# Background Paper 5 Links between housing assistance and employment

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| Key points |
| * Housing assistance — in the form of Commonwealth Rent Assistance (CRA) or the provision of public housing — has the potential to limit recipients’ incentives to work, and may reduce employment rates among housing assistance recipients. * A large dataset compiled from the Department of Employment’s Research and Evaluation Database was used to assess the effect of housing assistance on employment. The data consist of confidentialised individual‑level information about eligibility for and payment of income support between 2004 and 2013, and provide a unique opportunity for an in‑depth analysis of the possible effects of housing assistance on employment. * Regression analysis takes into account differences in the characteristics of Income Support Payment (ISP) recipients and allows for the effects of housing assistance to be isolated from other factors that may also affect employment. Two regression techniques are used in this paper: * Cross‑sectional models that take into account differences between individuals that are observed in the data. * Fixed effects regressions that isolate the effects of housing assistance on employment from individual characteristics recorded in the data and characteristics that are not recorded. These techniques rely on the assumption that unobserved characteristics do not change over time. * After accounting for differences in observed characteristics, residents of public housing have a predicted probability of employment in the order of 15 per cent, about 6 percentage points below that of ISP recipients who do not reside in public housing. Recipients of CRA have a slightly lower predicted probability of employment than ISP recipients who do not receive housing assistance. * However, the fixed effects models indicate that, once time‑invariant unobserved characteristics have been accounted for, housing assistance has a very small effect on employment. That is, individual characteristics of ISP recipients, rather than their housing assistance status, affect whether or not they are in employment. For public housing, this result is consistent with the provision of housing assistance to high needs individuals, who may have difficulty finding and maintaining employment. * The effect of neighbourhood disadvantage on employment was also examined, with the analysis restricted to public housing residents to minimise problems of selection bias. Living in a highly disadvantaged area was found to be associated with lower levels of employment, even after accounting for the effects of individual differences, but this effect is small when compared to other determinants of employment. |
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## 1 Introduction

Employment decisions typically involve a process where the expected benefits of employment are weighed up against the expected costs associated with working, including, for parts of the population, the potential loss of income support payments (ISPs) and housing assistance. The net benefits of employment are likely to vary across individuals, depending on their likelihood of finding and maintaining employment, the wages that they can expect and their individual circumstances, including whether they have children, their level of education and the neighbourhood in which they live. To assess whether housing assistance affects employment, it is necessary to account for the various factors that affect the decision to enter paid work.

This paper focuses on the potential effects of two key housing assistance strategies on ISP recipients’ employment:

* rent subsidies provided by the Australian Government in the form of Commonwealth Rent Assistance (CRA)
* public housing provided by state housing authorities.[[1]](#footnote-2) People with urgent housing needs, including those who are homeless or are at risk of homelessness, are typically prioritised in the allocation of public housing.[[2]](#footnote-3)

Detailed unit record information derived from administrative ISP records allows an empirical assessment of the relationship between housing assistance and employment.

### Why might employment be affected by housing assistance?

Housing assistance could reduce a recipient’s incentive to work (box 1, with more details in Background Paper 2 (BP 2)).[[3]](#footnote-4) This might occur because the recipient faces either:

* an ‘unemployment trap’, where the financial benefits of remaining out of work are greater or not substantially less than the benefits of participation in paid work, or
* a ‘low‑income trap’, where they have little incentive to increase earnings through additional hours (Hulse et al. 2003; Whiteford and Angenent 2002).

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| Box 1 An economic approach to assessing the effect of housing assistance on employment |
| Housing assistance may affect the employment of recipients by influencing their incentives to work.[[4]](#footnote-5) The conventional economic approach to the supply of labour describes an individual’s employment decision as the outcome of a constrained optimisation problem, where individuals allocate their time between paid work and unpaid activities to maximise utility. Employment is rewarded in terms of wages — used to purchase goods or services that yield utility — whereas unpaid activities are assumed to yield utility directly.  The choice of time allocation is subject to a budget constraint that is based on feasible combinations of paid and unpaid activities for a given level of wages. The budget constraint is determined by an individual’s time endowment, the wage rate at which they are offered work and any non‑labour income, including transfer payments. Time spent on unpaid activities, such as childcare and commuting, is valued at the wage rate that an individual faces. In the absence of transfer payments or other forms of unearned income, an individual allocating an additional hour to unpaid activities foregoes an hour’s wages.  Unearned income — such as transfer payments — may reduce incentives to work, as it enables consumption without paid employment. The higher income associated with a transfer payment may allow increased allocation of time to non‑work activities (an ‘income effect’). Public housing could have a similar effect, due to the subsidy implied by the difference between market rent and rent paid by a tenant.  The tapered withdrawal of transfer payments as market income increases can affect work incentives in two ways. Individuals who increase their employment receive the financial benefit of working, less any transfer payments that are withdrawn. This reduction in the net returns to work (in comparison with a situation where benefits were not withdrawn), induces a ‘substitution effect’ toward non‑work activities. At the same time, individuals will have less disposable income for a given number of hours worked (than would be the case if transfers were not withdrawn), meaning that there is an incentive to work more (the income effect associated with benefit withdrawal). The overall effect of the tapered withdrawal of transfer payments is the sum of the income and substitution effects.  As with all models, this approach to explaining labour supply makes simplifying assumptions. For example, it is assumed that individuals choose to work the number of hours that maximise the utility that they gain from their income and unpaid activities. In fact, the number of hours worked is generally a ‘lumpy’ decision with a small number of discrete choices — something that will limit the ability to choose the utility‑maximising number of hours, especially where there are caring obligations. Further, minimum wages may limit employment opportunities for low productivity workers by precluding them from accepting lower wages in order to engage in employment commensurate with their expected productivity. This paper does not examine the effect of minimum wages on the ability of low productivity workers to find work. |
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CRA potentially affects a recipient’s incentive to work through its interaction with the withdrawal of transfer payments as earnings increase. As market income increases beyond a specified threshold, income support is steadily withdrawn. Different thresholds are applied to different ISPs. For example, Disability Support Pension (DSP) payments are reduced by 50 cents for each dollar earned in excess of $160 in a given fortnight.[[5]](#footnote-6) For private renters who receive CRA because they are eligible for an ISP, CRA is withdrawn at the same rate as the ISP, once the primary ISP reaches $0.[[6]](#footnote-7) This means that effective marginal tax rates associated with the withdrawal of transfer payments persist over a broader income range for individuals who receive CRA (Hulse and Randolph 2005; BP 2).

The provision of public housing is likely to affect the work decisions of recipients differently. For most public housing tenants, rent is set at about 25 per cent of their assessable income, capped at the market rent for the property occupied. This means that their rent increases as their earnings increase, until rent paid is equal to market rent.[[7]](#footnote-8) This, combined with the withdrawal of ISPs as income increases, reduces returns to entering, or increasing, work. Public housing tenants face effective marginal tax rates that are higher than comparable CRA recipients at low levels of income (BP 2). The measure of income used to determine the amount of rent paid by a household can include the income of working‑age children who reside at home, meaning that children who live with parents in public housing may also face a disincentive to find work.

Other factors may affect the net benefits of employment for public housing residents, including:

* eligibility requirements, where public housing residents may become ineligible if their income exceeds a threshold
* mobility restrictions — the limited availability of public housing means that residents seeking to relocate to areas with better employment prospects may be required to move into a private rental tenancy, which may mean higher rents and a less secure tenancy; this is likely to reduce the incentive to relocate for employment purposes
* the stability afforded by secure, ongoing public tenancies may provide public housing residents with better opportunities to find and maintain employment than would otherwise be the case
* the location of affordable rental housing — either public or subsidised — may be in areas where there is geographically concentrated disadvantage, including limited employment opportunities, which could reduce the probability of entering employment.

The key hypothesis examined in this paper is that housing assistance has a negative effect on the employment of housing assistance recipients. The focus of the analysis is on employment status, rather than the number of hours worked by ISP recipients, due to limitations of the administrative data used in this analysis. The data used are discussed in section 2.

The research examines the extent to which receipt of housing assistance affects employment, once the characteristics of those who receive it are taken into account. The effect of parental receipt of housing assistance on the employment of their children who live at home is also tested. In addition, the effect of neighbourhood disadvantage on employment status is briefly examined.

### Previous research

Previous research has shown that housing assistance recipients are less likely to be in paid employment than other people. In particular, the employment rate of public housing residents is recognised as being substantially below that of residents of other tenures (Groenhart and Burke 2014; Wood, Ong and Dockery 2009).

A negative relationship between housing assistance and participation in employment may be expected, given that housing assistance is targeted towards people with low income and with complex needs. But it is important to distinguish the extent to which lower employment rates among recipients are related to housing assistance itself or to recipients’ characteristics.

Recent Australian studies that attempt to make this distinction by using multivariate approaches include Whelan (2004), Whelan and Ong (2008), Dockery et al. (2008) and Wood, Ong and Dockery (2009). These studies rely on survey data and cross‑sectional methods to isolate the employment effects of housing assistance.

Whelan (2004), Whelan and Ong (2008) and Dockery et al. (2008) use the Household, Income and Labour Dynamics in Australia (HILDA) survey to estimate the relationship between CRA and employment status, after taking into account individuals’ characteristics.[[8]](#footnote-9) They find that CRA has a small negative effect on employment, however, many of the estimates are not statistically significant.

Wood, Ong and Dockery (2009) use repeated cross‑sections from the ABS Survey of Income and Housing Costs between 1982 and 2002. Most of the decline in employment among male public housing tenants is attributed to changes in their observed characteristics. However, differences in observed characteristics do not explain the decline in employment rates among female residents of public housing, relative to women residing in other tenures. The authors suggest that unobserved characteristics are one potential explanation for lower employment among this group.

Like all empirical research projects, these studies faced some data limitations. In particular, the HILDA‑based studies have no direct indicator of CRA status. CRA status is inferred using reported income, income support payments, demographic characteristics and tenure status (Whelan 2004, Whelan and Ong 2008 and Dockery et al. 2008). In addition, the comparatively small number of public housing residents means that there is a very small number of corresponding observations in the HILDA survey. For example, the 2001 HILDA survey reports 379 households living in public housing (Whelan 2004). The small number of observations means that it can be difficult to estimate any housing assistance effects precisely.

The reliance on survey data that include limited housing assistance information suggests that panel models with large longitudinal administrative datasets of the type used in this paper could provide additional insights into the effects of housing assistance on employment.

## 2 Data used in this paper

The Research and Evaluation Database (RED) is a large database consisting of the confidentialised administrative records of ISP recipients, extracted from Centrelink’s Income Security Integrated System and the Department of Employment’s Integrated Employment System. RED includes de‑identified, individual‑level income support, demographic, housing assistance and employment earnings information for all ISP recipients (box 2).[[9]](#footnote-10)

The estimation dataset comprised a series of linked annual cross‑sections, with each cross‑section consisting of ISP recipients aged between 16 and 65 active at June 30 of each year. Recipients of the Age Pension are not included due to the focus on employment status.

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| Box 2 The Research and Evaluation Database |
| The Research and Evaluation Database (RED) is a large administrative database maintained by the Department of Employment. It consists of confidentialised information about eligibility for, and receipt of, income support payments (ISPs) over time. These longitudinal data include changes in individuals’ circumstances over time that affect ISPs and housing assistance. Any changes in employment‑related earnings are recorded.  As an administrative database, RED provides comprehensive coverage of ISP recipients and, because of its size, allows the examination of detailed population subgroups. RED also identifies recipients of Commonwealth Rent Assistance (CRA) directly, which is a distinct advantage when compared with other sources, such as the Housing, Income and Labour Dynamics in Australia survey, in which CRA status must be imputed.  RED also has a number of limitations. First, it does not include information about ISP recipients’ highest level of education. To the extent that education remains constant over time, this is taken into account in the fixed effects model, discussed below. Second, the number of hours worked by ISP recipients is an unreliable variable as it is not collected for all ISP recipients, and was not mandatory for any ISP recipients prior to July 2006. This precluded analysis of the relationship between housing assistance and hours worked.  Third, RED only includes individuals receiving ISPs, so does not include all working age recipients of housing assistance. Specifically, RED does not include information about: public housing residents who do not receive an ISP; recipients of Department of Veterans’ Affairs pensions; and people who receive CRA because they receive Family Tax Benefit Part A but do not receive an ISP. Excluding these groups from an analysis of the links between housing assistance and participation in employment may be justified on the basis that:   * public housing residents who do not receive an ISP are likely to be paying market rents, and therefore not receiving a housing subsidy that might reduce their incentive to work * a large majority of Department of Veterans’ Affairs pensioners are older than 65 years of age (DVA 2014) * people who do not receive income support but are eligible for CRA because they receive Family Tax Benefit Part A are not included in all RED tables, and so cannot be included in the multivariate analysis. This group accounts for about 14 per cent of the CRA population, has relatively high rates of employment, and typically lives in households with higher incomes than ISP recipients (chapter 3 in volume 1 of this report).   Fourth, as noted above, RED does not allow the separate identification of community housing recipients. This is a comparatively small group of ISP recipients who are likely to face similar incentives to those residing in public housing, even though they are in receipt of CRA.  Finally, RED does not specifically identify working age ISP recipients who live with their parents who receive housing assistance. However, it is possible to link some young ISP recipients (aged 16–24) to their parents who also received an ISP, and assign the young ISP recipient their parent’s housing assistance status. Linking is made possible by virtue of the fact that a parent had previously applied either for Family Tax Benefit Part A or Child Care Rebate payments. Linked parents and children who live in the same (SA1) geographic region are assumed to be living together. This work is discussed later in this section. |
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Data for the years between 2004 and 2013 were initially extracted from RED. People who were receiving an ISP at 30 June of a given year were included in this data extraction. However, the housing assistance status variable used in the analysis was lagged by one year, to address the potential for reverse causality, meaning that the estimation dataset spans from 2005 to 2013. (Reverse causality and the use of lagged housing assistance as an approach to addressing this problem are discussed in section 3.) As a result of using lagged housing assistance status, people must appear in RED at 30 June in two consecutive years to be included in the estimation dataset — that is, information about their housing assistance at 30 June of the previous year as well as contemporaneous information for other variables, must be available.

The estimation dataset comprised over 18 million observations of over 4.1 million working age ISP recipients between the years 2005 and 2013. On average, there were around 2 million individual observations in each year of the dataset. While RED provides information on ISP recipients from 1998 onwards, the lack of a reliable housing assistance variable prior to late 2002 and the size of the database precluded using all available observations.

The panel data are not balanced. While around 18 per cent of ISP recipients are present in all years of the panel dataset, the remainder appear only in a portion of the panel because they transition into and out of the longitudinal dataset over time (figure 1). Given that RED contains a comprehensive representation of ISP recipients at any point in time, the transitions out of the data represent people dying, reaching retirement age or moving off income support as their income changes. It is not possible to ascertain whether income support ceases because people become employed or for other reasons.

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| Figure 1 Number of times a person appears in the data, 2005–2013**a** |
| |  | | --- | | This figure shows the number of times an individual appears in the panel dataset. The highest frequency is two appearances, with over 820,000 people appearing twice. About 730,000 appear in all nine years. | |
| a Number of ISP recipients aged 16–65 at 30 June of each year. Individuals who make a single appearance in the estimation dataset have one contemporaneous observation and were in the dataset at the preceding 30 June (so their housing assistance status at that point is known). |
| *Source*: Author estimates, Research and Evaluation Database. |
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Variables drawn from RED and used in the estimation dataset are described in table 1.

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| Table 1 Variables used in housing assistance analysis |
| |  |  | | --- | --- | | Variable | Definition | | Employment | Indicates employment status, imputed from reported earnings. | | Age group | Age group in a given year. | | Female | Indicates if an ISP recipient is female. | | Married/de facto | Indicates if an individual is married or in a de facto relationship. The variable is binary, with the default category being ‘single’. | | Indigenous | Indicates if an individual identifies as an Aboriginal or Torres Strait Islander. | | English as preferred language | Indicates if an individual’s preferred spoken language for communication is English. | | Dependent children, aged 0–4 | Number of dependent children under the age of 5. | | Dependent children, aged 5–14 | Number of dependent children aged between 5 and 14 years. | | Medical condition | Indicates if an individual has been assessed as suffering from a medical condition that impairs their work capacity. These assessments are made for people who receive a Disability Support Pension or who apply for a variation to their activity requirements while receiving another ISP. People may suffer from unobserved medical conditions that are not recorded by this variable. | | Housing assistance | Indicates if a person had rented from a state housing authority, whether they — or their partner — received CRA, or whether they did not receive any housing assistance. The housing assistance variable is lagged by one year. | | ISP type | Indicates the income support payment received by the individual. | | State | State or territory of residence. | | Region | Indicates if an individual resides in a major city, an inner regional, outer regional area, or a remote or very remote region.a | | Number of address changes | Number of postcode changes recorded within the preceding year. Used as an indicator of an individual’s stability of residence. | | Neighbourhood disadvantage | Neighbourhood disadvantage is based on the Index of Relative Socioeconomic Disadvantage (IRSD) (ABS 2013), which ranks geographic areas in terms of the relative disadvantage of their residents. A lower score indicates greater disadvantage. The decile of IRSD score assigned to the Statistical Area level 1 (SA1 level) in which an individual lives is used in the regression models presented below.b,c | |
| a Region is classified according to the ABS Remoteness Structure(ABS 2010). Remote and very remote regions are combined due to a comparatively small number of observations. b The IRSD is an index value assigned to the geographical area in which an individual lives. It is based on the characteristics of the population living in an area such as the prevalence of unemployment and low‑skilled employment, low income and/or overcrowded households, single parent families, people with disability, low levels of education and/or poor English skills and a lack of access to cars and the internet among residents. c The SA1 level is the most disaggregated geographical unit for which the IRSD is available. Under the 2011 Australian Statistical Geography Standard there were over 54 000 different SA1 areas across Australia, with an average population of 400 people. |
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### Characteristics of people in the estimation dataset

On average, there were around 640 000 CRA recipients, 230 000 residents of public housing and 1.1 million ISP recipients who did not receive housing assistance included in the estimation dataset at 30 June of each year (figure 2).

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| Figure 2 Number of ISP recipients, by housing assistance status, at 30 June 2005–2013**a,b** |
| |  | | --- | | This figure shows the number of ISP recipients who either received CRA, were residents of public housing, or received no housing assistance between the years 2005 and 2013. The number of public housing residents remains relatively constant over time, as does the number of ISP recipients receiving no housing assistance. The number of CRA recipients increases from around 550,000 in 2005 to around 580,000 in 2013. | |
| a Number of ISP recipients aged 16–65 at 30 June of each year. b Housing assistance status is a lagged variable and indicates an individual’s housing assistance at June 30 of the preceding year. |
| *Source*: Author estimates, Research and Evaluation Database. |
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Housing assistance status is not static, with between 10 and 12 per cent of ISP recipients changing housing assistance status each year (table 2). For example, about 4–4.5 per cent of public housing residents exit public housing and become CRA recipients, and between 1.6–2.5 per cent of CRA recipients enter public housing in any given year.

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| Table 2 Housing assistance transitions, 2005–2013**a,b**  Current housing assistance status by housing assistance status in preceding year |
| |  |  |  |  |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | | Lagged housing assistance | Current housing assistance | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | | CRA | CRA | 469 627 | 486 218 | 481 812 | 479 646 | 517 608 | 565 548 | 599 728 | 630 326 | 670 542 | | Public housing | 12 696 | 14 644 | 14 289 | 12 817 | 11 479 | 11 401 | 11 707 | 12 075 | 12 655 | | No housing assistance | 73 959 | 82 716 | 82 493 | 78 830 | 85 804 | 91 850 | 90 971 | 94 287 | 96 368 | | Public housing | CRA | 9 962 | 9 442 | 9 183 | 9 255 | 10 354 | 9 963 | 9 961 | 9 226 | 9 421 | | Public housing | 206 099 | 208 673 | 207 724 | 208 917 | 210 752 | 213 089 | 211 188 | 212 114 | 212 550 | | No housing assistance | 7 622 | 8 074 | 8 896 | 8 105 | 8 942 | 8 693 | 8 973 | 8 326 | 9 057 | | No housing assistance | CRA | 83 008 | 91 363 | 93 022 | 97 796 | 116 946 | 123 207 | 122 553 | 127 320 | 132 974 | | Public housing | 10 877 | 12 379 | 12 800 | 12 770 | 12 918 | 13 226 | 12 437 | 13 621 | 14 162 | | No housing assistance | 988 885 | 997 124 | 964 717 | 938 777 | 966 621 | 1 008 499 | 1 014 792 | 1 024 161 | 1 013 161 | | No. of individual observations | | 1 862 735 | 1 910 633 | 1 874 936 | 1 846 913 | 1 941 424 | 2 045 476 | 2 082 310 | 2 131 456 | 2 170 890 | |
| a Number of ISP recipients aged 16–65 at 30 June of each year. b Lagged housing assistance indicates an individual’s housing assistance at June 30 of the preceding year. |
| *Source*: Author estimates, Research and Evaluation Database. |
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The characteristics of the people in each wave of the longitudinal dataset have remained stable across waves. As a result, the demographic characteristics of a particular wave can be viewed as a reasonable representation of characteristics in other waves.

ISP recipients living in public housing differ from those either receiving CRA or not receiving housing assistance in several ways that are likely to be related to employment (table 3). These differences are reasonably consistent in each wave of the dataset. For example, in each wave, public housing residents are more likely to be older, be of an Indigenous background, receive the DSP, suffer a medical condition or reside in areas of relative disadvantage.

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| Table 3 Characteristics of ISP recipients by type of housing assistance, 30 June 2013**a** | | | | | | | |
|  |  | No housing assistance | | Commonwealth Rent Assistance | | Public housing | |
|  | Unit | Mean | sd | Mean | sd | Mean | sd |
| Employed | Per cent | 18.9 |  | 19.8 |  | 9.8 |  |
| *Age* |  |  |  |  |  |  |  |
| Aged 15 to 19 | Per cent | 9.3 |  | 1.2 |  | 0.4 |  |
| Aged 20 to 24 | Per cent | 17.6 |  | 12.4 |  | 3.7 |  |
| Aged 25 to 34 | Per cent | 16.3 |  | 26.7 |  | 14.7 |  |
| Aged 35 to 44 | Per cent | 14.5 |  | 24.8 |  | 23.3 |  |
| Aged 45 to 54 | Per cent | 16.3 |  | 19.1 |  | 28.8 |  |
| Aged 55 to 65 | Per cent | 25.9 |  | 15.8 |  | 29.2 |  |
| Female | Per cent | 55.3 |  | 62.0 |  | 62.7 |  |
| Married/de facto | Per cent | 30.5 |  | 19.9 |  | 23.6 |  |
| Indigenous | Per cent | 13.2 |  | 10.8 |  | 18.0 |  |
| English as preferred language | Per cent | 91.3 |  | 93.0 |  | 90.0 |  |
| Parent | Per cent | 21.2 |  | 36.3 |  | 30.3 |  |
| Children aged less than 5b | Number | 0.7 | 0.8 | 0.7 | 0.8 | 0.6 | 0.8 |
| Children aged 5 to 14b | Number | 1.1 | 1.0 | 1.2 | 1.0 | 1.5 | 1.1 |
| Medical condition | Per cent | 40.6 |  | 41.2 |  | 58.5 |  |
| *Income support payment* |  |  |  |  |  |  |  |
| Disability Support Pension | Per cent | 32.0 |  | 30.5 |  | 52.4 |  |
| Newstart Allowance | Per cent | 25.2 |  | 29.3 |  | 20.7 |  |
| Parenting Payment (Single) | Per cent | 6.9 |  | 16.5 |  | 10.5 |  |
| Parenting Payment (Partnered) | Per cent | 3.5 |  | 5.3 |  | 2.6 |  |
| Youth Allowance (Student) | Per cent | 11.3 |  | 6.1 |  | 0.2 |  |
| Youth Allowance (Jobseeker) | Per cent | 6.7 |  | 1.9 |  | 0.6 |  |
| Carers Payment | Per cent | 9.3 |  | 6.6 |  | 10.1 |  |
| Otherc | Per cent | 5.0 |  | 3.8 |  | 2.9 |  |
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| Table 3 (continued) | | | | | | | |
|  |  | No housing assistance | | Commonwealth Rent Assistance | | Public housing | |
|  | Unit | Mean | sd | Mean | sd | Mean | sd |
| *State* |  |  |  |  |  |  |  |
| NSW | Per cent | 32.6 |  | 33.7 |  | 32.6 |  |
| Vic | Per cent | 27.5 |  | 23.3 |  | 20.0 |  |
| Qld | Per cent | 18.6 |  | 24.2 |  | 17.0 |  |
| SA | Per cent | 8.7 |  | 7.7 |  | 11.5 |  |
| WA | Per cent | 7.4 |  | 7.2 |  | 10.1 |  |
| Tas | Per cent | 3.4 |  | 2.9 |  | 3.9 |  |
| NT | Per cent | 1.0 |  | 0.4 |  | 2.4 |  |
| ACT | Per cent | 0.7 |  | 0.6 |  | 2.5 |  |
| *Region* | |  |  |  |  |  |  |
| Major city | Per cent | 64.5 |  | 64.7 |  | 68.5 |  |
| Inner regional | Per cent | 21.8 |  | 24.0 |  | 17.1 |  |
| Outer regional | Per cent | 11.2 |  | 10.3 |  | 10.2 |  |
| Remote or very remote | Per cent | 2.5 |  | 1.0 |  | 4.2 |  |
| *Address changes in previous year* | |  |  |  |  |  |  |
| None | Number | 80.6 | 0.4 | 70.0 | 0.5 | 89.7 | 0.3 |
| 1 change | Number | 12.8 | 0.3 | 21.0 | 0.4 | 7.0 | 0.3 |
| 2 changes | Number | 4.2 | 0.2 | 5.8 | 0.2 | 2.1 | 0.2 |
| 3 or more changes | Number | 2.3 | 0.2 | 3.1 | 0.2 | 1.2 | 0.1 |
| SA1 IRSD deciled | Decile | 5.6 | 2.7 | 5.5 | 2.7 | 4.1 | 2.4 |
| Number of observations | Number | 1 160 297 | | 779 565 | | 231 028 | |
| a The housing assistance variable indicates housing assistance status at 30 June 2012. The use of lagged variables is discussed in section 3. b The average number of children in the care of a parent. c Other payments include a range of less common income support payments, including Bereavement Allowance, Wife’s Pension, Wife’s Disability Support Pension, Austudy, Partner Allowance, Sickness Allowance, Special Benefits, Widow Allowance and Abstudy. d The average decile of the Index of Relative Socioeconomic Disadvantage at the Statistical Area 1 geographic unit level. A lower decile indicates greater disadvantage. | | | | | | | |
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In contrast, CRA recipients tend to have characteristics more similar to those of ISP recipients who receive no housing assistance. For instance, in all waves, the likelihood of having a medical condition is similar across both groups, as are the socioeconomic characteristics of the areas in which they live. That said, there are some differences between CRA recipients and ISP recipients who do not receive housing assistance. For example, CRA recipients are more likely to be single, and are more likely to have moved in the last year than are ISP recipients who do not receive any housing assistance.

#### Young people living with parents or guardians

As mentioned above, the employment of people living with parents or guardians may be negatively affected by rent setting rules in public housing.[[10]](#footnote-11) While rules relating to younger household members vary, all states include the incomes of some younger members in determining the rent paid by a household living in public housing. Table 3.2 in volume 1 of this report presents a summary of differences in how the income of young people is treated in setting households’ public housing rents.

The RED data do not directly identify working age young people who receive an ISP and live with parents who receive housing assistance. In order to assess if parental housing assistance has any effect on the employment of younger household members, it is necessary to infer the housing assistance status of some young people from their parents’ information.

Data for ISP recipients aged between 16 and 24 can be linked to that of their parents who also receive an ISP. While there is no direct information about whether the younger ISP recipients reside at the same address as their parents, they are assumed to live with their parents if they reside in the same Statistical Area Level 1 (SA 1) region.[[11]](#footnote-12)

Young ISP recipients living with parents in public housing are less likely to work than those living with their parents in other housing tenures (table 4). They are more likely to be Indigenous, live in an area of high disadvantage, or have a medical condition. They are less likely to be receiving the Youth Allowance (Student) payment.

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| Table 4 Characteristics of young ISP recipients living at home by their parent’s type of housing assistance, 30 June 2013**a** | | | | | | | |
|  |  | No housing assistance | | Commonwealth Rent Assistance | | Public housing | |
|  | Unit | Mean | sd | Mean | sd | Mean | sd |
| Employment | Per cent | 24.1 |  | 19.1 |  | 13.7 |  |
| Female | Per cent | 50.0 |  | 50.0 |  | 47.8 |  |
| Married/de facto | Per cent | 2.8 |  | 2.9 |  | 3.5 |  |
| Indigenous | Per cent | 13.4 |  | 18.5 |  | 28.4 |  |
| English as preferred language | Per cent | 98.7 |  | 97.1 |  | 98.8 |  |
| Parent | Per cent | 5.7 |  | 8.3 |  | 10.6 |  |
| Children aged less than 5b | Number | 1.2 | 0.5 | 1.2 | 0.5 | 1.2 | 0.5 |
| Medical condition | Per cent | 20.4 |  | 20.9 |  | 28.2 |  |
| *Income support payment* |  |  |  |  |  |  |  |
| Disability Support Pension | Per cent | 14.1 |  | 12.9 |  | 19.2 |  |
| Newstart Allowance | Per cent | 9.1 |  | 8.7 |  | 10.7 |  |
| Parenting Payment (Single) | Per cent | 3.8 |  | 6.2 |  | 7.5 |  |
| Parenting Payment (Partnered) | Per cent | 1.0 |  | 0.9 |  | 1.2 |  |
| Youth Allowance (Student) | Per cent | 46.7 |  | 34.4 |  | 22.5 |  |
| Youth Allowance (Jobseeker) | Per cent | 21.2 |  | 30.1 |  | 30.4 |  |
| Carers Payment | Per cent | 2.9 |  | 4.5 |  | 5.5 |  |
| Otherc | Per cent | 1.2 |  | 2.3 |  | 3.0 |  |
| *State* |  |  |  |  |  |  |  |
| NSW | Per cent | 34.2 |  | 39.6 |  | 34.1 |  |
| Vic | Per cent | 32.7 |  | 23.5 |  | 21.9 |  |
| Qld | Per cent | 14.6 |  | 21.9 |  | 17.8 |  |
| SA | Per cent | 8.2 |  | 6.8 |  | 9.2 |  |
| WA | Per cent | 5.8 |  | 5.5 |  | 9.5 |  |
| Tas | Per cent | 2.8 |  | 2.3 |  | 3.1 |  |
| NT | Per cent | 1.3 |  | 0.2 |  | 2.5 |  |
| ACT | Per cent | 0.4 |  | 0.2 |  | 1.9 |  |
| *Region* |  |  |  |  |  |  |  |
| Major city | Per cent | 70.8 |  | 67.7 |  | 71.8 |  |
| Inner regional | Per cent | 17.6 |  | 22.1 |  | 15.0 |  |
| Outer regional | Per cent | 8.8 |  | 9.2 |  | 8.4 |  |
| Remote or very remote | Per cent | 2.8 |  | 1.0 |  | 4.7 |  |
| SA1 IRSD deciled | Decile | 5.4 | 2.7 | 5.2 | 2.6 | 4.0 | 2.4 |
| Number of observations | Number | 49 283 | | 37 047 | | 24 542 | |
| a Housing assistance indicates an individual’s parent’s housing assistance status at 30 June 2012. The use of a lagged housing assistance variable is discussed in section 3. b The average number of children in the care of a parent. c Other payments include a range of less common income support payments, including Bereavement Allowance, Wife’s Pension, Wife’s Disability Support Pension, Austudy, Partner Allowance, Sickness Allowance, Special Benefits, Widow Allowance and Abstudy. d The average decile of the Index of Relative Socioeconomic Disadvantage at the Statistical Area 1 geographic unit level. A lower decile indicates greater disadvantage. | | | | | | | |
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### Housing assistance and employment

Public housing tenants were consistently less likely to be in work than other ISP recipients over the period considered in this study. On average, around one in five ISP recipients reported earning income from employment at 30 June of each year between 2005 and 2013 and are considered as being employed (figure 3). The average figure for those residing in public housing was substantially lower, at approximately 12 per cent.

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| Figure 3 Employment rates, by housing assistance status, 2005 to 2013**a,b**  Per cent |
| |  | | --- | | This figure shows the employment rates of ISP recipients with different housing assistance status between 2005 and 2013. The employment rates of all people  increase slightly between 2005 and 2008, before decreasing. Employment in public housing was around 9.5 per cent in 2013. Among CRA recipients and people not receiving any housing assistance, employment was just under 20 per cent at this time. | |
| a ISP recipients aged 16–65 at 30 June of each year. b The housing assistance variable indicates housing assistance status in the previous year. The use of lagged variables is discussed in section 3. |
| *Source*: Author estimates based on the Research and Evaluation Database. |
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Although rates of employment vary considerably across different types of income support, public housing residents record lower employment rates than CRA recipients and other income support recipients who do not receive housing assistance across all ISP types (figure 4).

The rates of employment of young ISP recipients (aged 16–24) living at home with parents who also receive an ISP, appear to be related to their parents’ housing assistance status. Across all ISP types, between 2005 and 2013 young recipients living with their parents in public housing had lower employment rates than their peers in other tenures (figure 5). Overall, about 15 per cent of young ISP recipients living with parents in public housing were employed, compared to around 21 per cent of children living with parents who receive CRA and 26 per cent of those living with parents who were not receiving housing assistance.

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| Figure 4 Employment of housing assistance recipients by income support payment type, 2005 to 2013**a,b,c**  Per cent |
| |  | | --- | | This figure shows the employment rates among recipients of different income support payments, with recipients classified according to their housing assistance status. Employment among public housing residents is generally lower than those who receive no housing assistance or receive CRA, although employment varies by ISP. Employment is highest among recipients of Parenting Payment (Single), Youth Allowance (Student) and Newstart Allowance. | |
| a ISP recipients aged 16–65 at 30 June of each year. b The housing assistance variable indicates housing assistance status in the previous year. The use of lagged variables is discussed in section 3. c Other payments include a range of less common ISPs, including Bereavement Allowance, Wife’s Pension, Wife’s Disability Support Pension, Austudy, Partner Allowance, Sickness Allowance, Special Benefits, Widow Allowance and Abstudy. |
| *Source*: Author estimates, Research and Evaluation Database. |
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| Figure 5 Employment of young ISP recipients living at home, by parents’ housing assistance status, 2005 to 2013**a,b,c**  Per cent |
| |  | | --- | | This figure shows the rates of employment among recipients of different income support payments that are aged between 16 and 24, by their parent’s housing assistance status. Employment among public housing residents is generally lower than those who receive no housing assistance or receive CRA, although employment varies by ISP. Employment is highest among recipients of Youth Allowance (Student), Youth Allowance (Job seeker) and Newstart Allowance. | |
| a ISP recipients aged 16–24 at 30 June of each year. b Housing assistance indicates an individual’s parent’s housing assistance status in the previous year. The use of a lagged housing assistance variable is discussed in section 3. c Other payments include a range of less common income support payments, including Bereavement Allowance, Wife’s Pension, Wife’s Disability Support Pension, Austudy, Partner Allowance, Sickness Allowance, Special Benefits, Widow Allowance and Abstudy. |
| *Source*: Author estimates, Research and Evaluation Database. |
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## 3 Modelling the relationship between housing assistance and employment

To test whether housing assistance affects employment, other characteristics of housing assistance recipients that are typically associated with employment have to be taken into account. Regression analysis allows the relationship of each factor with employment to be individually quantified.

To evaluate whether the financial incentives created by housing assistance affect employment, the incentives would ideally be taken into account explicitly in the modelling. This could be achieved by incorporating a measure of the financial incentives faced by each individual into a model of employment. This would allow, for example, the effect of public housing on employment through a stability effect to be examined separately from the effect of public housing through the financial effect. However, this was not possible within the timeframe of this project. Instead, as per Whelan (2004), a ‘reduced form’ approach is adopted, where the overall effect of the receipt of housing assistance on employment is estimated by including variables indicating whether someone receives CRA, lives in public housing, or receives no housing assistance.

This section outlines the approach to modelling the relationship between housing assistance and employment. The employment model, and the control variables that are included are discussed first. A simple pooled cross‑sectional model that adjusts for observed differences between ISP recipients is then outlined. The pooled cross‑sectional model permits estimation of the employment rates of people with different housing assistance status that are adjusted for differences in their observed characteristics. This is followed by a discussion of possible endogeneity between employment and housing assistance and how it is dealt with; and the potential for unobserved characteristics to affect results. The fixed effects model used to counter bias associated with unobserved characteristics is then presented.

### A model of employment and housing assistance

As discussed above, people make decisions about whether or not to participate in work by comparing the benefits and costs of working (box 1). The reduced form model does not specifically include these benefits and costs, but examines the relationship between receipt of housing assistance — which is hypothesised to reduce the relative benefits of working — and the likelihood of observing employment. The relationship between employment, housing assistance and a series of control variables can be represented by a ‘latent’ variable approach[[12]](#footnote-13), similar to that presented in Whelan (2004) and Whelan and Ong (2008).

for and [1]

[2]

In this model:

* is a binary variable indicating whether individual *i* is in paid employment at 30 June of year *t.*
* indicates a vector of individual characteristics, and location and neighbourhood variables that might affect an individual’s likelihood of employment. These characteristics act as control variables, isolating the effect of housing assistance on employment.
* is a latent variable used to relate explanatory variables in equation [1] with the binary employment status variable, .
* is a vector of binary variables indicating whether an individual received CRA, was a resident of public housing or received no housing assistance at 30 June of the preceding year.
* is a vector of binary variables indicating the year an observation was recorded, designed to control mainly for the effect of changes to policies and labour market conditions.
* , and are vectors of parameters to be estimated, and is a randomly distributed error term.

In the analysis presented below, this model of employment and housing assistance is implemented as a logistic model, rather than a probit model (as in Whelan 2004 and Whelan and Ong 2008). This is similar to the approach taken by Dockery, Ong and Wood (2008). While there is little practical difference in the two approaches, the logit model is preferred as it allows for the comparison of results with the fixed effects logit model below.[[13]](#footnote-14)

#### Control variables

In the estimations of this model presented below, the control variables — indicated by above — are consistent with those typically included in analyses of labour supply, and in previous analyses of the relationship between housing assistance and employment (including Dockery, Ong and Wood (2008), Whelan and Ong (2008), and Whelan (2004)).

Control variables include a range of factors expected to affect employment (table 1). Age is included as a categorical variable, with categories selected to account for the impact of crucial states of a person’s working life on employment decisions. This treatment of age allows for the inclusion of year variables.

A series of interaction variables are included in the modelling, allowing the effect of housing assistance to vary by state and ISP. The model is estimated both with and without these interaction terms. There are about 70 explanatory variables in the model with interaction terms, and about 40 in the specification without them.

Several variables included in other research are not included in the final specification. Non‑work income was excluded as it directly affects the eligibility for and receipt of housing assistance. Partner income was not included due to difficulties in establishing a reliable indicator in RED.[[14]](#footnote-15) Both of these variables were found to have a small and statistically insignificant effect on employment by Dockery, Ong and Wood (2008).

More importantly, RED does not include sufficient information to account for the effect of differences in the level of education on the employment prospects of ISP recipients. RED includes only limited information about the educational attainments of recipients of Newstart Allowance, Youth Allowance and Austudy payments who have undertaken further education in order to meet the activity requirements associated with receipt of those payments. The absence of this information and the potential for omitted variable bias is discussed below.

### Pooled cross‑sectional estimation

Using the economic model of employment described above, the conditional probability of individual *i* being employed at time *t* can be expressed as:

*, =*  for [3]

where F(.) represents the logistic function that is consistent with the distribution of in equation [1].

To the extent that accurately reflects differences in individuals’ characteristics, location and neighbourhood, the coefficients represent the impact of housing assistance on the likelihood of employment.

The pooled data include multiple observations of the same people across time, meaning that observations in the pooled data are not independent. To account for this, the pooled cross‑sectional model was estimated using robust standard errors.

### Endogeneity of employment and housing assistance

Modelling of the relationship between housing assistance and employment using regression analysis is complicated by the potential endogeneity of housing assistance.[[15]](#footnote-16) Dockery et al. (2008) identify two possible sources of endogeneity that need to be addressed in order to obtain unbiased estimates of the effect of housing assistance on employment, namely:

* reverse causality of housing assistance and employment
* unobserved characteristics of housing assistance recipients.

#### Reverse causality

The research hypothesis stated in section 1 assumes a causal relationship between housing assistance and employment — housing assistance alters an individual’s incentive to work, thereby affecting their employment status. However, the reverse is also possible — an individual who gains employment may earn sufficient income to become ineligible for housing assistance.

The longitudinal nature of RED allows the use of lagged housing assistance to address the problem of reverse causality, as per Dockery et al. (2008). When an individual’s employment income affects the rent that they pay for public housing, the causality is clear: their employment status affects their housing assistance. However, if employment at a given point in time (time *t*) is modelled as a function of an individual’s housing assistance status in the preceding time period (time *t‑1*), then employment in the current time period cannot ‘cause’ housing assistance in the previous period. As with the employment model presented by Dockery et al. (2008), the possibility of reverse causality is addressed by lagging housing assistance status by one year in the models presented in this paper.[[16]](#footnote-17)

#### Unobserved characteristics of housing assistance recipients

Where the receipt of housing assistance and employment are affected in a systematic way by unmeasurable or unobserved factors — such as motivation or education — the estimated effect of housing assistance on employment can be biased.[[17]](#footnote-18) That is, estimates of the effect of housing assistance on employment will reflect both the relationship between housing assistance and employment, and the relationship between unmeasurable or unobserved factors and employment.

For example, the severity of a disability affects employment prospects among people with a disability (Wilkins 2003). At the same time, DSP recipients with a severe disability may be more likely to be allocated public housing and less likely to be employed than those with a moderate disability. However, information about the severity of an individual’s disability is unobserved. This means that any observed association between housing assistance and employment could incorporate both the effect of housing assistance *and* level of disability.

The administrative data used do not include information on some potentially important correlates of employment and housing assistance, such as education and mental health status. As a result, there is potential for the measured effect of housing assistance on employment to be biased.

Two strategies were used to minimise bias associated with unobserved characteristics:

* As many relevant independent variables as possible were included in the model in order to minimise the likelihood of unobserved variable bias.
* The panel nature of the data was exploited through the use of fixed effects models to examine how an individual’s housing assistance affects their employment status after taking into account unobserved characteristics that remain constant across time.

Limiting the sample to ISP recipients — as is necessarily the case when using RED — will limit the variation attributable to unobserved factors to some extent, given that receipt of an ISP (or Family Tax Benefit Part A) is a prerequisite for the receipt of CRA(Whelan and Ong 2008; Whelan 2004). However, even within this subpopulation, there is likely to be a selection effect, where unobserved factors affect both an individual’s selection into housing assistance and their employment.

### Fixed effects models

Panel regression techniques can be used to account for individual differences that do not change over time, irrespective of whether those differences are observed or not. In a fixed effects model, assuming that those differences are constant over time, and observing an individual over time, any variation in employment is attributed to the observed characteristics that do vary over time.

In the panel framework, an individual’s probability of employment at time *t* may be thought of as a function of their observed demographic characteristics (for example, age, marital status, number of children), their housing assistance status and their unobserved individual‑specific characteristics (for example, motivation or risk of poor mental health), which are assumed to remain constant over time. In essence, the panel model is an extension of the cross‑sectional model presented above, with the addition of an individual‑specific term that is constant over time (:

[4]

for and .

The choice of panel model is dependent on the nature of the individual‑specific term. If the expected value of the individual‑specific term is equal to zero and randomly distributed given the individuals’ characteristics, then a random effects model can be used.[[18]](#footnote-19) If this condition does not hold then a fixed effects model is appropriate. A fixed effects model can therefore be thought of as more flexible than a random effects model, as it places no restrictions on the distribution of the individual‑specific term. A fixed effects panel model is used in this instance.[[19]](#footnote-20)

The fixed effects model is estimated using the Chamberlain estimator, a method that allows for the consistent estimation of parameters , , and in a way that does not depend upon the individual‑specific term, (Chamberlain 1980). Producing estimates of , , and that are independent of the individual‑specific term relies on characteristics of the logit functional form to remove from the estimation equation (Wooldridge 2002). In practical terms, this means that the parameters can be estimated without knowing or estimating .

There are two limitations to the fixed effects model.

First, where there is little or no variation in a control variable over time, it is not possible to estimate the effect of that variable on employment. For example, it is not possible to quantify the effect that gender has on employment status using a fixed effects model. Any effect of gender is controlled for by the inclusion of the time‑invariant fixed effect.

Second, as the individual‑specific fixed effect is never estimated, it is necessary to adopt a value for the underlying ‘baseline’ employment rate in order to calculate the estimated impact of changes to key variables on employment rates. Specifically, in the results from the fixed effects estimation presented below:

* the expected rate of employment of people receiving a particular type of housing assistance in a given state is estimated by multiplying the odds of employment in New South Wales (which is treated as the default state in the logistic regressions) by the estimated odds ratio associated with the type of housing assistance received and the given state of residence
* the expected rate of employment of people receiving a particular ISP and living in a particular state is estimated by multiplying the odds of employment among Carers Payment recipients by the estimated odds ratio associated with the type of housing assistance and ISP received.

Despite these limitations, the ability to account for time‑invariant unobserved characteristics makes the fixed effects model preferable to the pooled cross‑section approach. This is primarily because of the absence of information about individual factors that may substantially affect employment in the estimation dataset, and the potential that this biases coefficients in the pooled cross‑section model. If unobserved characteristics did not affect employment, there would be no substantial difference between the results from the fixed effects and pooled cross‑sectional models.

## 4 Results

This section presents results from both the pooled cross‑sectional and the fixed effects models.

The pooled cross‑sectional model takes into account a range of observed characteristics; this model is used to test the extent to which observed characteristics can account for the differences in employment rates between public housing tenants, CRA recipients and other ISP recipients that were observed in section 2. Given the different characteristics of recipients of different ISPs, results are presented separately for different ISP types. Similarly, as rules regarding eligibility, lease terms and rent‑setting in public housing vary between the states and have the potential to lead to different employment outcomes, results are also presented for each state.[[20]](#footnote-21) Estimates of the effects of housing assistance on the employment of young ISP recipients who live with their parents are also included, with effects presented for different ISPs separately.

The fixed effects model accounts for observed and unobserved characteristics that do not vary over time as well as the observed differences that do vary. This model is used to test whether the differences in employment rates that were observed in section 2 can be better explained by also accounting for the time‑invariant characteristics of ISP recipients. As with the pooled cross‑sectional model, results are presented separately for each ISP type and state.

The effect of parental receipt of housing assistance on the employment of children who live at home is not tested using the fixed effects model. This is because it is considered inappropriate to assume that education (an important unobserved variable) remains fixed over time within this cohort.[[21]](#footnote-22) Finally, the relationship between stability of residence and employment is considered in the context of the preferred, fixed effects model. The potential for neighbourhood disadvantage to affect employment is also briefly examined.

### Accounting for observed characteristics: pooled cross‑sectional estimates of the relationship between housing assistance and employment

After taking into account the observed characteristics of ISP recipients, this model indicates that public housing tenants are still less likely than other ISP recipients to be employed (annex A, table 1). That is, based on the results in this section, one might conclude that public housing residents are less likely to be employed *as a result of* receiving housing assistance. However, as shown by the fixed effects results below, this conclusion is likely to be incorrect.

Overall, on the basis of the observed characteristics, residents of public housing have a predicted probability of employment net of other factors that is:

* around 6.2 percentage points lower than that of a CRA recipient
* around 6.4 percentage points lower than that of a comparable recipient of income support who receives no housing assistance.

#### Income support payment type and state of residence

As noted above, the inclusion of interaction terms in the pooled cross‑sectional employment model allows housing assistance status to have different effects for people living in different states or receiving different income support types.[[22]](#footnote-23) The predicted probability of employment for public housing residents across both ISP types and states is consistently lower than it is for other ISP recipients.

Across ISPs, the predicted employment probabilities vary considerably by housing assistance status (figure 6). For example:

* the predicted employment probability for DSP and Newstart Allowance recipients residing in public housing is around 3.5 percentage points less than the predicted probability for those who do not receive any housing assistance.
* the gap for recipients of Parenting Payment (Single) is about 15 percentage points
* the gap for Youth Allowance recipients is about 11 percentage points.

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| Figure 6 Predicted probability of employment, by housing assistance type and income support payment type**a,b**  Average predicted probability of employment |
| This figure shows predicted probabilities of employment derived from the cross-sectional logit employment model. Predicted probabilities for people receiving different income support payments and with different housing assistance statuses are shown. Residents of public housing have consistently lower predicted employment probability than ISP recipients who do not receive housing assistance or who receive CRA. |
| a ISP recipients aged 16–65, between 2005 and 2013. Estimates are calculated using a pooled cross‑sectional logit model that includes interactions between housing assistance and ISP type. Odds ratios for all covariates are presented in annex A. b Other payments include a range of less common ISPs, including Bereavement Allowance, Wife’s Pension, Wife’s Disability Support Pension, Austudy, Partner Allowance, Sickness Allowance, Special Benefits, Widow Allowance and Abstudy. |
| *Source*: Author estimates, Research and Evaluation Database. |
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|  |

Across most states, the gap in the predicted probability of employment between CRA recipients and public housing residents is between 5.5 and 7 percentage points (figure 7). The exception is the ACT, where CRA recipients can be expected to have an employment rate that is 9.2 percentage points higher than ISP recipients living in public housing.

The predicted probabilities of employment for CRA recipients are similar to those of people who do not receive housing assistance in each of the states and territories, with the exception of the Northern Territory. While the predicted probability of employment of CRA recipients in the Northern Territory is comparable to that in other states (about 18 per cent), the predicted probability of employment for those who do not receive housing assistance is lower than in other states and is almost the same as it is for those living in public housing (12.3 and 12.1 per cent, respectively). The relatively low employment rates among people receiving no housing assistance in the Northern Territory can be explained by the high concentration of Indigenous people and the high proportion of people living in remote areas in the Northern Territory. Indigenous status and remoteness both have large, negative marginal effects on employment (around 5.7 and 3.2 percentage points, respectively).

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| Figure 7 Predicted probability of employment, by housing assistance type and state/territory**a**  Average predicted probability of employment |
| This figure shows predicted probabilities of employment derived from the cross-sectional logit employment model for people in each state and territory with people classified according to their housing assistance..  Residents of public housing have consistently lower predicted employment probability than ISP recipients who do not receive housing assistance or who receive CRA. |
| a ISP recipients aged 16–65, between 2005 and 2013. Estimates are calculated using a pooled cross‑sectional logit model that includes interactions between housing assistance and ISP type. Odds ratios for all covariates are presented in annex A. |
| *Source*: Author estimates, Research and Evaluation Database. |
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#### Young people living with parents or guardians

As with the broader population of ISP recipients, after taking into account the characteristics of young people living with parents who receive an ISP, the model still indicates that young ISP recipients who reside with their parents in public housing are less likely to be employed than other ISP recipients.

However, differences in the probability of employment are reduced once observed factors are taken into account, although there remains considerable variation between different ISP types (figure 8). Young people with parents in public housing have a predicted probability of employment, net of other factors, that is:

* around 2.4 percentage points lower than that of comparable children whose parents receive CRA
* around 6.1 percentage points lower than that of comparable children whose parents do not receive any housing assistance.

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| Figure 8 Predicted probability of employment of younger household members, by parental housing assistance status**a,b**  Average predicted probability of employment |
| This figure shows predicted probabilities of employment derived from the cross-sectional logit employment model for ISP recipients aged between 16 and 24, by the type of ISP they receive and their parent’s housing assistance status. Employment rates among public housing residents are lower than employment rates among other ISP recipients who receive Newstart, Parenting Payment (Single), and either Youth Allowance. However, for younger household members who received either Disability Support Pension, Parenting Payment (Partnered) or Carer Payment, housing assistance status appears to make little difference. |
| a ISP recipients aged 16–24, between 2005 and 2013. Estimates are calculated using a pooled cross‑sectional logit model that includes interactions between housing assistance and ISP type, and housing assistance and state. b Other payments include a range of less common ISPs, including Bereavement Allowance, Wife’s Pension, Wife’s Disability Support Pension, Austudy, Partner Allowance, Sickness Allowance, Special Benefits, Widow Allowance and Abstudy. |
| *Source*: Author estimates, Research and Evaluation Database. |
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### Accounting for observed and unobserved characteristics: fixed effects estimates of the relationship between housing assistance and employment

The pooled cross‑sectional model shows that residents of public housing have lower predicted probabilities of employment than other ISP recipients, after taking into account observed differences. CRA recipients have slightly lower predicted probabilities of employment than ISP recipients who do not receive housing assistance. However, as discussed above, CRA recipients and residents of public housing may have unobserved characteristics that relate both to the receipt of housing assistance and to the probability of finding employment. If those relationships do exist and the unobserved characteristics are not taken into account, estimates of the effect of housing assistance on employment might be biased.

This section presents results of fixed effects models of the relationship between housing assistance and employment that take into account the time‑invariant unobserved characteristics of individuals. The fixed effects estimates in annex A are presented as odds ratios, which represent the strength of an association between employment and the characteristics that determine employment (box 3). As mentioned above, the odds ratios are used to generate expected differences in employment rates for recipients of different types of housing assistance.

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| Box 3 Interpreting odds ratios |
| The crude ‘odds’ of an outcome is the number of times an event is expected to occur, relative to the number of times that event is expected *not* to occur. For example, when rolling a six‑sided die, there is a 16.6 per cent chance of rolling a three — a person trying to roll a three can expect to be successful in one of their first six attempts, and unsuccessful in the other five rolls. This means that the odds of rolling a three are 1/5, or 20 per cent.  A change in odds represents a change in the probability of the event occurring. An increase in the odds of an event means that the event is more likely to happen. An increase in the odds of someone finding employment from 0.25 to 0.5 means that their likelihood of finding employment has doubled.  Outputs from logit regressions are often presented as ‘odds ratios’ — a measure of association between an outcome (such as employment) and a characteristic expected to affect that outcome (such as housing assistance).  An odds ratio greater than one indicates that a person with the associated characteristic is more likely to be employed than a person without the characteristic. The converse applies for an odds ratio less than one. The greater the difference between the odds ratio and one, the larger the relative impact of a characteristic on the likelihood of employment. For example, the pooled cross‑sectional estimate of the odds ratio for those living in public housing is reported as 0.617 (table 5). This means that the expected odds of employment — adjusted for all other control variables — among public housing residents are around 0.617 times that of the expected odds of employment among ISP recipients who do not receive housing assistance. |
|  |
|  |

After both observed and unobserved factors are taken into account, the odds ratios associated with the housing assistance variables are found to be close to one (table 5). That is, according to these results, housing assistance has little effect on the probability of employment. Odds ratios for all covariates in the pooled cross‑sectional and fixed effects models are presented in annex A, table 1.

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| --- |
| Table 5 Association between housing assistance and employment  Crude, pooled cross‑sectional and fixed effects odds ratios |
| |  |  |  |  | | --- | --- | --- | --- | | Housing assistance | Crude  odds ratioa,b | Pooled cross‑sectional  odds ratiob | Fixed effects  odds ratio | | Commonwealth Rent Assistance | 1.167 | 0.980 | 1.080 | | Public housing | 0.547 | 0.617 | 1.015c | |
| a The crude odds ratio represents the odds of employment among recipients of housing assistance, relative to the odds of employment among ISP recipients who receive no housing assistance. b Both the crude and cross‑sectional odds ratios are calculated on a pooled sample of observations from 2005 to 2013. The fixed effects odds ratios are the result of the panel model estimated over the period 2005 to 2013. c With the exception of the fixed effects odds ratio for public housing, all results are significantly different from one at the one per cent level. |
| *Source*: Author estimates using Research and Evaluation Database. |
|  |
|  |

Further, the difference in the odds of employment among ISP recipients living in public housing and those receiving no housing assistance is not statistically significant at the one per cent level. This is despite the very large dataset used, which leads to many other parameter estimates to be significantly different from one at the one per cent level. The odds of employment among recipients of CRA are slightly higher than the odds for those receiving no housing assistance. While the difference is statistically significant, the effect is small and is, therefore, of limited relevance from a policy perspective.

These results are consistent with the observation that the allocation of public housing is targeted at persons in greatest need and that some of the characteristics associated with that level of need are likely to be associated with lower employment rates. In other words, the relatively low probability of employment among ISP recipients living in public housing is related to their individual characteristics rather than their receipt of housing assistance.

#### Income support payment type and state of residence

While the effect of housing assistance on employment is small in aggregate, it could have a larger effect on some groups. This section considers the possible effect for recipients of different ISPs and across states. As described above, odds ratios are combined with a ‘baseline’ probability of employment to produce estimates of an effect of housing assistance on employment. This is presented as a percentage point difference relative to the baseline. The odds ratios are presented in annex A, and the baseline probability is the probability of employment for a person in the relevant default category, as described in the notes for figures 9 and 10.

The expected effect of housing assistance on employment is relatively small for most ISP types and states (figure 9).

* Public housing has a small positive effect on employment amongst recipients of Newstart Allowance and Parenting Payment (Partnered) of about 2 and 4 percentage points, respectively. There is little difference in the expected employment probabilities, relative to those not in public housing, for other ISP recipients.
* Public housing is associated with a decrease in employment probability of around 0.8 percentage points in New South Wales and an increase of around 2 percentage points in the ACT. The effect of public housing on employment in all other states lies between ‑0.3 and 0.9 percentage points.

The differences in expected employment effects between public housing and receipt of CRA are also small. A move from public housing to CRA would be expected to increase the probability of employment by less than one percentage point, although the effect varies slightly across ISPs. A move from public housing to CRA could be expected to increase employment by about 1.8 percentage points for recipients of DSP, and by 1.7 percentage points for recipients of Parenting Payment (Single) payments. The expected effects for all other ISPs are less than 1.2 percentage points (figure 10).

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| Figure 9 Expected effect of housing assistance on employment by ISP type and state, 2005–2013**a,b**  Percentage point difference relative to no housing assistance |
| |  | | --- | | **Income support payment type** | | This figure shows the expected effect of housing assistance on employment — in terms of percentage points — for recipients of different ISP types and residents of different states. These expected effects are derived from the fixed effects logit model, and take into account both observed and unobserved characteristics of ISP recipients. Unlike previous figures, the expected effect is relatively small for all housing assistance types across ISP types and states. | | **State** | | This is the second panel for figure 9, and is discussed above. | |
| a The employment effect of housing assistance is calculated using odds ratios from a fixed effects logit model that includes interaction terms between housing assistance type and ISP, and takes into account unobserved characteristics of ISP recipients. As the odds ratio is a relative measure, the expected effects are calculated on the basis that 12.2 per cent of Carers Payment recipients who do not receive any housing assistance and that 18.3 per cent of ISP recipients in NSW who do not receive any housing assistance are employed. b Other payments include a range of less common ISPs, including Bereavement Allowance, Wife’s Pension, Wife’s Disability Support Pension, Austudy, Partner Allowance, Sickness Allowance, Special Benefits, Widow Allowance and Abstudy. |
| *Source*: Author estimates, Research and Evaluation Database. |
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| Figure 10 Expected employment effect of receipt of CRA, relative to public housing by ISP type, 2005–2013**a,b**  Percentage point difference |
| |  | | --- | | This figure shows the expected effect on employment — in percentage points — of receiving CRA, relative to the expected effect of public housing residency. These expected effects are derived from the fixed effects logit model, and take into account both observed and unobserved characteristics of ISP recipients. The figure shows that the expected effect is relatively small, irrespective of what ISP an individual receives. | |
| a The employment effect of housing assistance is calculated using odds ratios from a fixed effects logit model that includes interaction terms between housing assistance type and ISP, and takes into account unobserved characteristics of ISP recipients. As the odds ratio effect is a relative measure, the expected effect is calculated on the basis that 12.2 per cent of Carers Payment recipients who do not receive any housing assistance are employed. b Other payments include a range of less common ISPs, including Bereavement Allowance, Wife’s Pension, Wife’s Disability Support Pension, Austudy, Partner Allowance, Sickness Allowance, Special Benefits, Widow Allowance and Abstudy. |
| *Source*: Author estimates, Research and Evaluation Database. |
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#### Stability of residence

The stability afforded by secure, ongoing public tenancies may provide public housing residents with better opportunities to find and maintain employment than would otherwise be the case. In the results presented in this paper, stability of residence is indicated by the number of times an individual has moved postcode in the preceding 12 months.

The fixed effects estimates provided evidence that stability is positively related to employment. Even a single move seems to be associated with sufficient disruption to reduce the probability of employment (figure 11). Beyond that, people who had relocated twice in the previous year were 4.6 percentage points less likely to be employed than ISP recipients who had not moved in that time, and those who had moved three or more times were 6.4 percentage points less likely to be employed.

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| Figure 11 Expected employment effects of moving house  Percentage point difference |
| |  | | --- | | This figure shows the expected effect on employment — in percentage points — of moving house. It shows that moving house once in the previous 12 months reduces expected employment probability by around 3 percentage points, moving twice is associated with a 4.6 percentage point reduction, and moving three or more times is associated with a 6.4 percentage point reduction. These expected effects are derived from the fixed effects logit model, and take into account both observed and unobserved characteristics of ISP recipients. | |
| a The employment effect of housing assistance is calculated using odds ratios from a fixed effects logit model that includes interaction terms between housing assistance type and state, and takes into account unobserved characteristics of ISP recipients. As the odds ratio is a relative measure, the expected effect is based on the fact that 20.8 per cent of ISP recipients who did not move in the preceding year were employed. |
| *Source*: Author estimates, Research and Evaluation Database. |
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#### Neighbourhood disadvantage and employment

The fixed effect model is used to obtain some information about the likely effects of neighbourhood disadvantage on employment.[[23]](#footnote-24)

It makes intuitive sense that neighbourhood disadvantage can be associated with poor education, employment and health outcomes. Growing up and living in a poor neighbourhood may limit an individual’s opportunities to access quality services, expose them to negative socialisation and criminal behaviours, and lead to a disconnection from mainstream society and job finding networks (Manley and van Ham 2012).

However, it is difficult to demonstrate a causal link between neighbourhood disadvantage and poor employment and educational outcomes:

There is no doubt that neighbourhood poverty and individual disadvantage are strongly correlated, but it is much less certain that there is a causal relationship between the two. (Manley and van Ham 2012, p. 148)

In particular, demonstrating a causal link between neighbourhood disadvantage and individual employment status is hampered by the problem of selection bias — the neighbourhood in which an individual lives is unlikely to be independent from their employment prospects. That is, people with a lower probability of employment may be more likely to live in neighbourhoods with lower housing costs and greater disadvantage. The relationship between neighbourhood disadvantage and employment may, therefore, not be causal, but simply reflect people’s limited choices when choosing a neighbourhood in which to live.

That said, the process by which people end up living in different neighbourhoods allows insight into the possible effects of neighbourhood disadvantage on employment (Hedman and van Ham 2012). Private renters who receive CRA have some ability to choose the neighbourhood in which they live — subject to budgetary constraints and the availability of affordable housing. In contrast, public housing residents have little, if any, choice over where they live — they are *assigned* housing by the respective State Housing Authorities.

The limited ability of public housing residents to choose their neighbourhood minimises the problem of selection bias in estimating neighbourhood effects among that sub‑population (Manley and van Ham 2012).

In order to gauge the relationship between neighbourhood disadvantage and employment, the employment model was run for public housing residents only. The results provide some indication that living in a highly disadvantaged area is associated with lower levels of employment, but this effect is less important than other variables in explaining differences in employment probabilities. The ratio of odds of employment among public housing residents living in areas in the bottom two quintiles of the Index of Relative Socioeconomic Disadvantage to the odds of employment of those living in the top three quintiles, was 0.93.[[24]](#footnote-25) As the employment rate of public housing residents is about 12.2 per cent over the panel as a whole, this is equivalent to about 0.7 percentage points.

## 5 Conclusions

This background paper examined whether housing assistance reduces the employment of housing assistance recipients. The hypothesis was tested using a longitudinal dataset drawn from the Research and Evaluation Database (RED) — a comprehensive administrative database covering Australian income support recipients, many of whom either live in public housing or receive Commonwealth Rent Assistance (CRA). Access to RED provided a valuable opportunity to advance the available knowledge about the employment effects of housing assistance. Previous research had largely relied on survey data that included small numbers of public housing residents and imprecise identification of CRA recipients.

Consistent with previous research (Groenhart and Burke 2014; Wood, Ong and Dockery 2009), residents of public housing in RED have markedly lower employment rates than other ISP recipients, even after observed differences are taken into account. That said, there is little difference between the employment rates of CRA recipients and ISP recipients who do not receive any housing assistance.

However, the lower rates of employment among public housing residents cannot be attributed to the receipt of housing assistance. Public housing residents are more likely to have a number of observed characteristics that are typically associated with lower levels of employment. For example, ISP recipients who live in public housing are more likely to receive the DSP, suffer a medical condition that impairs their ability to work, live in a disadvantaged area and are more likely to be Indigenous, than other ISP recipients.

Other characteristics that are not directly observed in the data are also likely to affect employment. These may be unobserved because they could not be measured with sufficient accuracy for empirical analysis, or because they were not required for the purposes of administering income support and so were not recorded. For example, characteristics like risk of poor mental health, motivation and education are not captured in the administrative data used in this study. A fixed effects logit model was used to isolate the effects of housing assistance on employment from the effects of time‑invariant unobserved factors.

When both observed and unobserved characteristics are taken into account, differences in expected rates of employment between public housing tenants and other ISP recipients are shown to be very small. Similarly, there is little difference in the employment rates of ISP recipients who receive CRA and those who do not. In other words, it is the characteristics of the individual ISP recipients rather than their housing assistance status that explain the differences in employment rates between public housing tenants, CRA recipients and other ISP recipients.

Three other issues were briefly considered in this background paper. First, the effect of parental receipt of housing assistance on the employment of young ISP recipients living with parents or guardians was examined. While differences in observed characteristics explain some of the difference in the employment rates of youths, the predicted probability of employment among young people whose parents live in public housing is still substantially lower than for those with parents not receiving any housing assistance. It was not appropriate to apply the fixed effects model to this cohort, given the assumption about unobserved characteristics (that includes education) remaining fixed over time. As a result, it is not possible to conclude whether the difference in predicted employment rates is attributable to housing assistance or unobserved individual characteristics.

Second, moving between different postcodes was found to reduce the probability of employment. This suggests that housing stability may provide ISP recipients with opportunities to find and maintain employment.

Third, the effect of neighbourhood disadvantage on employment among public housing residents was also considered. The fixed effects employment model was re‑estimated using only public housing residents so as to minimise problems of selection bias. Living in a highly disadvantaged area is associated with lower levels of employment, even after accounting for observed and unobserved characteristics, but this effect appears relatively small when compared with other determinants of employment. Further work in this area could explore the question of neighbourhood effects by make greater use of the rich administrative data included in the RED. In particular, the data provide an opportunity to examine the effects of location on employment status using spatial regression and analysis techniques, which could not be applied in the timeframe of this project.

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1. States and territories are referred to throughout the paper as states. [↑](#footnote-ref-2)
2. The administrative data used in modelling the relationship between housing assistance and employment do not identify community housing residents, who are likely to receive CRA. Because community housing is a relatively uncommon form of tenure, results for CRA recipients are interpreted as if all recipients are renting privately. [↑](#footnote-ref-3)
3. This background paper (BP) is one of six produced as part of a research project examining the links between housing assistance and employment. [↑](#footnote-ref-4)
4. Employment of housing assistance recipients is affected by their willingness and ability to work and employer demand for their labour. Where employers use housing assistance status to ‘screen’ possible employees, housing assistance could affect labour demand. However, as employer attitudes towards housing assistance recipients have not been previously identified in quantitative research as an impediment to the employment of housing assistance recipients, this analysis focuses on how housing assistance might affect labour supply. [↑](#footnote-ref-5)
5. The DSP withdrawal rate and threshold were current as of 19 March 2015 (DHS 2015). [↑](#footnote-ref-6)
6. Private renters who receive Family Tax Benefit part A (with or without receiving an ISP) receive CRA as part of that payment (provided they are paying rent above a minimum threshold). In their case, CRA is withdrawn alongside other elements of the Family Tax Benefit. [↑](#footnote-ref-7)
7. Assessable income includes gross market income (except in Tasmania, where the calculation is based on net market income) and most major transfer payments (the pension supplement, for example, is not included). As market income increases, withdrawal of transfer payments means that assessable income increases by less than a dollar when market income increases by a dollar. Public housing rent increases by 25 per cent of assessable income, or a smaller percentage of the additional dollar of market income. Over the market income range that transfer payments are withdrawn, the effective marginal tax rates associated with public housing rents are less than 25 per cent (BP 2). [↑](#footnote-ref-8)
8. While HILDA is a longitudinal survey, the studies mentioned use cross-sectional models. For example, Dockery et al. (2008) estimate an employment model using a pooled cross-section of the first three waves of HILDA. [↑](#footnote-ref-9)
9. Employment status is inferred from earnings information in RED. [↑](#footnote-ref-10)
10. The term ‘parents’ is used to refer to both parents and guardians. [↑](#footnote-ref-11)
11. There are around 54 000 SA1s across Australia, with each area including an average of around 400 people (ABS 2010). [↑](#footnote-ref-12)
12. The latent variable approach is a way of relating independent variables to a binary dependent variable. The latent variable can be thought of as a continuous variable indicating a person’s underlying propensity for employment, as inferred from equation [1]. Where this propensity for employment is positive () an individual is predicted to be employed (Likewise, where an individual’s propensity for employment is equal to or less than zero (), they are not predicted to be in employment ( See Wooldridge (2002) for a technical explanation of latent variable models. [↑](#footnote-ref-13)
13. The choice of logit or probit model makes little difference to the results reported here. When calculated with a probit model (using pooled cross-sectional data), the marginal effect of public housing on employment is 6.0 per cent. In comparison the same marginal effect using a logit model is 6.3 per cent. [↑](#footnote-ref-14)
14. An indicator of whether a partner also received an ISP was examined, but was found to be highly collinear with marital status. [↑](#footnote-ref-15)
15. Endogeneity refers to correlation between a dependent variable and the error term, that results in a biased coefficient. It is necessary to account for possible endogeneity to ensure that the coefficient associated with a particular variable is unbiased. [↑](#footnote-ref-16)
16. Shorter lag periods were examined using monthly panels of data, but involved insufficient variation to obtain meaningful results. [↑](#footnote-ref-17)
17. Unobserved factors are all factors that are not included in the available dataset. In comparison, unobservable factors are all factors that are unmeasurable and can therefore never be observed. Omission of unobserved (and unobservable) factors will bias the coefficients on the observed factors where they are correlated with the observed factors. If uncorrelated, then the absence of factors that do matter for the outcomes from the model increases the standard error. [↑](#footnote-ref-18)
18. In other words, random effects models assume that each person’s individual-specific and time-invariant value for — that represents their unobserved characteristics — is randomly distributed around zero, meaning that the value for is zero for the average person. [↑](#footnote-ref-19)
19. Both random and fixed effects models were considered. As per Greene (2008), a Hausman test showed that the data are not consistent with the random effects assumption. A linear model did not fit the data well; nonparametric classification models were not considered within this project because of time constraints. [↑](#footnote-ref-20)
20. For example, New South Wales has offered fixed term leases to new tenants since 2006, whereas public housing residents in Victoria have ongoing tenure. Differences in public housing arrangements across states are discussed in section 4 of BP 1. [↑](#footnote-ref-21)
21. While it may be reasonable to assume that the education levels of adult ISP recipients remain unchanged over time, this assumption is unlikely to be realistic for many young people. [↑](#footnote-ref-22)
22. This is achieved by interacting housing assistance with both the state/territory variables and the ISP variables. Odds ratios for the interaction terms are presented in annex A. [↑](#footnote-ref-23)
23. Neighbourhood disadvantage was controlled for in the pooled cross-sectional models, but the effect was not analysed in view of the unobserved variable bias problem in those models. [↑](#footnote-ref-24)
24. Results for the fixed effects logit model that was applied only to residents of public housing are included in annex A. In contrast to the other model specifications shown in this paper, a categorical variable describing neighbourhood disadvantage was used in this specification. This was to allow for the possibility that disadvantage may only have an employment effect beyond a particular threshold. [↑](#footnote-ref-25)