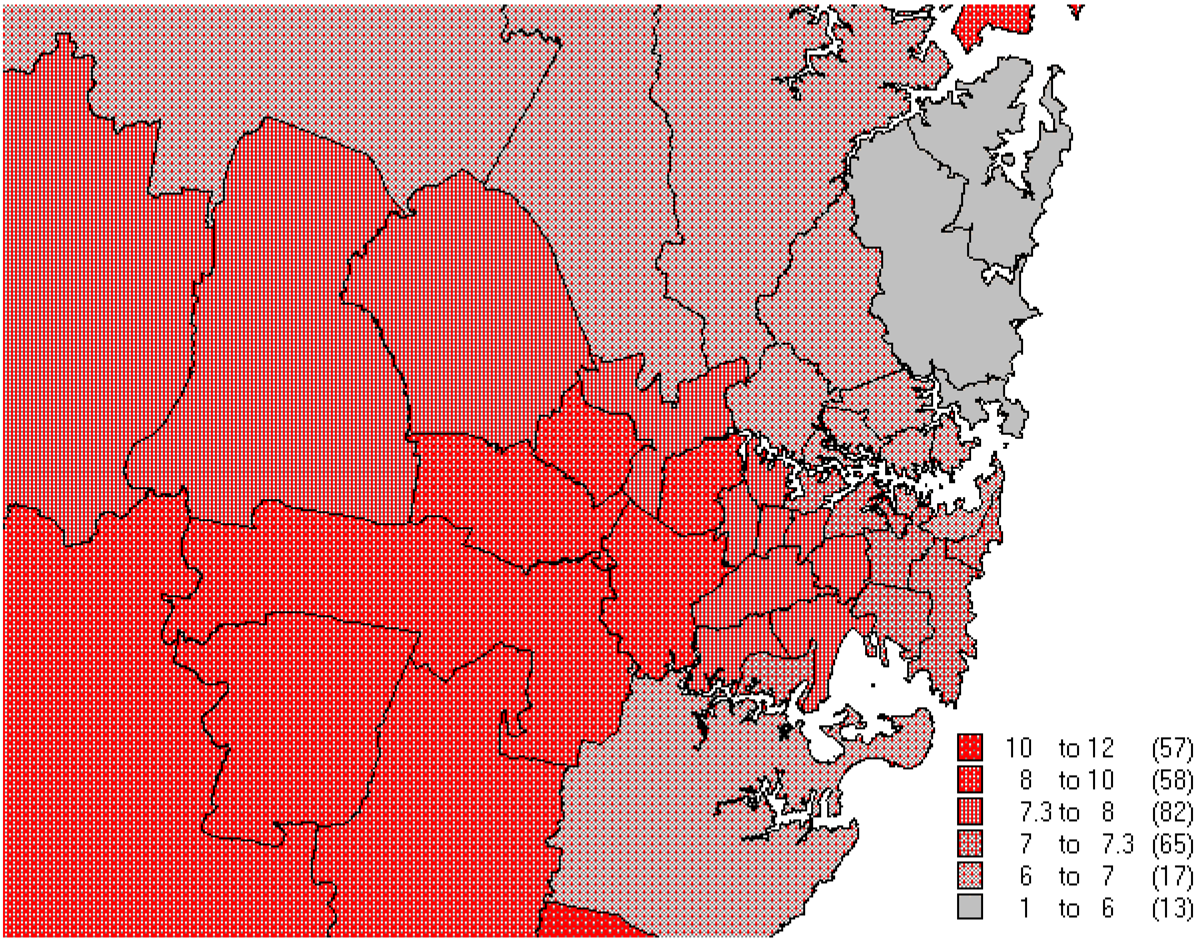
33 This assumes that the number of new jobs is proportional to the number of existing jobs. A more refined measure would be the unemployed to vacancy ratio, but this information is not available.

panel shows the work locations for people living in each region. Note that the people in areas 1 and 2 all work in employment region c.

This data is used to calculate the excess labour supply index for each employment region. Note that the index is 2% for regions a and b because these only have workers from region 3 and 4, where the unemployment is 2% in each case. Finally, this is used to calculate the travel region unemployment rate. Residential regions 1 and 2 now have the same rate. This is because people from both areas all work in region c.

The geographic pattern of travel region unemployment rates for the Sydney region is shown in Figure A.0.1. Note that the Northern Beaches areas have the lowest rates. This is because people from these areas do not work in the areas (mainly west of the city centre) where people from residential regions with high unemployment work.

Figure A.0.1 Travel Region Unemployment Rate in the Sydney Region



Note: The numbers in brackets in the legend are the number of SLAs in NSW with travel region unemployment rates within the indicated ranges.

Table A.1 Hypothetical Example of Unemployment Rate Averaging Based On Journey to Work Data

A. Actual Regional Unemployment Rates

Region of Residence	Unemployment Rate
1	20.0%
2	2.0%
3	2.0%
4	2.0%

B. Number of People Living and Working in Different Regions

Region of Residence	Employment Region			
	a	b	c	Total
1	0	0	20	20
2	0	0	10	10
3	5	5	0	10
4	4	4	2	10
Total	9	9	32	50

C. Excess Labour Supply Index

Employment Region		
a	b	c
2.0%	2.0%	13.3%

D. Travel Region Unemployment Rate

Region of Residence	Averaged Unemployment Rate
1	13.3%
2	13.3%
3	2.0%
4	4.3%

E. Similarity Matrix, C

Region of Residence	Region of Residence			
	1	2	3	4
1	0.63	0.31	0.00	0.06
2	0.63	0.31	0.00	0.06
3	0.00	0.00	0.56	0.44
4	0.13	0.06	0.44	0.37

APPENDIX B: DETAILED TABLES

Table B.1 Logit Regressions of the Probability of Moving Location

		Move Type		
		Moved postcode	Moved more than 10 km	Moved more than 100 km
Proportion of fortnight pairs associated with move		1.3%	0.9%	0.4%
Proportion of unemployment payment fortnight pairs associated with move		2.4%	1.6%	0.8%
Proportion of non unemployment payment fortnight pairs associated with move		0.9%	0.6%	0.3%
	Sample Means	Estimated coefficients		
Unemployment payment recipient	0.3060	0.71***	0.74***	0.80***
Women	0.5494	0.02	-0.01	-0.10***
Married	0.3822	-0.11***	-0.10***	-0.12***
Youngest child aged less than 13	0.2895	0.06	-0.03	-0.08
Youngest child aged 13 to 15	0.0395	-0.23***	-0.31***	-0.33***
Number of dependent children	0.6315	-0.11***	-0.10***	-0.11***
Women				
Married	0.2082	-0.07***	-0.08**	0.04
Youngest child aged less than 13	0.2213	0.19***	0.27***	0.25***
Youngest child aged 13 to 15	0.0276	0.25***	0.26**	0.19
Number of dependent children	0.4729	0.04**	0.03	0.05
Age in years				
20-24	0.1170	-0.06***	-0.03	0.10***
25-29	0.1082	-0.14***	-0.10***	0.02
30-34	0.1060	-0.27***	-0.22***	-0.10***
35-39	0.1077	-0.39***	-0.37***	-0.24***
40-44	0.0944	-0.48***	-0.43***	-0.23***
45-49	0.0866	-0.60***	-0.54***	-0.33***
50-54	0.0942	-0.67***	-0.64***	-0.47***
55 plus	0.2002	-0.81***	-0.80***	-0.62***
Born overseas	0.2652	-0.15***	-0.20***	-0.29***
Born overseas (English speaking country)	0.0561	0.17***	0.23***	0.29***
ATSI	0.0290	0.40***	0.41***	0.57***
Received earned income	0.1939	-0.44***	-0.51***	-0.54***
Earned income ($/100)	0.4023	-0.02**	-0.04***	-0.10***
Earned income squared ($/10000)		1.10E-05	3.4E-05	8.60E-05**
Received unearned income	0.2689	-0.31***	-0.29***	-0.18***
Unearned income ($/100)	0.0021	1.66	1.18	-3.29
Unearned income squared ($/10000)		-0.47	-0.27	1.21*
Housing				
Pays rent and lives in public rental	0.0876	-0.89***	-0.89***	-0.88***

Pays no rent and owns a home	0.3076	-1.26***	-1.17***	-1.13***
Pays no rent but does not own a home	0.1814	-0.29***	-0.22***	-0.13***
Housing cost indicator ($)	-3.9291	8.30E-4**	3.68E-04	-6.50E-04
Travel Region Unemployment rate	9.5870	-0.02***	-0.03***	-0.05***
No. jobs within 20 km (relative to 500,000+)				
<5000	0.1170	0.04	0.76***	1.38***
5-49,999	0.2980	0.08***	0.67***	1.30***
50,000-399,999	0.2290	0.15***	0.49***	0.55***
300,000-499,999	0.1640	0.22***	0.38***	0.41***
Unemployment payment recipients ×				
Housing cost indicator	-1.1874	6.34E-04	4.86E-04	1.34E-04*
T. R. Unemployment rate	3.0766	-4.09E-03	-2.21E-03	4.38E-03
No. jobs within 20 km	0.0821			
<5000		0.08**	0.03	-0.05
5-49,999		0.07**	0.04	-0.02
50,000-399,999		0.01	-0.04	-0.01
300,000-499,999		0.02	0.03	-5.3E-04
Intercept		-3.74***	-4.45***	-5.52***
No. of observations	3,625,464			
-2 Log L		476255	341771	187122

*** 1% level of significance

** 5% level of significance

* 10% level of significance

Table B.2 Characteristics of income support recipient in fortnight before move by unemployment rate gap associated with move

Note: The cells of the table show the proportion of people with the indicated unemployment rate gap who have the indicated characteristic. For example, of those unemployment rate recipients whose move was associated with a fall in the unemployment rate of two or more per cent, 28.8 per cent were women.

	Move Type (unemployment rate gap)				
	<= - 2	Between –2 and -1	-1 to 1	Between 1 and 2	>= 2
Unemployment payment recipients					
Women	28.8	41.5	35.3	41.0	27.3
Married	16.3	14.9	14.7	14.0	17.0
Overseas born	11.2	14.7	19.8	15.6	11.9
ATSI	7.6	9.0	5.9	9.9	8.0
Age in years					
< 20	20.1	21.5	20.3	20.0	19.8
20-24	27.8	28.3	28.6	28.4	26.3
25-29	18.4	17.5	17.2	17.7	19.1
30-34	11.1	11.6	11.3	13.3	11.2
35-39	7.7	8.0	8.0	6.7	8.0
40-44	6.2	5.1	5.7	5.0	6.4
45-49	4.3	3.8	4.2	4.8	4.3
50-54	2.5	2.3	2.8	2.4	2.8
55 +	2.0	2.0	2.0	1.8	2.4
Youngest child < 13 years	7.1	6.5	7.2	6.6	7.5
Youngest child 13-15 years	0.3	0.2	0.4	0.4	0.4
Number of children	0.15	0.14	0.15	0.15	0.16
Housing					
Pays rent and lives in private rental	66.7	66.6	71.7	69.4	67.4
Pays rent and lives in public rental	1.1	2.0	2.0	1.7	1.5
Pays no rent and owns a home	4.2	3.4	2.7	3.2	4.2
Pays no rent but does not own a home	28.0	28.0	23.6	25.7	26.9
received earned income	7.1	7.9	9.3	6.9	6.9
earned income ($)	12.3	13.5	18.2	12.3	13.3
received unearned income	7.9	6.3	5.9	6.3	6.7
Other recipients					
Women	62.6	74.1	70.6	75.3	61.3
Married	30.0	26.7	25.8	26.1	29.9
Overseas born	15.1	19.4	24.7	20.3	17.1
ATSI	7.6	5.9	5.0	6.5	6.6
Age in years					
< 20	9.8	9.8	10.5	9.1	8.2
20-24	17.2	18.4	17.1	17.1	15.3
25-29	14.8	18.1	17.2	16.5	14.1
30-34	12.1	13.6	13.3	14.0	12.6
35-39	10.8	10.7	11.6	10.8	9.8
40-44	8.4	6.3	8.4	8.2	8.5
45-49	7.1	6.4	5.9	7.8	7.7
50-54	7.3	6.1	6.1	6.9	8.2
55 +	12.5	10.5	10.1	9.7	15.8
Youngest child < 13 years	46.3	51.7	48.9	61.3	43.9
Youngest child 13-15	3.1	2.5	3.5	4.1	2.6

years					
number of children	0.90	0.97	0.93	0.98	0.85
Housing					
Pays rent and lives in private rental	62.5	61.2	63.5	62.0	58.9
Pays rent and lives in public rental	5.2	7.2	7.1	7.2	5.9
Pays no rent and owns a home	12.8	11.1	9.9	11.7	15.3
Pays no rent but does not own a home	19.5	20.5	19.5	19.1	19.9
Received earned income	7.1	7.8	11.1	8.4	6.7
Earned income ($)	17.2	20.2	34.0	25.0	15.3
Received unearned income	16.6	14.2	15.9	15.5	20.4

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