Bridges, traps & half-way houses:
Casualisation and labour market transitions in Australia

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Ian Watson

Freelance Researcher &
Visiting Senior Research Fellow
Macquarie University & SPRC UNSW

mail@ianwatson.com.au
www.ianwatson.com.au

Abstract

In this paper [1] I re-examine the familiar debate on whether casual jobs represent a 'bridge' into permanent employment, or a 'trap' which keeps workers locked into ongoing casualised work or joblessness. My analysis looks at the labour market destinations of casual workers over time, making use of the HILDA data for the period 2001 to 2009. I focus on four populations—male and female casuals and male and female fixed-term employees—and examine the range of individual, locality and job characteristics which are most strongly associated with various labour market destinations. These destinations are: gaining permanency, remaining casual or fixed-term, becoming self-employed or becoming jobless. Using random intercepts multinomial logit panel models I estimate various conditional predicted probabilities for a range of different labour market destinations.

The findings show that as far as individual characteristics are concerned, age and years in paid employment matter a great deal, while education matters much less. Increasing age leads to worse outcomes, more years in paid employment lead to better outcomes, and increased levels of educational qualification have only a modest link to better outcomes. In regard to locality, the more disadvantaged the area, the more likely that casual jobs will persist, transitions to permanent jobs will diminish and transitions to joblessness increase. In regard to the jobs themselves, casualisation persists in those industries where casual density is high, where organisations are small, where the work is part-time, and where skills development is limited. These findings suggest that systemic influences count for a great deal, while human capital elements count for much less.

The results from this analysis are used to reconceptualise casual employment in the context of the periodisation of neo-liberalism and the operations of the reserve army of labour. I conclude that casual employment is a 'half-way house' between being employed and being in the reserve army of labour. As such it is a situation which facilitates the engagement and disengagement of labour from production and thereby exerts downward pressure on wages.

1 Introduction

The vast majority of new jobs created during the 1990s were casual jobs (Borland et al. 2001) and the pattern for the 2000s seems likely to continue this trend. Researchers have been divided over whether this is a good or a bad thing. Some argue that it shows the Australian labour market has become more 'flexible', something they regard as desirable (Wooden 2001; Wooden and Warren 2004). Others argue that it represents a growing polarisation in the labour market between good 'jobs'—those with permanency—and 'bad' jobs. From this perspective, casual jobs are seen as poor quality jobs, insecure, poorly paid and with little long term prospects for career advancement (Watson et al. 2003; Burgess and Campbell 1998*b*; Burgess and Campbell 1998*a*). As Chalmers and Waddoups (2007, p. 2) observe, the growth of casual employment raises the prospect of creating a large pool of 'second-class industrial citizens'.

[1] I would like to thank Hielke Buddelmeyer for generously making available the computer code and the unpublished results from his modelling of employment transitions.
This conference paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (MIAESR). The findings and views reported in this paper, however, are those of the author and should not be attributed to either FaHCSIA or the MIAESR.

Within this debate an interesting set of metaphors have arisen. While the defenders of labour market casualisation sometimes concede that the jobs are of poor quality, they suggest that they play an important bridging role, providing stepping stones for the unemployed to re-enter the labour market. On the other hand, the critics of casualisation suggest that such bridges are illusory and that most casuals stayed trapped in a cycle of job churning. Burgess and Campbell (1998*a*, p. 32) pose the problem well. Do casual employment arrangements

> constitute a bridge from which temporary workers can proceed to more secure and longer term employment arrangements. Or ... a trap, into which incumbents are forced to accept many insecure and low paying jobs ... which are perhaps interspersed with spells in unemployment or outside of the labour market.

This issue has been pursued in the international literature as well, although it is important to note that Australia's system of casual employment is quite unique and overseas experiences with 'contingent' employment and 'temporary' employment do not map precisely onto the Australian system (Burgess and Campbell 1998*b*; Campbell and Burgess 2001). The overseas findings appear to be ambiguous. Early studies for the Nordic countries suggested that temporary employment had 'elements of both traps and bridges' (Nätti 1993, p. 459). More recent research by Gash (2008) used survival analysis to analyse the labour market transitions of temporary workers in four European countries (Denmark, France, West Germany and the United Kingdom). She found her results were sensitive to the definition of a trap. If it included all other 'non-integrative exits' (ie. further temporary work or labour market inactivity), then only West Germany emerged in a positive light. If the definition was relaxed to focus on obtaining a permanent job, then both West Germany and the United Kingdom provided 'bridges' (Gash 2008, p. 663). Overall, the conclusions she drew were positive, but far from conclusive:

> the majority of temporary workers do, eventually, get permanent jobs [but those with temporary jobs may] ... experience negative consequences in the longer term. The current analysis did not reveal the relative quality of the jobs they entered, nor did it identify the stability of these new-found permanent jobs (Gash 2008, p. 264).

Using a slightly different metaphor, Booth et al. (2002) explored whether temporary jobs were 'stepping stones' or 'dead ends'. Using British panel data for the 1990s they looked at both temporary seasonal jobs as well as fixed-term contract jobs and examined their characteristics and long-term wage outcomes. While they found evidence of the stepping stone phenomenon, the 'wage growth penalty' for having worked in seasonal/casual jobs was substantial. Compared to seasonal/casual work, fixed-term employment had less severe consequences among men. In the case of women, there was no long-term wages penalty (Booth et al. 2002, p. F212). Their overall conclusion was that fixed-term jobs (and to a lesser extent, seasonal-casual jobs) did act as stepping stones to permanent work, but this came at a considerable cost for some workers.

The Booth et al. (2002) study is useful for the current analysis because of its distinction between casual and fixed-term employment. While the former is not exactly the same as in Australia (their definition is tied to the seasonal dimension), it is crucial to appreciate that Australia has two types of casual work, something obscured by the conventional Australian Bureau of Statistics definition which emphasises an absence of leave entitlements. As this paper will show, casual workers in Australia, and their fixed-term counterparts, share much in common, but they are also quite distinctive populations and these differences must be recognised. Fortunately, the HILDA data allows for this recognition.

The literature in Australia is also somewhat ambiguous in its findings. The early study by Burgess and Campbell (1998*a*) concluded that for job seekers casual jobs did not serve as a bridge. Looking at the mid 1990s SEUP data,[2] Burgess and Campbell (1998*a*) found that casual jobs did not lead to permanent jobs and they argued that 'casual employment is just another form of exclusion and precariousness that encompasses unemployment and income deprivation' (Burgess and Campbell 1998*a*, p. 48).

With access to more recent data—in the form of the HILDA survey—a number of researchers have returned to the question. Chalmers and Waddoups (2007) used four waves of HILDA data to apply survival analysis to casual employment. They found that people's duration in casual jobs was associated with factors such as job tenure and part-time employment. Their overall judgement on the bridge / trap question was, however, inconclusive.

Also using the HILDA data, and also using survival analysis, Mitchell and Welters concluded in a more negative vein. They showed that structural factors, such as industry location, firm size and locality played an important role in whether workers found themselves trapped in casual jobs (Mitchell and Welters 2008). In a later study, which examined duration dependence in casual jobs, the authors concluded that 'casual employment does lock in workers, which is in line with findings from studies who cannot find conclusive evidence that casual employment functions as a stepping stone towards non-casual employment' (Welters and Mitchell 2009, p. 11).

A different econometric approach, which modelled employment transitions between different labour market states, was undertaken by Buddelmeyer and Wooden (2011), also using the HILDA data. They found more positive results for casual jobs, although this depended on gender. They concluded, in the case of men, that workers were 'better off accepting casual work rather than remaining unemployed'. For women, however, 'we find that unemployment has the edge over casual employment when it comes to enhancing the probability of permanent employment 1 year onwards' (Buddelmeyer and Wooden 2011, p. 128).

Comparing the different approaches taken by Buddelmeyer and Wooden (2011) vis-a-vis Mitchell and Welters (2008) is particularly illuminating. Buddelmeyer and Wooden (2011) used a series of dynamic, multinomial logit panel models with random intercepts to estimate transition probabilities between various labour market states over adjacent years. These states were a set of comprehensive destinations—which included self-employment, unemployment and not in the labour force (NILF) as well as the casual, fixed-term and permanent categories. By comparing all labour market transitions, the authors were able to construct the counter-factual: 'what would have happened to persons working in non-standard jobs had they been in a different labor market state instead' (Buddelmeyer and Wooden 2011, p. 116). The random intercepts specification allowed them to control for unobserved heterogeneity. As is well known, heterogeneity effects are common in labour market processes. These might be educational, motivational or skill characteristics of the worker or contextual aspects of their location. Some of these can be controlled for explicitly—such as educational attainment—but others are not measurable. Incorporating random intercepts into the modelling allows researchers to control for these unobserved effects.

[2] The ABS Survey of Employment and Unemployment Patterns, conducted between 1994 and 1997 as part of the data collection to accompany the Commonwealth Government's *Working Nation* program.

There is a serious downside to the approach taken by Buddelmeyer and Wooden (2011), one which the studies by Mitchell and Welters explicitly target. While there are some measures of locality included, the majority of the regressors in these models of labour market transitions are individual characteristics: things like educational background, age, years in paid employment, marital status, presence of children. The inclusion of the lagged employment state (and the original employment state) are the only regressors which capture systemic aspects of the labour market situation which are not reducible to these individual characteristics, but they are not explicitly identified as would be the case were they included as specific regressors. The authors' preference for this approach is partly philosophical and partly statistical. The perspective behind the Buddelmeyer and Wooden (2011) approach is overwhelmingly supply-side neo-classical economics, a framework which is based on methodological individualism. When it comes to their statistical approach, the authors are restricted in their options because their regressors must be chosen from those common to all labour market states. Important job characteristics are available in the HILDA data, but only for those respondents who were employees at the time of the interview.[3]

Mitchell and Welters (2008) sum up the shortcomings of this approach:

> The supply-side emphasis on the individual's ascriptive characteristics also reflects the tendency in neoclassical models to assume away demand side constraints. The exclusive focus on employee behaviour also allows these models to explain the failure of those casually employed workers to move into non-casual employment in terms of their individual characteristics. Policy is then targeted at the individual's capacities and/or attitudes rather than at employer, regional or macroeconomic deficiencies. (Mitchell and Welters 2008, p. 5).

By way of contrast, Mitchell and Welters (2008, p. 5) argue for an analysis which incorporates both individual and systemic influences, an approach which takes account of local labour market conditions and the level of macroeconomic activity. They are able to do this because their philosophical perspective alerts them to the wider structural settings in which labour market outcomes occur, and because their method is based on survival analysis for those currently employed in casual jobs. They thus have access to a wide range of job characteristics from which to fashion their regressors. The downside to their approach, inherent in using survival analysis, is that they can only model non-casual outcomes as a single category, that is, as an exit from casual employment.

In the analysis which follows, I pursue the emphasis on systemic influences but I also consider all possible labour market outcomes. In this respect, my approach 'bridges' these two divergent methodologies. Like Buddelmeyer and Wooden (2011) I estimate transition probabilities using multinomial logit panel models with random intercepts. While I examine *all* possible labour market outcomes, *the subjects for this analysis are those individuals currently working in casual jobs*. In this way, like Mitchell and Welters I am able to draw upon a wider range of systemic influences in choosing my regressors, particularly the characteristics of the casual jobs. Unlike Buddelmeyer and Wooden (2011) I do not model all labour market transitions since I do not examine how individuals who are unemployed, permanent employees, or self-employed fare. In this respect, I am not considering the counterfactual, of how the same person might have fared had they been a permanent worker, for example, instead of a casual.

[3] While there is some information collected on the previous job held by persons not currently employed, it is not comparable to the full set of data items for those currently employed.

The question this analysis asks is thus: in what labour market situation does a male (female) casual (fixed-term) worker find themselves in the following year? How does this relate to their demographic characteristics (age, education, years in paid employment etc); to the locality where they live (the unemployment rate, the socio-economic characteristics, etc); and to the casual or fixed-term job itself (hours, pay, industry, organisational size, etc)? Many of the regressors used for this analysis are common in most labour market studies, but the richness of the HILDA data also allows for some quite unique variables to be included. These include the effects of social support networks and the skills opportunities which jobs offer. Most importantly, the HILDA data allows the researcher to distinguish between casual and fixed-term employees, and this proves to be a fundamental distinction in this subject area.

2 Data and analysis

The HILDA survey is a household-based longitudinal survey covering a broad range of social and economic questions which has been conducted annually since 2001 (for more details, see `http://www.melbourneinstitute.com/hilda/`). Respondents are surveyed each year (called a 'wave'), generally in the latter half of the year, and respond to both interviewer-administered questionnaires and a self-completion questionnaire. There are a core of questions which remain the same every year, thereby allowing for a valuable accumulation of consistent data on the same individual over time. New individuals are recruited into the survey each wave, allowing the sample size to remain high and compensating for the loss of individuals through attrition.

The data for this analysis comes from 9 waves of the HILDA survey. I work with four subsets of the data: male and female casual employees and male and female employees on fixed-term contracts. While the categories casual and fixed-term employee are often merged in labour market studies—due to a reliance on the ABS definition of a casual which is based on leave entitlements—it is possible with the HILDA data to separate the two categories because a question is included which explicitly asks interviewees how they are employed. Research over the last decade using this distinction has emphasised its importance, with the situation of fixed-term employees being quite different to that of casuals. An obvious, and very important difference, is that fixed-term employees are dominated by management and professional occupations while casual jobs are dominated by sales and labouring occupations.[4]

A further restriction on the population studied here is that the age range of the subjects spans 15 to 64 and excludes full-time students in the current year and in the subsequent year. The exclusion of students is crucial, since a considerable proportion of casual jobs are held by students whose working situation usually changes abruptly once they graduate. A casual job in hospitality, for example, is usually very transitory for a full-time student studying accountancy or teaching. Including full-time tertiary students in a study of labour market destinations is bound to bias the analysis towards more positive findings (such as permanent jobs). At the same time, including casual workers still at school will bias the study towards more negative findings (since many will go on to further study and show up as jobless, ie. not in the labour force, or still in casual jobs). One should not assume that that such biases will cancel each other out.

[4] Managers and professionals make up nearly half of all fixed-term jobs, where as they only make up about 13 per cent of casual jobs. On the other hand, sales and labouring occupations make up about 44 per cent of casual jobs, but only 11 per cent of fixed-term jobs.

A person's current labour market state—either casual or fixed-term—is the basis for defining each population, and the regressors are ones which are available for that current situation. These include individual aspects, such as age, education, health status and years in paid employment; and locality aspects, such as the local unemployment rate, the socio-economic characteristics of the area and the extent of social support networks. In the case of women, household responsibilities (in the form of dependent children) and marital status are also included.[5] Finally, and most importantly, a wide range of job characteristics are included: industry density, organisational size, earnings, hours, opportunities to acquire skill and job tenure. In the case of industry density, three categories have been constructed: industries which are below average in casual/fixed-term density, industries which are around average density, and industries with well above average density. Organisational size has been dichotomised into small and large, with 20 or more employees as the criterion. Some of these regressors are included purely as controls, but the majority are interesting conceptually. The latter form the basis for the presentation of results in this paper and the coefficients for all regressors are shown in the modelling results in the appendix.[6]

The outcome variable is the labour market state *in the following year*. This is composed of six categories: permanent, casual, fixed-term, self-employment, unemployment and not in the labour force (NILF). The use of a lead-variable (ie. the situation the following year) reduces the sample to 8 waves of data, and the other restrictions mentioned above further reduce the sample size: 2,731 observations for male casuals; 4,725 for female casuals; 1,849 male fixed-term employees; and 2,008 female fixed-term employees. Transition outcomes are not normally distributed but follow an extreme value type 1 (EV1) distribution, which makes fitting a multinomial logit model (MNL) the appropriate estimation strategy.[7]

When the researcher works with longitudinal data, such as the HILDA survey panel data, the estimation strategy needs to change. We now have repeated observations on the same individuals, a situation which is both a problem and an asset. On the one hand, this repetition violates the regression assumption of independence of observations; on the other hand, it provides the opportunity to take account of unobserved individual heterogeneity (unobserved differences in the probability of the outcome) because the panel data provides the opportunity to follow the same individuals over time. The appropriate model is a random intercepts MNL model in which the probability of observing an outcome j is conditional on observed characteristics X_{it} and unobserved individual effects α_i. The former vary over time and between individuals, the latter vary between individuals, but are time invariant. The notation for this model (Haan and Uhlendorff 2006, p. 230) is as follows:

$$Pr(j|\mathrm{X}_{it},\alpha_i) = \frac{exp(\mathrm{X}_{it}\beta_j + \alpha_{ij})}{\sum_{k=1}^{J} exp(\mathrm{X}_{it}\beta_k + \alpha_{ik})}$$

Here j represents one of the possible outcomes, i is the individual, and t represents the time period, that is, the wave in which is the individual is observed. In the analysis for this paper, j is actually j_{t+1} and reflects the fact that the outcome is for the following

[5] While it would be good for consistency to fit the same set of regressors to every model, the constraints of panel data modelling makes it important to drop regressors which make the models unstable. For this reason the male and female models differ, and the casual and fixed-term models also differ.

[6] While the sample sizes for each population are quite reasonable, the numbers in two of the destinations for male fixed-term employees—unemployment and NILF—are quite small, leading to model estimates for these two destinations which have very low precision. For this reason, no emphasis is placed on these two destinations in the results which follow, but they are retained for purposes of consistency in presentation.

[7] As Hensher et al. (2005, p. 84) note, the differences between the normal and the EV1 distribution become important when there are a large number of alternatives, as is the case in this study.

year. The unit of analysis is an 'occasion', which is nested within an individual person. The unobserved individual effects, α_i can be modelled as random intercepts and while they do not (by definition) have parameters, their variability can be estimated (this is shown as the standard deviation of the random intercept in the modelling results in the appendix).[8]

Models such as these are referred to as mixed MNL models or multi-level MNL models depending on the discipline (Gelman and Hill 2007; Pinheiro and Bates 2004; Skrondal and Rabe-Hesketh 2004) and they require particular estimation procedures. Whereas the conventional MNL can be fit using maximum likelihood estimation, with convergence achieved within a few seconds, for the random intercept MNL model used in this study, estimation is more complex because the likelihood function entails evaluating integrals with higher dimensions. With modern fast computers, simulation methods have become practical as an important solution to this estimation problem. Two of the more common methods are Markov chain Monte Carlo (MCMC) simulations and maximum simulated likelihood (MSL) estimation. The latter method is used for this analysis.[9]

When it comes to interpretation, the MNL coefficients for each of the observed characteristics, that is, the covariates X_{it} for each of the $J - 1$ outcomes, can be presented as raw estimates or as relative risk ratios (RRRs). The RRRs are similar to the odds ratios common in logistic regression and have the appealing property that they reflect a linear change in the odds of the outcome, conditional on the covariates. However, in the context of multiple outcomes, some of this appeal is lost. Because one of the J categories must serve as a base (or reference outcome), all the coefficients, and the RRRs, must be interpreted relative to this base. When the regressors are also categorical—which also entails making reference to an omitted category—the final meaning of any coefficient or RRR for a particular covariate entails a double comparison, something which makes simple interpretation of the estimates elusive. For this reason, it is common to present the results of the MNL model as predicted conditional probabilities. Unlike the RRRs, however, these probabilities are non-linear and their value depends on the values of the regressors in the model.

A common presentation device is to set all the values of the regressors, apart from the variable of interest, to their mean value, and to allow the variable of interest to alternate between set values. In practice, for a categorical variable, such as educational qualifications, this means successively setting each of the categories to equal 1, with the others left at 0. In effect, this method allows a researcher to say: net of all other variables (those set at their mean), for those individuals with say, a university degree, the probability of becoming permanent is x%, while for those with only Year 12 the probability is y%. And so forth. As well as this approach, sometimes termed *predictions at the mean*, one can also average across all observations, with most variables left at their original values and the variable of interest alternating between 0 and 1. Such an approach, termed *mean predictions* (and sometimes 'the method of recycled predictions')[10] is the approach taken in this paper. The calculation of these predicted conditional probabilities can also be compared

[8] The data used in this analysis is unbalanced. This is necessary due to the research design (because many individuals leave casual employment) and does not present problems in terms of model estimation. Where some individuals are only observed twice (that is, in their current year and in the following year) they constitute one observation in this dataset. As Gelman and Hill (2007, p. 276) argue, with these kinds of models it is acceptable to have one observation in many of the groups.

[9] For a good introduction to MSL see the special issue of the *Stata Journal* Vol.6, No.2. (2006) which is devoted to this topic. The random intercept MNL models used in this study have been estimated using the *NLOGIT* software which is part of *LIMDEP* (Greene 2007). 250 Halton draws were used for this analysis. The remainder of the analysis for this paper has has been conducted in *R* with the plots produced by *ggplot2* (R Development Core Team 2011; Wickham 2009).

[10] Also called the 'method of predictive margins'. See *Stata Version 12 Manual* [R] mlogit postestimation, p. 1225.

with a set of unconditional probabilities, and the extent of the difference is one indication of the importance of that regressor. For example, the unconditional probability of being jobless may be 10 per cent, but the probability for a particular age group, or people with a certain level of education, may be 20 per cent. The size of such differences is informative in assessing the influence of age and education on labour market outcomes.

3 Results

The unconditional probabilities for each of the labour market destinations for the four populations are shown in Table 1. The destinations are for the following year, and are shown in the vertical rows. The percentages shown here suggest that duration dependence—that is, being stuck in the same situation—is very high for casuals but weaker for fixed-term employees. Amongst casuals, nearly half of males, and more than half of females, remain casuals the following year. In the case of fixed-term employees, the fraction is closer to two-fifths. The latter have much better odds of becoming permanents: 48 per cent for male fixed-term employees and 44 per cent for females. By contrast, among casuals the proportions who become permanents are just 28 per cent and 21 per cent. These are, nevertheless, higher proportions than those who become jobless: 13 per cent of male casuals end up either unemployed or outside the labour force; the equivalent figure for females is 15 per cent, with most of these leaving the labour force.

Table 1: Unconditional transition probabilities: destinations in following year for each population

	Casuals		Fixed-term	
	Male	Female	Male	Female
Permanent	28	21	48	44
Casual	48	54	5	8
Fixed-term	5	5	39	38
Self-employed	6	4	4	3
Unemployed	6	3	2	2
NILF	7	12	3	5
Total	100	100	100	100
Sample size:	2,792	4,815	2,006	2,118

Notes: Unweighted data. All waves of data. Includes repeated observations. Note that the sample sizes for estimation are slightly smaller than these numbers because of missing observations for some of the covariates.

One can see why researchers regard the bridge / trap debate as inconclusive. On the one hand, permanent destinations outweigh jobless destinations, particularly for male casuals. On the other hand, poor labour market outcomes—in the form of remaining casual or becoming jobless—considerably outweigh good labour market outcomes. However, if the purpose of the research exercise is more than just drawing up a crude balance sheet then these unconditional probabilities are not very informative in themselves. If the research goal is to actually understand the dynamics, and the generative mechanisms, within casual labour markets, then conditional probabilities are what really matter. We need to know not only which individuals—in terms of personal characteristics—stay locked in casual employment, but what kinds of jobs and what kinds of localities consistently reproduce this kind of work.

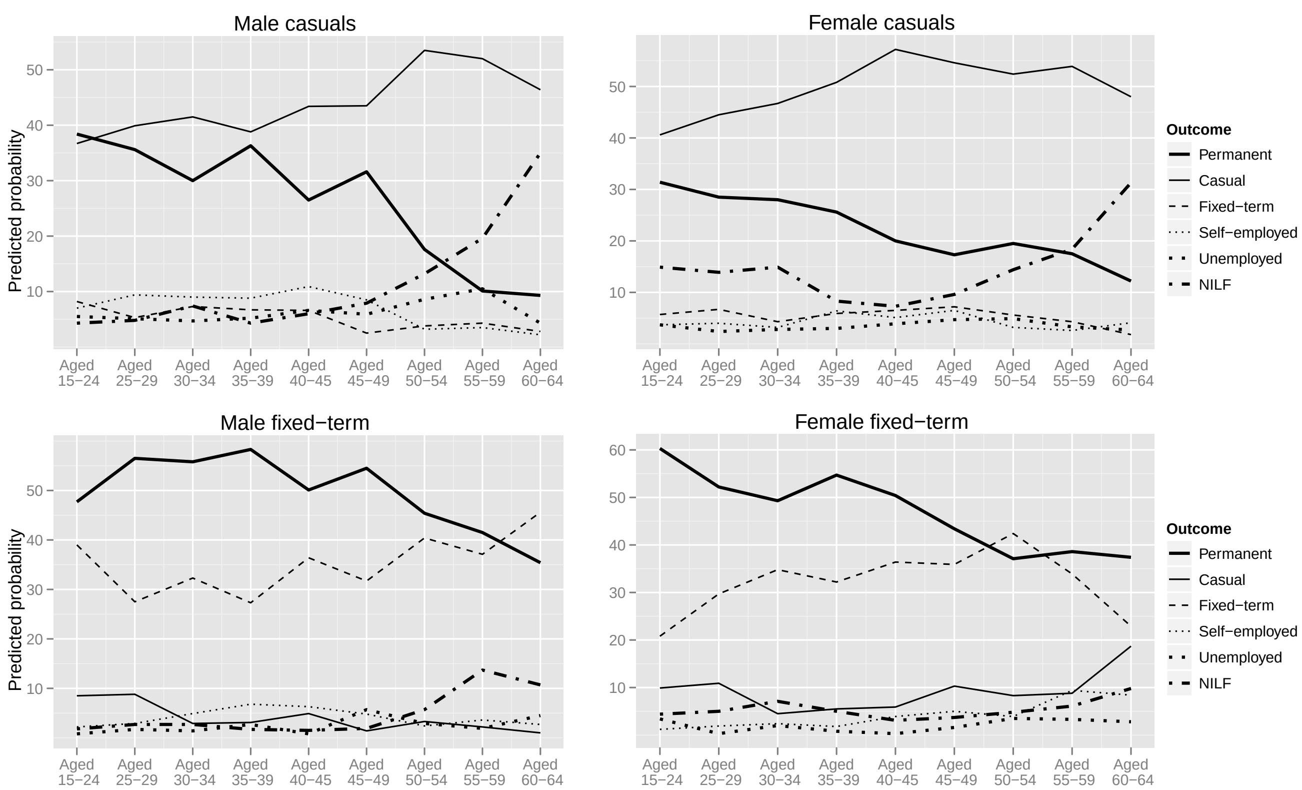
In this respect, the most important findings about individuals from this analysis are that age and years in paid employment matter a great deal, while education matters much less. Increasing age leads to worse outcomes, more years in paid employment lead to better outcomes, and increased levels of educational qualification have only a modest link to better outcomes. In regard to locality, the more disadvantaged the area, the more likely that casual jobs will persist, transitions to permanent jobs will diminish and transitions to joblessness increase. In regard to the jobs themselves, casualisation persists in those industries where casual density is high, where organisations are small, where the work is part-time, and where skills development is limited. In summary, systemic influences count for a great deal, while human capital elements count for much less.

In the discussion which follows I often refer to 'joblessness' as an outcome, a categorisation where unemployment and not in the labour force (NILF) are lumped together. While for women, the NILF category can be a unique destination given the gendered nature of unpaid domestic labour and caring work, for men in the working age population used in this study (keeping in mind the exclusion of full-time students) the NILF category often masks hidden unemployment or forced early retirement. In this respect, this category of 'jobless' is quite a reasonable measure of the lack of employment opportunities for this population.

3.1 Age, years in paid employment and education

The effect of age is shown as a series of line plots in Figure 1. All present the same sobering story that movement into permanent jobs falls with age, particularly once workers reach their mid forties. For male casuals, the fall (as a trend line) is modest until the mid forties, but then drops sharply. For female casuals, it's a steady downhill slide from their twenties.

Figure 1: Predicted probabilities for age groups (%)



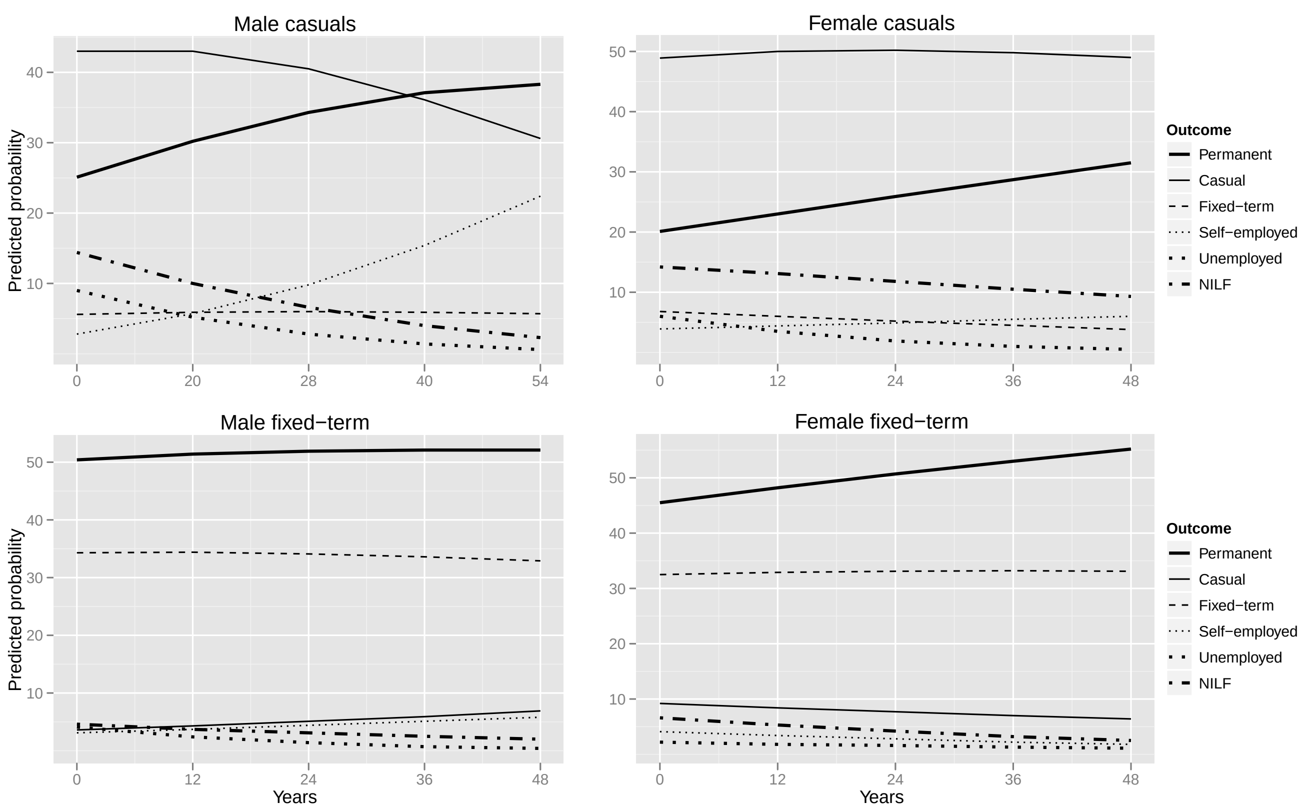
Male fixed-term workers fare somewhat better, with the fall (again, as a trend line) quite slight until the mid forties, but then a sharp drop sets in. Female fixed-term workers resemble their casual counterparts in that the downhill slide (as a trend line) is steadily downward from their twenties onwards.

The other destinations show considerable variation. For male casuals, casual destinations continue to rise with age, right through into the fifties. Unemployment rises during the late forties, but it is movement outside the labour force which takes off dramatically when male casuals enter their fifties. For female casuals, casual destinations stop rising after they reach their forties, and the same pattern as for men is evident with the NILF outcomes.

Male fixed-term workers are inclined to stay in that labour market state over the life course, with no (trend) decline evident. This is not the case for women, whose fixed-term job destinations begin to decline once they reach their fifties. While male fixed-term workers have virtually no movement into casual jobs, for female fixed-term workers this destination actually increases towards the end of their working lives.

The results for years of paid employment are also shown as a series of line plots in Figure 2. With the exception of male fixed-term employees, these plots show a steady increase in permanent destinations for those workers with longer years of paid employment behind them. They also show some other interesting variations. For male casuals, casual employment falls as a likely destination and self-employment becomes much more likely. Jobless outcomes also decline for workers with a longer history of paid employment, though these effects are confined to casuals.

Figure 2: Predicted probabilities for years in paid employment (%)



Among male casuals, job tenure has no impact on their employment destinations, nor on their prospects of avoiding joblessness (Table 2). For women, however, the impact is considerable. Longer job tenure in their current casual job considerably increases their prospects of employment and reduces their prospects of being unemployed. But when it comes to staying employed, job tenure actually increases the prospects of remaining casual rather than moving into permanent employment. Whereas a female casual with one year's job tenure has odds of about 1.3 (23 per cent to 17 per cent) of staying casual rather than becoming permanent, once that job tenure stretches out to four years, the odds have more than doubled (51 per cent to 24 per cent).

Table 2: Predicted probabilities by job tenure for casuals (%)

	Male					Female				
	Under 1 yr	One yr	Two yr	Three yrs	Four yrs	Under 1 yr	One yr	Two yr	Three yrs	Four yrs
Permanent	30	30	30	30	30	11	17	22	24	24
Casual	44	44	44	44	44	13	23	35	44	51
Fixed-term	6	6	6	6	6	4	5	6	6	6
Self-employed	7	7	7	7	7	2	3	4	4	5
Unemployed	6	6	6	5	5	63	40	21	8	3
NILF	7	7	8	8	8	8	11	13	13	13

Notes: Because of the nature of their contracts, job tenure is not included as a regressor for fixed-term employees.

The results for educational qualifications are shown in Table 3. For male casuals, a degree does indeed confer an advantage in attaining permanency, particularly vis-a-vis early school leavers. But the advantage is slight if the comparison is with those holding Certificates III/IV. Moreover, holders of a diploma (or advanced diploma) are no better off than early school leavers. Compared with others kinds of qualifications, degree-holding does make it more likely that male casuals will move on to fixed-term jobs. Finally, degree holding does make it less likely that male casuals end up jobless.

Table 3: Predicted probabilities by highest educational level (%)

	Male					Female				
	Degree†	Dip/Adv Dip	Yr 12	Cert III/IV	Yr 11‡	Degree†	Dip/Adv Dip	Yr 12	Cert III/IV	Yr 11‡
Casuals										
Permanent	36	26	30	32	27	22	20	26	24	24
Casual	37	41	46	41	48	45	50	50	50	52
Fixed-term	12	6	7	5	4	10	9	4	6	4
Self-employed	6	11	5	10	4	6	6	5	5	3
Unemployed	4	8	4	5	7	3	2	4	3	4
NILF	6	9	9	8	8	14	12	11	12	13
Fixed-term										
Permanent	43	50	60	59	55	47	50	54	52	50
Casual	4	5	2	4	8	7	10	8	9	9
Fixed-term	46	31	29	28	25	36	28	29	31	30
Self-employed	5	5	3	4	4	3	4	3	3	2
Unemployed	1	2	2	2	2	2	3	2	2	1
NILF	1	6	3	3	7	5	5	5	3	7

Notes: † includes those with post-graduate degrees. ‡ includes Certificate I/II and those with less than Year 11.

In the case of female casuals, the results are much weaker. Degrees do not confer any advantage in attaining permanency, though they do make it slightly more likely that incumbents will move on to fixed-term employment. There is no association between degrees and destinations outside the labour force.

For workers on fixed-term contracts the results are similar. The best prospects for permanency are found among Year 12 graduates and Certificate III/IV, rather than those with higher qualifications. Among males, degrees holders are just as likely to stay fixed-term as to gain permanency, though for females permanency is more likely than continuing as fixed-term. It's important to keep in mind that many fixed-term employees are working as professionals so the association between continuity and degree holding is not particularly informative.

3.2 Job characteristics

As mentioned earlier, industry has been defined according to its casual or fixed-term density. The notes below Table 4 show which industry divisions have been allocated to which category, with the general rule being that *low* density refers to below average levels of casualisation / fixed-term employment, *moderate* refers to about average, and *high* refers to considerably above average. Table 4 shows that those industries with high density have the worst outcomes for permanency, particularly for fixed-term employees. The likelihood of staying a casual increases steadily with density for males and jumps suddenly for females in high density industries. Among male fixed-term employees remaining in that category increases as one moves from low to moderate density, while for female fixed-term employees the jump is again from moderate density to high density.

Table 4: Predicted probabilities by industry density (%)

	Male			Female		
	Low density†	Moderate density‡	High density*	Low density$^{\diamond}$	Moderate density$^{\sharp}$	High density*
Casuals						
Permanent	32	29	27	24	25	22
Casual	40	45	49	49	46	54
Fixed-term	6	6	6	7	6	4
Self-employed	7	6	6	4	6	4
Unemployed	6	6	6	3	4	3
NILF	9	8	7	12	13	13
Fixed-term						
Permanent	56	48	50	52	54	43
Casual	4	5	6	8	7	9
Fixed-term	30	37	37	29	28	39
Self-employed	5	4	2	4	3	2
Unemployed	2	2	2	3	2	1
NILF	3	4	3	4	5	5

Notes: † defined as: agriculture etc, mining, manufacturing, utilities, construction, wholesale, transport etc.; ⋆ defined as: accommodation, food services, arts, recreation and other services; ‡ defined as: public admin, education, health and social assistance.

The results for earnings quintiles suggest little variation in outcome (Table 5). There are a few anomalies worth noting. Among male casuals, the top earnings quintile is more likely to stay a casual and less likely to move into permanent work than the lower quintiles. Among female casuals, however, there are no patterns evident. Where women do stand out is in fixed-term jobs: those in the top quintile also follow this pattern of being less likely to move into permanent work. None of the quintiles is more vulnerable to joblessness than any of the others.

Table 5: Predicted probabilities by earnings quintile (%)

	Male					Female				
	Bottom	Second	Middle	Fourth	Top	Bottom	Second	Fourth	Third	Top
Casuals										
Permanent	30	32	30	29	24	21	25	24	27	21
Casual	42	45	44	44	49	49	52	49	49	53
Fixed-term	6	4	6	9	6	6	4	8	6	5
Self-employed	6	5	8	6	8	6	3	4	5	6
Unemployed	7	5	6	5	4	5	4	2	3	2
NILF	9	8	6	8	8	14	12	13	11	12
Fixed-term										
Permanent	48	55	55	55	48	51	57	49	46	42
Casual	5	4	6	3	4	8	7	8	8	11
Fixed-term	35	33	33	33	37	30	28	36	36	33
Self-employed	5	5	2	3	5	3	2	2	2	6
Unemployed	2	3	2	1	2	3	2	1	2	2
NILF	4	1	2	3	4	4	4	4	6	6

Notes: The quintile cut-points have been calculated using hourly rates of pay across all categories of employee (though the incumbents in these quintiles are casuals and fixed-term employees).

When it comes to organisational size, the results suggest that male casuals have better prospects for permanency if they work for large organisations. However, among women casuals their destination patterns do not differ according to organisational size (Table 6). On the other hand, among female fixed-term employees, being employed in a large organisation does favour permanency. Male fixed-term employees show no difference here, but they are more likely to become casuals if they work in small organisations. Among all groups there is a tendency for working for a small organisation to be associated with a higher probability of becoming self-employed.

Table 6: Predicted probabilities by organisational size (%)

	Casuals				Fixed-term			
	Male		Female		Male		Female	
Organisational size	Large	Small	Large	Small	Large	Small	Large	Small
Permanent	32	26	24	22	52	53	50	43
Casual	45	42	50	50	4	7	8	12
Fixed-term	6	5	7	3	36	29	33	33
Self-employed	4	11	3	7	4	8	2	8
Unemployed	6	6	4	3	2	0	2	1
NILF	7	9	12	15	3	2	5	3

Notes: Small defined as organisations with 20 or less employees.

The results for hours of work are dramatic. As Table 7 shows, the prospects of a full-time casual gaining permanent employment in the following year are nearly 10 percentage points higher than for a part-time casual. This applies to both men and women. Among male fixed-term employees, the advantage conferred on full-timers is even higher: 17 percentage points. Vulnerability to subsequent joblessness is also higher among part-time casuals, particularly men. Some 17 per cent of male part-time casuals face this prospect compared to 11 per cent of male full-time casuals.

Table 7: Predicted probabilities by hours of work (%)

	Casuals				Fixed-term			
	Male		Female		Male		Female	
	Full-time	Part-time	Full-time	Part-time	Full-time	Part-time	Full-time	Part-time
Permanent	34	25	31	22	53	36	52	43
Casual	42	46	45	51	4	14	6	13
Fixed-term	7	5	7	6	35	32	34	32
Self-employed	6	8	5	5	4	10	3	3
Unemployed	6	6	3	4	2	5	2	2
NILF	5	11	9	13	3	4	4	6

One of the more common criticisms levelled at casual jobs is that they are often 'dead-end' jobs. While not necessarily boring or repetitive, 'dead-end' jobs lead nowhere because they offer no prospects for a worker to enlarge their capacities. One useful measure of this is the question in the HILDA self-completion questionnaire which asked respondents about their opportunity to learn new skills in a job. The raw scores (scaled from 1 to 7), when averaged across the various labour market states show considerable differences: permanents average 4.8, casuals 3.9 and fixed-term employees 5.0. At the same time, however, the variance of these scores is much closer and is actually larger among casuals than among permanents (1.9 to 1.7). In other words, while some casual jobs are very 'dead-end' others provide considerable potential for skills acquisition. The interesting question therefore arises as to whether the latter jobs are associated with transitions into permanent jobs.

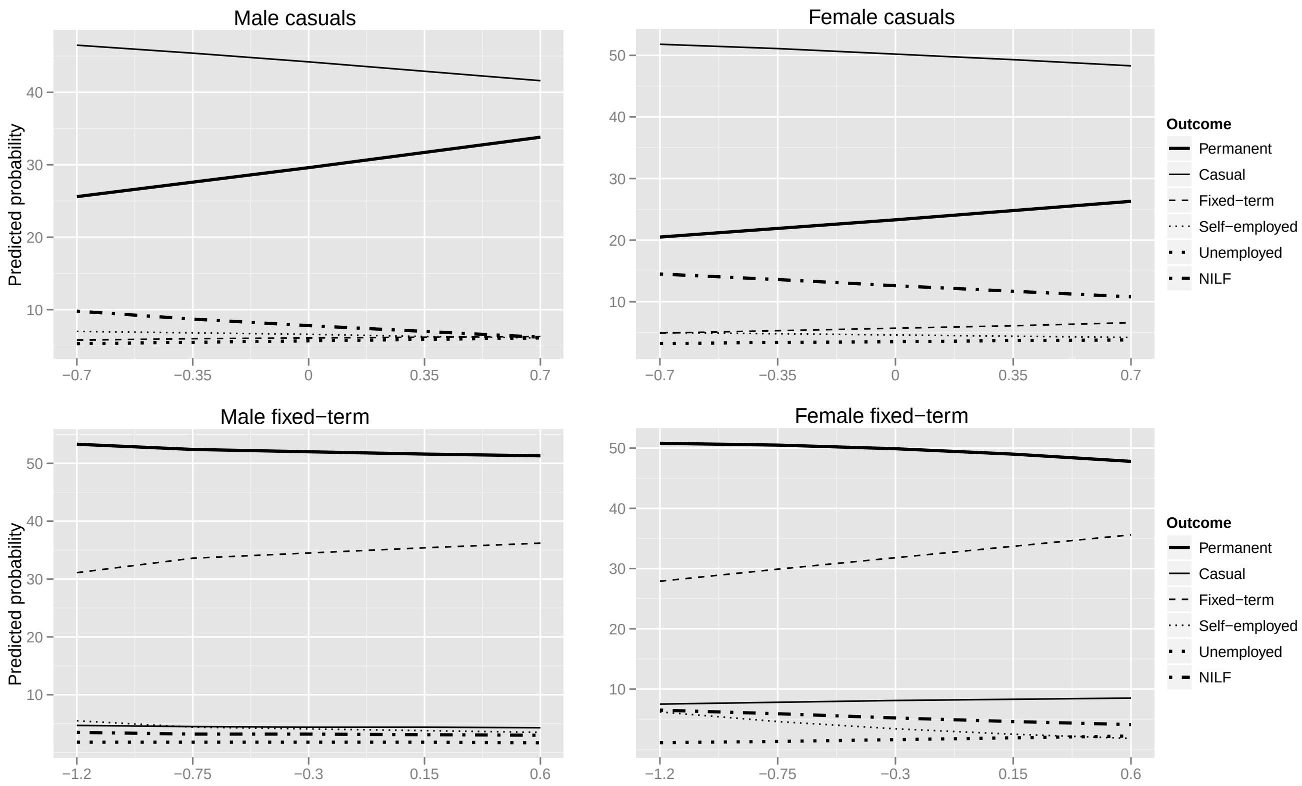
Figure 3 presents the results for this data item on skills. As with all the continous measures in this analysis, the results have been standardised such that the units in the scale beneath each plot represent two standard deviations, rather than the original scale of 1 to 7. This approach has advantages in modelling the data and interpreting the coefficients (Gelman and Hill 2007, pp. 56–57).[11] In a sense, one can regard the x-axis units as arbitrary, with the middle of the axis indicating the average position for that population, and the far left and far right of each axis indicating the range of the data. In other words, there is no extrapolation in the predicted probabilities beyond the range of the data and the most realistic results lie in the middle regions of the plot.

Figure 3 suggests that for male casuals the skills content of the job does have implications for its incumbent. As one moves along the scale measuring this potential, the probability of attaining permanency in the following year rises steadily. At the same time, the probability of staying in a casual job, or ending up outside the labour force, also declines. The results are similar for women, but weaker in strength. By way of contrast, the potential skills of fixed-term jobs is largely irrelevant. As we saw in the averages above, fixed-term jobs are already relatively high in skills content. Interestingly, for female fixed-

[11] This approach has also been used for those variables where the results are shown as years, eg. years in paid employment and job tenure. The results have been converted back into years for presentation purposes.

term employees, an increase in this skills content actually increases their probability of remaining in a fixed-term job the following year.

Figure 3: Predicted probabilities by opportunity to learn new skills (%)



3.3 Aspects of locality

As well as the characteristics of the job, an individual's locality also makes a difference. Areas with higher unemployment rates provide fewer employment opportunities for local residents. Such areas are also characterised by greater levels social disadvantage in a broader sense. As Figure 4 shows, the higher an area's unemployment rate (again on a standardised scale) the worse are the prospects of gaining permanent employment. This applies to both males and females, and to both casuals and fixed-term employees. Instead, staying a casual, or staying fixed-term, is much more likely in these areas.

A more direct measure of social disadvantage can be found in the SEIFA indices which measure the economic resources of households at an area level (things like income, expenditure, assets, dwelling size).[12] As Figure 5 suggests, these indices are also associated with labour market outcomes, though these effects are almost exclusively confined to casuals. As one moves to higher levels of the SEIFA index (again on standardised scale), the probability of staying in a casual job drops, and the probability of moving into a permanent job increases. This association is stronger for women than men in terms of moving to permanency, but stronger for men than women in terms of escaping casual jobs.

[12] SEIFA: 'socio-economic indicators for areas' are constructed by the ABS and based on the 2001 Census.

Figure 4: Predicted probabilities by area unemployment rate (%)

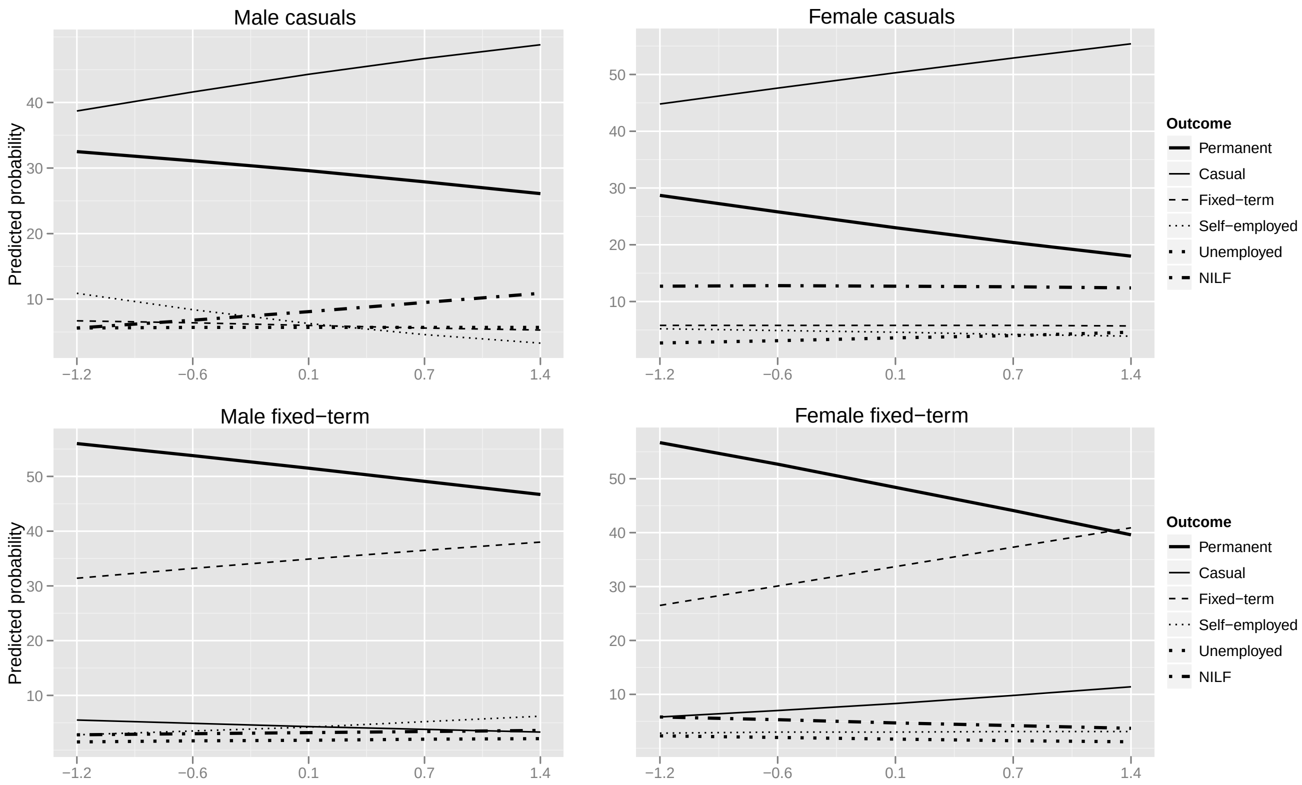
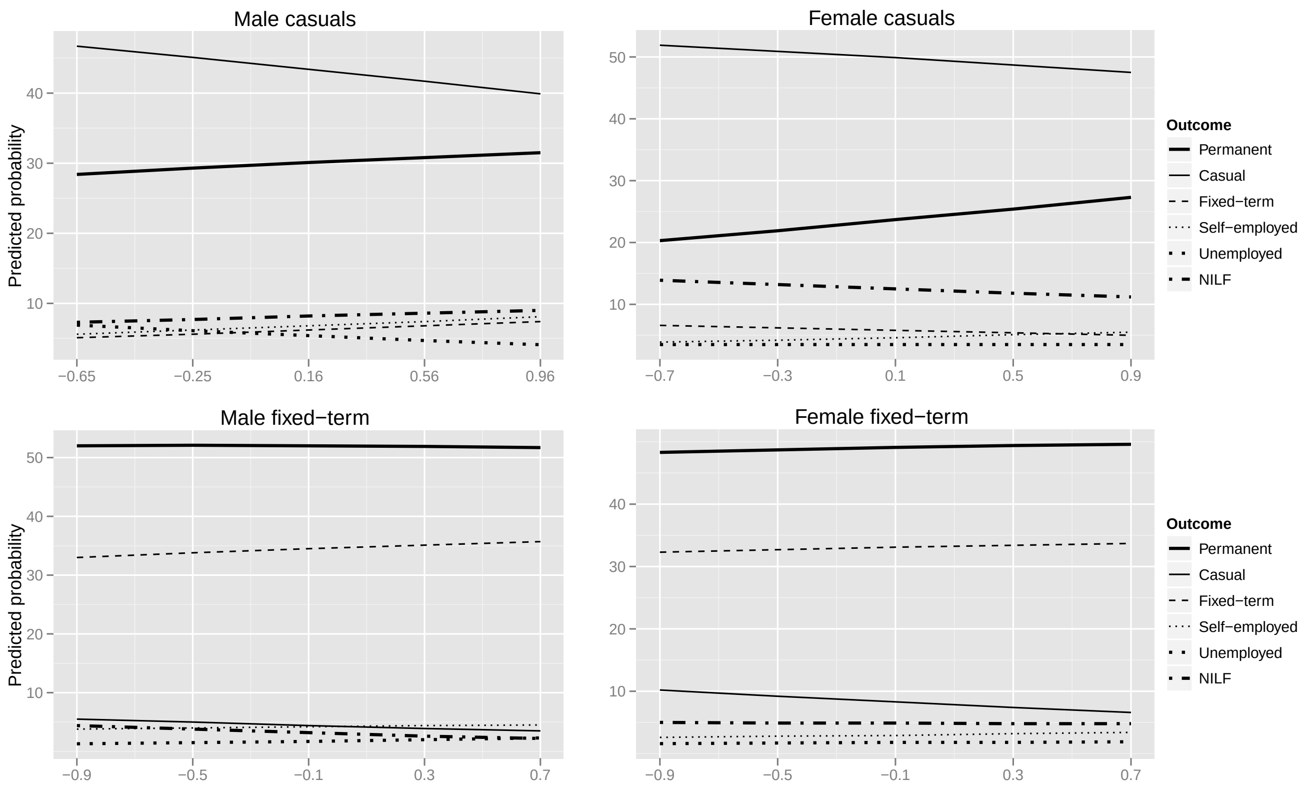


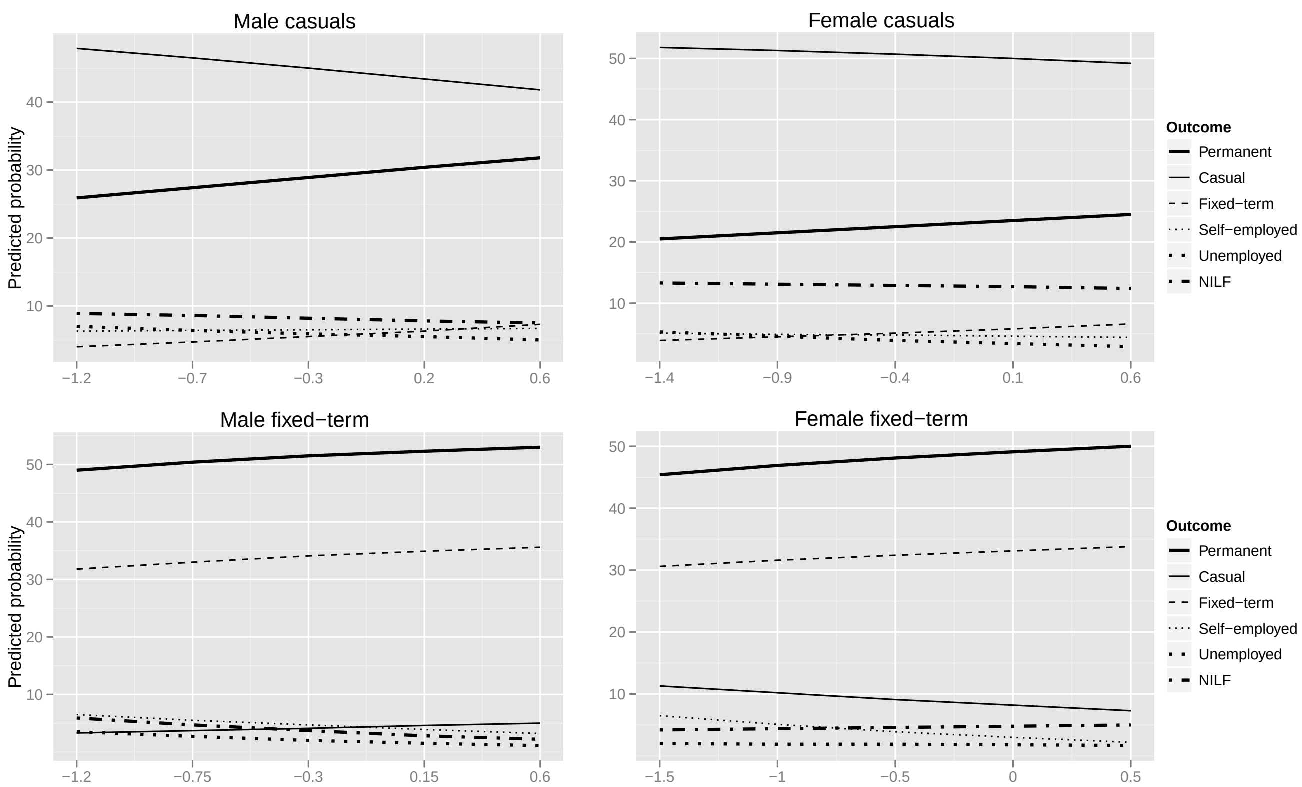
Figure 5: Predicted probabilities by socio-economic indicators (%)



The social support networks in which people live also shape their labour market prospects.[13] This can happen at a personal level, in the sense that support and encouragement can assist with confidence. It can happen in practical ways in that job openings are mediated through personal networks. In a more general sense, such networks are also an indicator of the depth of social capital in neighbourhoods.

Figure 6 suggests that male casuals, in particular, benefit from social support networks, with their probability of moving to permanent jobs being higher with greater degrees of social support. Their likelihood of remaining casual, or becoming jobless, also declines with more social support. For female casuals the effect is much weaker, as it is with female fixed-term employees.

Figure 6: Predicted probabilities by social support networks (%)



3.4 Cumulative effects

Many of the factors considered in the exposition above do not operate in isolation. While regression analysis is useful for gauging the *net effect* of a particular factor of interest, in practice the situation is more likely to be cumulative. This can be illustrated with cameos, where a number of factors are combined in their more likely combinations and a combined probability calculated. This is done in Table 8 which illustrates the impact of locality and job characteristics. It does this by combining the three measures of locality just discussed and highlighting the difference by contrasting 'unfavourable' and 'favourable' combinations of factors. In other words, comparing a locality with a high unemployment rate, low SEIFA score and low social support networks, with a locality with the opposite characteristics. In the real world, the contrast will not be this stark, but the contrast illustrated here shows what the 'outer boundaries' are likely to be. The same contrast is done with job characteristics: a job with part-time hours, in a small organisa-

[13] Social support is based on a summation of the questions about friendship, loneliness and access to personal support in the HILDA Self Completion Questionnaire. The final score was standardised for this scale.

tion, at the lowest level of pay and with low opportunities for skill, is contrasted with its opposite.

Table 8: Predicted probabilities for contrasting cameos (%)

	Casuals				Fixed-term			
	Male		Female		Male		Female	
	Unfav	Fav	Unfav	Fav	Unfav	Fav	Unfav	Fav
Locality								
Permanent	21	36	13	34	44	57	35	58
Casual	55	32	58	41	3	5	19	4
Fixed-term	3	10	4	6	33	33	36	27
Self-employed	3	13	4	6	8	2	6	2
Unemployed	8	3	7	2	3	1	1	2
NILF	11	6	14	11	9	1	3	6
Job characteristics								
Permanent	16	37	14	34	30	53	34	48
Casual	48	42	54	43	28	2	20	7
Fixed-term	4	8	1	11	22	35	29	33
Self-employed	11	4	8	4	15	4	11	4
Unemployed	7	4	4	2	1	1	1	3
NILF	14	4	18	7	4	4	5	4

Notes: Unfav = unfavourable combination of factors; fav = favourable combination of factors.
For locality, unfavourable means high unemployment rate, low SEIFA index and low social support score. Favourable means the opposite. For job characteristics, unfavourable means part-time hours, working in a small organisation, being in the bottom earnings quintile, and having the lowest opportunity to learn new skills. Favourable means the opposite.

As the top panel in Table 8 shows, the prospects for permanency among male casuals jump from 21 per cent to 36 per cent as one moves from an 'unfavourable' to 'favourable' locality and among female casuals the increase is even greater, from 13 per cent to 34 per cent. Not only are prospects for casualisation greater in the 'unfavourable' localities, but joblessness is also much more likely: 19 per cent for male casuals and 21 per cent for female casuals. The equivalent figures are about half this in the 'favourable' localities. Fixed-term employment departs from this pattern. While there is a similar contrast in terms of permanency (but weaker in strength), there is no change in the fixed-term outcome among males. Only among women does the fixed-term destination fall as one moves from 'unfavourable' to 'favourable' localities.

The results of the cameo for job characteristics also illustrate a sharp difference between 'unfavourable' and 'favourable' combinations. Those male casuals in 'unfavourable' jobs have only a 16 per cent probability in the following year of gaining permanency in employment and a 21 per cent probability of ending up jobless. Self-employment—possibility a form of hidden unemployment—is also much more likely for this group. By contrast, male casuals in 'favourable' jobs have a 37 per cent probability of getting permanent jobs and only an 8 per cent probability of joblessness. The pattern for female casuals in 'unfavourable' jobs closely follows that of the male pattern, though with self-employment less likely and remaining in casual jobs somewhat higher.

As with the locality cameo, fixed-term employees also depart from the pattern found with casuals. Certainly their prospects for permanency increase as one moves from the 'unfavourable' to the 'favourable' category, but their likelihood of remaining fixed-term in the following year actually *increases*, whereas among casuals continuation in that category falls. What seems to be happening is that the other destination categories—ending up in casual jobs or in self-employment—fall away as one moves from the 'unfavourable' to the 'favourable' combination of job factors. These findings are consistent with the fact that fixed-term employment is dominated by professional and managerial jobs.

3.5 Conclusion

These various results defy an easy human capital explanation and suggest a difficult conundrum for conventional analysis. On the one hand, increasing age reduces the prospects of good outcomes, such as permanency, and makes it more likely casuals will either stay casual, or enter joblessness. At the same time, years in paid employment have the opposite effect. Ordinarily, the latter is conceptualised as 'experience' in a human capital framework, and is often operationalised by the recourse to age (when no other direct measure is available.) Here they have opposite effects, and are not correlated at all. At the same time, education, the other key human capital variable, has an impact on improving good outcomes only for male casuals, and only at certain levels.

One explanation for these intriguing results lies in reconceptualising casualised labour markets, and recognising that they exist as a secondary labour market in their own right, with their own dynamics and their own internal system of regulation. One unspoken convention in the labour market is that by a certain age, 'good workers' will have settled into a career path and their increasing maturity will see them consolidating the advantages of incumbency, such as higher earnings and promotions. But for casual workers this axiom does not apply: to be in a casual job in one's mature years signals 'failure'. As many retrenched workers find, this judgment may apply even if the current casual job was preceded by decades of permanent employment. In other words, *the casual job itself turns age into a liability*.

On the other hand, years in paid employment ('experience') is definitely an asset. The reason this does not correspond to increasing age is because it actually represents continuity of employment. Extended periods of casual employment usually mean an intermittent labour market history, with periods in and out of joblessness. Such a history makes gaining a permanent job much harder, because the work-based networks which assist such a transition are continually disrupted by such intermittency. Even if the prior employment was in casual work, the continuity makes a difference. Earlier modelling work (not shown in this paper) suggested that the lagged-employment state also made a difference to the employment state in the following year. In other words, those casuals who had been employed in the prior year, whether casual or permanent, had better prospects in the following year than those who had been jobless. It is patterns like these which lie behind the adage 'any job is better than unemployment' which surfaces in some of the literature. The point that it illustrates, in this analysis, is that continuing attachment to employment is a major asset, but that *by their very nature, casual jobs constantly undermine this attachment*.

As we saw, job tenure had no appreciable influence on the results. In human capital terms, *employment* tenure represents 'general experience and skills' whereas *job* tenure represents 'firm specific experience and skills'. Clearly, in casualised labour markets, the latter has no value for employers if value is measured as transitions to permanency. This is the assumption behind the notion that casual jobs can provide probationary periods for employees. Yet here we see casuals kept on indefinitely, but with no progression to permanency. They have presumably passed their 'probation', but their prospects have not improved. The most likely explanation lies in the nature of the job: these are the casual jobs which are not intended to ever become permanent jobs. Keeping a reservoir of casual jobs is clearly part of the employment strategies of many firms.

The results for hours of work exemplify the commodification of labour power which is implicit in the casual labour market. Labour market researchers often despair at the layperson's loose use of language when 'casual' and 'part-time' are used interchangeably. For researchers, these represent two separate dimensions: mode of engagement and working hours. Yet the layperson's view is probably closer to the reality that the two are really interchangeable. With the ready availability of *permanent part-time* work a rarity, anyone seeking part-time hours must usually make do with accepting a casual job. From the employer side, seeking part-time workers generally means seeking casual employees. Not only is this 'flexible' employment strategy focussed on buying smallish chunks of labour power, but it also aims to buy the ability to turn such labour power on and off with ease.

In terms of the bridge / trap debate, the unconditional probabilities outlined at the beginning of this section suggest that ones conclusions depend on how one defines a 'good' outcome. The bridge metaphor emphasises gaining permanency, or avoiding joblessness, while the trap metaphor emphasis continuing casualisation and intermitten joblessness. In looking at the conditional probabilities in this section, it is clear that the characteristics of casuals jobs, in themselves, are a major factor in perpetuating this kind of work. It seems reasonable to conclude that casual jobs do indeed operate as labour market traps, and they are actually crafted to do so.

Why does the casual labour market operate in this way? After all, secondary labour markets were analysed in the 1960s and 1970s, well before casual jobs began to mushroom. They operated in those decades using 'dispensable' workers, with immigrant labour in particular providing the kind of flexibility employers sought. To understand how casualisation has re-entered the picture we need an analysis which draws on a periodisation of neo-liberalism and a concept of the reserve army of labour.

4 Discussion

4.1 Casualised labour markets and neo-liberalism

Casualised labour markets have been a hallmark of capitalism since its inception. The reduction of workers to the commodity, labour power, has meant that their engagement with economic activity has fluctuated with the vicissitudes of the capitalist production process. From the earliest days of primitive accumulation, free labour became the basis for the early development of capitalist relations of production. Workers were 'free' in the double sense: they were no longer tied to traditional obligations which hampered the development of a capitalist labour market—such as feudal relationships–and they were also free in the sense that they were severed from their own means of production and thus depended on capitalist employment for their livelihoods.

While wage labour was slow to develop (much of the early factory system was based on self-employment), once it did come into existence as the dominant mode of employment, it was by no means secure. As the illuminating study of Victorian London by Gareth Stedman Jones (1971) showed, casual labour markets were the basis for much working-class poverty. Indeed, for much of the late 19th century and early 20th century, casual employment was the basis for the distinction between 'respectable' and 'rough' segments of the working class: the latter were those labourers who had access to only intermittent employment.

Employment security only became the norm after the Second World War (Macintyre 1985), as part of the post-war settlement, the compromise between capital and labour which ushered in the modern welfare state.[14] David Harvey refers to this period as embedded liberalism (Harvey 2010); Duménil and Lévy (2011) refer to it as the social democratic/Keynesian compromise. For both, the subsequent period, from the late 1970s onwards, marks the period of neo-liberalism. It can be viewed as project to revitalise capitalist profitability, which had fallen during the 1970s, and to restore capitalist class power. It also marked the 'second reign' of finance capital. A fuller discussion of this periodisation can be found in Duménil and Lévy (2011, ch. 1). Its significance for this paper is that it marks a turning point in the evolution of the capitalist labour market. The neo-liberal epoch marks the period in which the state began unwinding the post-war settlement, dismantling the welfare state, and returning employment relations to their earlier more precarious basis. The two dimensions were intimately linked: the protections which had been provided by the welfare state had hampered wages entering into competition. Unemployment benefits, despite their miserly level, had taken away the sharp edge of poverty and had prevented wages being driven relentlessly downward. The project to restore capitalist profitability was thus also a project to make labour free again: free from other sources of livelihood and thereby free to be engaged and disengaged more readily from the production process.

4.2 The reserve army of labour

One of the key concepts for understanding this engagement and disengagement of labour is the *reserve army of labour*. As Howard Botwinick has argued (Botwinick 1993, pp. 96–99), the existence of a large pool of available labour which facilitates the easy engagement and subsequent expulsion of labour from production helps maintain a constant downward pressure on wages, particularly at the bottom of the labour market. In an earlier article (Watson 2002, p. 92) I argued that we can update this 19th century concept to fit contemporary Australia. The reserve army of labour can be seen as composed of a number of segments:

- the *floating* segment: those with interrupted spells of employment in the 'centres of modern industry'.
- the *latent surplus* population: those who are 'constantly on the point of passing over into ... the proleteriat'. In the 19th century the agricultural population filled this role; in the last half of the 20th century women have regularly moved between the latent and floating segments.
- the *stagnant segment*: composed of those who have become surplus through modernisation of industry, particularly those in 'decaying branches of industry'. The fate of rural and regional areas of Australia, and Australia's post-war blue-collar migrants, come to mind.
- the *pauper segment*: those unable to work on a steady basis, through illness, disability or demoralisation. Again, Australia's poorest working class suburbs come to mind, with sub-populations composed of the long-term employed, ex-prisoners, the homeless, and those addicted to drugs and alcohol.

[14] This is not to say that permanent employment was uniform everywhere. As Burgess and Campbell (1998*a*, p. 33) note: "that 'permanency' acquired different meanings in each country in accordance with labour regulatory systems, the sphere and types of trade union organisation and the methods of labour co-ordination. Nevertheless, in each country the full-time permanent employment contract—with a varied set of attendant rights and benefits—came to be the central element in a concept of 'standard' employment ..."

The last decade has seen one formal measure of unemployment, the unemployment rate, drop to its lowest level in 30 years. A 'tight' labour market has not meant, however, that the reserve army of labour has been demobilised. Rather, employers have had easy access to global pools of labour, particularly through the increased immigration of skilled workers, both permanent and temporary. Whereas Australia's post-war immigration system had been solidly based on permanent migration—compared with the use of 'guest workers' in Europe—since the mid 1990s Australia has dramatically expanded its intake of temporary skilled migrants. The temporary business entry visa—the 457 visa category—was introduced in 1996 and one of its key elements was the relaxing of the requirement on employers to demonstrate that they could not find a suitably qualified Australian resident: 'employers can sponsor skilled migrants without any reference to whether there is a skill shortage in the field or note' (Kinnaird 2006, p. 51). The number of temporary workers under this category grew rapidly over the next fifteen years. From under 10,000 per year in the late 1990s it had reached nearly 50,000 by 2004–2005 and stood at 90,000 by 2010-2011 (Khoo et al. 2003; Khoo et al. 2007). Those workers in the 457 Visa category can remain in Australia for as long as 4 years, though this can be extended, and their wages are not pegged to current market rates (Kinnaird 2006). While the majority of these Visa holders work in managerial and professional occupations, a considerable minority are working in lower skilled categories. Outside the 457 system, large pools of lower skilled foreign labour have become become available to Australian employers via the backpacker phenomenon of agricultural harvesting in rural areas and via overseas students plugging gaps in the hospitality and cleaning industries. One can think of these sources of labour as composing the *floating* and *latent surplus* segments, similar to the role played by women following their expanded entry into the labour market from the 1960s onwards.

On the domestic front, the reserve army has continued to grow but the segments of most importance have been the *stagnant* and *pauper* segments. Recent research by Peter Davidson has highlighted the dimensions of the pauper segment in Australia. He found that in 2009 the number of long-term recipients of unemployment benefits was over 300,000. The proportion whose time on benefits was longer than two years had risen from 16 per cent (1990) to 43 per cent (2009) and for a duration of over five years the growth was from 5 per cent to 23 per cent. By 2002, the numbers of working age persons on Disability Support Pension had outgrown those on Newstart, and by 2010 they had reached nearly 800,000. In surveying these trends Davidson observed:

> ... as unemployment fell, the profile of recipients of unemployment payments became more disadvantaged ... with a higher incidence of Indigenous people, people of mature age, people with disabilities, and people with social barriers to work such as homelessness, addictions or mental illness (Davidson 2011, p. 83).

Where does the neo-liberal project fit into this picture? The post-war settlement, and its creation, the welfare state, had blunted the effectiveness of the stagnant and pauper sections of the reserve army of labour by shielding them from exposure to extreme poverty. As part of the project to restore capitalist profitability, neo-liberalism ushered in a period in which efforts were made to reactivate these segments of the reserve army of labour in a effort to maintain downward pressure on wages. From the late 1980s onwards, access to welfare on the basis of category entitlements was eroded in favour of more discretionary administrative procedures. The notion of welfare, as a citizen's right, was under pressure from the notion of welfare as an act of charity. There was an ideological component to this, evident in the resurrection of 19th century notions of the 'deserving poor', and an administrative component, evident in 'mutual obligation' and 'work for the dole'. As researchers like Davidson (2011) and Fowkes (2011) have shown, the operations of the jobs network during the Howard years epitomised the return of moralistic paternalism to this domain. The target for much of this moralism were the long-term unemployed, that is, elements within the pauper segment of the reserve army. More recently, the policy emphasis on increased labour force participation for those on the Disability Support Pension reflected an attempt to remobilise this segment of the reserve army. As well as the paternalism, the 'demographic time bomb' had become a new avenue for justifying the need to reactivate large segments of the reserve army of labour (see, in particular, Commonwealth Treasury 2002).

As well as the onslaught on the welfare state, neo-liberalism also ushered in an onslaught on permanent employment. Prior to the 1980s casual employment had remained relatively static, had been largely restricted to a number of services industries (particularly retail and hospitality), and had been predominantly the preserve of female part-time workers. From the 1980s onward, the landscape began to change. Overall growth rates were very high, with the number of employees working as casuals doubling between 1982 and 1997 (Burgess and Campbell 1998*a*, p. 35). By 2002, casuals represented 27 per cent of the employee workforce. Casualisation also extended more widely to cover male workers, and to cover full-time jobs. Importantly, it spread to more industries, including those where it had been previously been quite marginal: such as manufacturing, transport and communications (Watson et al. 2003, p. 69; Burgess and Campbell 1998*a*, p. 40).

So how does casual and fixed-term employment fit into this conceptual framework? I would argue that its rapid growth since the 1980s suggests that it now operates as the *half-way house* between secure residence in employment and long-term residence within the reserve army of labour. Where once the reserve army of labour was responsive to labour demand, since poverty acted as a sharp spur to labour market activity, by the late 1960s this was no longer the case. Casual employment helped eliminate this friction: women with caring responsibilities, and full-time students, could be quickly mobilised, and just as quickly demobilised through their engagement as casuals ('Numerical flexibility' is one term for this strategy (Burchell et al. 2002).) In service industries, for example, this meant covering the peaks of consumer demand by engaging casuals for the busiest parts of the day or week. In manufacturing, it can mean being 'on call', available for when production required sudden expansion (Watson et al. 1999). Casual labour had become 'just-in-time' labour.

That casual employment became a half-way house was an important development. Individual employers did not dip into the reserve army of labour in an ad hoc fashion—the costs of engaging and disengaging labour being onerous—and instead sought access to workers in a less problematic fashion. Employers have always been 'risk averse' to engaging the long-term unemployed, for example, whereas full-time students or women with young children were a much more palatable option. Casual employment became the ideal vehicle for this process, particularly where the work was relatively unskilled and the demand for labour fluctuated. At the same time, the appeal to employers of 'access to labour without obligation' (Gonos 1997) made casual employment part of a broader employment strategy. Through the use of fixed-term contracts, more highly skilled labour—both blue-collar and white-collar—could also be drawn into this system. Thus emerged a distinctively separate set of casualised labour markets, with their own dynamics and their own characteristics. In some cases, the engagement of casual workers could last for extended periods of time. While formally engaged on an hourly basis, many casuals found themselves employed as 'permanent casuals', a uniquely Australian oxymoron (Owens 2001). In other cases, the short-term nature of the contract was very much in place, as in the growth of the labour hire industry.

For workers, casualised labour markets meant job insecurity, irrespective of the duration of their engagement. In whatever fashion one analyses the job satisfaction data, the one area where casuals are distinctively unhappy is in terms job security (Wooden and Warren 2004; Watson 2005). For many less skilled workers, the expansion of casualised labour markets has meant working lives based on a chronic battle with bouts of employment, unemployment and under-employment. Such a pattern represents a classic reversion to 19th century casualised labour markets of the type familiar to labour historians. Casual jobs have become a half-way house because re-engaging labour in production is never further away than a phone call or a text message.

The extension of the reserve army of labour to professionals represents a new development, and reflects the evolution of the state under neo-liberalism. The retreat from social responsibilities which has marked the neo-liberal state—the 'treason of the state' as Mike Davis (2006) colourfully phrases it—has seen an extensive spread in fixed-term employment throughout public administration and education. As noted earlier, nearly one half of fixed-term employees are professionals or managers. Where once they might have routinely expected permanent employment (after a probationary period), many of these workers now exist in a labour market limbo. In many cases, the gaps between their contracts entail weeks, if not months, of unemployment. Teaching positions—particularly in higher education and TAFE—are notorious for this as workers usually find themselves unemployed outside of the teaching terms. These workers are not lost to the labour market, because residence in the the half way house becomes preferable to long-term residence in the reserve army. There is always the hope that a fixed-term job will become a permanent job. Against these are the strategies of defeat: two of the most common are re-entering the reserve army more fully (such as full-time domestic labour amongst women) and the other involves leaving the half-way house and settling for a permanent job well below one's qualifications. The research on over-qualification and over-skilling in the Australian labour market highlights the prevalence of the latter phenomenon (see, for example, Watson 2008; Mavromaras et al. 2009).

After nearly a decade of 'tight' labour markets, there has been no 'wages explosion' in the Australian economy. Only the mining sector shows evidence of exceptional wages growth. Elsewhere, a steady stream of overseas workers and the solid presence of a half-way house of casualised labour has ensured that wages have been contained, allowing profitability to grow unhindered.

A Appendix: detailed modelling results

Table 1: Model estimates and standard errors (in parentheses) for male casuals

	Outcome in following year (base: casual)									
Variable	Permanent		Fixed-term		Self-employed		Unemployed		NILF	
Aged 15-24	0.651	(0.302)	0.631	(0.619)	-0.634	(0.709)	-0.040	(0.498)	-0.289	(0.564)
Aged 25-29	0.435	(0.286)	-0.073	(0.598)	-0.187	(0.647)	-0.217	(0.504)	-0.224	(0.574)
Aged 30-34	0.208	(0.266)	0.238	(0.529)	-0.281	(0.574)	-0.336	(0.500)	0.289	(0.542)
Aged 35-39	0.505	(0.238)	0.275	(0.481)	-0.295	(0.506)	-0.164	(0.482)	-0.337	(0.576)
Aged 45-49	0.161	(0.255)	-1.117	(0.666)	-0.400	(0.499)	-0.119	(0.537)	0.335	(0.562)
Aged 50-54	-0.737	(0.307)	-1.013	(0.636)	-2.095	(0.703)	0.122	(0.602)	0.755	(0.605)
Aged 55-59	-1.317	(0.366)	-0.937	(0.716)	-1.878	(0.747)	0.421	(0.669)	1.393	(0.645)
Aged 60-64	-1.292	(0.422)	-1.351	(0.847)	-2.163	(0.898)	-0.505	(0.973)	2.500	(0.719)
Degree or above	0.521	(0.220)	1.037	(0.394)	0.370	(0.566)	0.132	(0.480)	-0.264	(0.434)
Adv dip/diploma	-0.049	(0.279)	-0.040	(0.546)	1.372	(0.636)	0.890	(0.489)	0.192	(0.515)
Cert III/IV	0.181	(0.180)	-0.220	(0.373)	1.260	(0.472)	0.349	(0.355)	-0.004	(0.359)
Cert I/II, Year 11 <	-0.184	(0.165)	-0.591	(0.346)	-0.156	(0.454)	0.619	(0.300)	-0.151	(0.323)
Years in paid employment	0.543	(0.344)	0.290	(0.725)	2.000	(0.845)	-1.355	(0.559)	-1.272	(0.550)
Years of job tenure	-0.028	(0.138)	0.297	(0.227)	0.008	(0.259)	-0.697	(0.439)	0.496	(0.183)
Long-term health prob	-0.227	(0.142)	-0.071	(0.290)	0.014	(0.311)	-0.105	(0.263)	0.960	(0.239)
SEIFA of local area	0.196	(0.117)	0.415	(0.234)	0.475	(0.279)	-0.268	(0.228)	0.322	(0.230)
Local unemployment rate	-0.203	(0.111)	-0.227	(0.226)	-0.767	(0.285)	-0.099	(0.211)	0.207	(0.217)
Level of social support	0.242	(0.109)	0.534	(0.239)	0.104	(0.264)	-0.122	(0.187)	-0.055	(0.211)
Learn new skills in job	0.335	(0.121)	0.227	(0.245)	-0.134	(0.286)	0.230	(0.231)	-0.379	(0.234)
Part-time hours	-0.515	(0.120)	-0.725	(0.247)	0.536	(0.283)	-0.020	(0.219)	0.972	(0.257)
Bottom earnings quintile	0.067	(0.158)	0.194	(0.324)	-0.333	(0.373)	0.329	(0.285)	0.464	(0.313)
Second earnings quintile	0.051	(0.150)	-0.325	(0.337)	-0.586	(0.359)	-0.122	(0.295)	0.249	(0.314)
Fourth earnings quintile	-0.038	(0.182)	0.604	(0.346)	-0.386	(0.411)	-0.258	(0.389)	0.162	(0.373)
Top earnings quintile	-0.375	(0.197)	-0.057	(0.381)	-0.105	(0.413)	-0.463	(0.427)	0.197	(0.384)
Industry: mod density	-0.244	(0.137)	-0.130	(0.278)	-0.276	(0.319)	-0.139	(0.255)	-0.183	(0.261)
Industry: high density	-0.411	(0.140)	-0.263	(0.285)	-0.575	(0.332)	-0.276	(0.256)	-0.577	(0.269)
Small organisation	-0.198	(0.117)	-0.268	(0.242)	1.645	(0.299)	0.133	(0.212)	0.453	(0.225)
Intercept	-0.012	(0.265)	-2.274	(0.594)	-3.951	(0.840)	-3.023	(0.583)	-3.910	(0.723)
SD random effects	0.851	(0.122)	1.803	(0.391)	2.251	(0.548)	1.285	(0.415)	1.755	(0.447)
Correlations*	Fixed	Self	Un	NILF						
Permanent by	-0.85	0.12	-0.32	-0.41						
Fixed-term by		-0.61	-0.01	0.02						
Self-emp by			0.27	0.68						
Unemp by				0.07						
No. observations†	2,731									
No. 'groups'‡	1,434									
Log likelihood	-3397									
LR chi-squared	2994									
McFadden Pseudo $R^2 \star$	0.31									

Notes: Random intercept multinomial logit model with estimation by maximum simulated likelihood (MSL) estimation using 250 Halton draws. Note that all the continuous regressors have been fitted as standardised values (see the discussion in the text on page 14), including those whose predicted probabilities were presented as years (eg. paid employment, job tenure.)

SD random effects = standard deviation of the random effects.

∗ correlations of the random intercepts.

† 'occasions', that is, individuals by years. ‡ separate individuals.

⋆ As is well known, pseudo R-squared is not analogous to R-squared in linear regression, and is regarded as uninformative by some authors (Long 1997, p. 102). Others see value in the McFadden version and have established an empirical mapping between the two measures. In this context, a pseudo R-squared of 0.3 for a MNL model is equal to approximately 0.6 for a linear regression model and indicates 'a decent model fit' (Hensher et al. 2005, p. 338).

Omitted categories: Aged 40–44; Year 12; No long-term health condition; Full-time hours; Middle earnings quintile; Industry: low density; Large organisation.

Source: HILDA Release 9.

Population: Male casuals aged 15 to 64, excluding full-time students.

Table 2: Model estimates and standard errors (in parentheses) for female casuals

Variable	Outcome in following year (base: casual)									
	Permanent		Fixed-term		Self-employed		Unemployed		NILF	
Aged 15-24	0.932	(0.226)	0.303	(0.375)	0.059	(0.487)	0.308	(0.453)	1.161	(0.276)
Aged 25-29	0.715	(0.222)	0.372	(0.359)	0.064	(0.453)	-0.321	(0.504)	0.989	(0.268)
Aged 30-34	0.627	(0.197)	-0.216	(0.350)	-0.260	(0.410)	-0.180	(0.456)	0.992	(0.242)
Aged 35-39	0.430	(0.173)	0.051	(0.293)	0.433	(0.323)	-0.181	(0.408)	0.285	(0.234)
Aged 45-49	-0.113	(0.174)	0.194	(0.272)	0.386	(0.323)	0.292	(0.389)	0.373	(0.233)
Aged 50-54	0.062	(0.205)	-0.064	(0.346)	-0.413	(0.439)	0.405	(0.472)	0.823	(0.248)
Aged 55-59	-0.100	(0.245)	-0.403	(0.443)	-0.636	(0.552)	-0.128	(0.612)	1.060	(0.277)
Aged 60-64	-0.393	(0.343)	-1.172	(0.795)	0.108	(0.640)	-0.267	(0.925)	1.823	(0.325)
Sep/div/widowed	0.048	(0.151)	0.186	(0.248)	-0.712	(0.348)	0.646	(0.310)	-0.152	(0.175)
Never married	0.131	(0.141)	0.024	(0.237)	-0.575	(0.329)	0.055	(0.289)	-0.631	(0.180)
One child 0-4 years old	-0.008	(0.144)	-0.301	(0.264)	0.330	(0.282)	-0.184	(0.328)	0.599	(0.158)
Two or more child 0-4	-0.186	(0.240)	-0.223	(0.420)	0.745	(0.406)	0.045	(0.533)	0.505	(0.248)
Degree or above	-0.060	(0.166)	1.195	(0.273)	0.547	(0.331)	-0.115	(0.391)	0.398	(0.200)
Adv dip/diploma	-0.229	(0.206)	0.942	(0.325)	0.377	(0.394)	-0.540	(0.530)	0.118	(0.248)
Cert III/IV	-0.057	(0.157)	0.386	(0.285)	0.089	(0.332)	-0.195	(0.332)	0.082	(0.192)
Cert I/II, Year 11 <	-0.144	(0.136)	-0.205	(0.268)	-0.449	(0.296)	0.046	(0.277)	0.131	(0.163)
Born ESB	0.276	(0.176)	-0.227	(0.320)	-0.100	(0.369)	0.216	(0.410)	-0.000	(0.217)
Born NESB	0.099	(0.166)	-0.592	(0.318)	0.183	(0.319)	-0.279	(0.403)	0.457	(0.183)
Years in paid employment	0.251	(0.174)	-0.283	(0.293)	0.213	(0.350)	-1.255	(0.374)	-0.208	(0.183)
Years of job tenure	-0.190	(0.109)	-0.290	(0.184)	-0.088	(0.212)	-1.856	(0.526)	-0.247	(0.129)
Long-term health prob	-0.038	(0.122)	0.111	(0.209)	0.110	(0.256)	0.364	(0.242)	0.319	(0.136)
SEIFA of local area	0.289	(0.102)	-0.105	(0.172)	0.315	(0.210)	0.054	(0.224)	-0.085	(0.121)
Local unemployment rate	-0.317	(0.095)	-0.126	(0.165)	-0.239	(0.197)	0.153	(0.206)	-0.115	(0.111)
Level of social support	0.143	(0.091)	0.330	(0.173)	-0.042	(0.185)	-0.350	(0.176)	-0.010	(0.107)
Learn new skills in job	0.275	(0.099)	0.301	(0.174)	-0.107	(0.209)	0.210	(0.219)	-0.178	(0.118)
Part-time hours	-0.583	(0.120)	-0.456	(0.200)	-0.259	(0.276)	0.052	(0.273)	0.208	(0.172)
Bottom earnings quintile	-0.169	(0.130)	-0.467	(0.220)	0.520	(0.282)	0.775	(0.306)	0.086	(0.152)
Second earnings quintile	-0.046	(0.127)	-0.878	(0.239)	-0.217	(0.301)	0.447	(0.314)	-0.139	(0.157)
Fourth earnings quintile	0.118	(0.153)	-0.444	(0.258)	0.312	(0.339)	0.199	(0.410)	-0.127	(0.198)
Top earnings quintile	-0.250	(0.176)	-0.618	(0.264)	0.539	(0.336)	-0.502	(0.534)	-0.125	(0.207)
Industry: mod density	0.080	(0.127)	-0.210	(0.220)	0.445	(0.249)	0.284	(0.280)	0.152	(0.150)
Industry: high density	-0.236	(0.117)	-0.858	(0.220)	-0.218	(0.255)	-0.122	(0.259)	-0.116	(0.140)
Small organisation	-0.178	(0.100)	-0.941	(0.209)	0.955	(0.199)	-0.316	(0.220)	0.286	(0.114)
Intercept	-0.536	(0.229)	-1.488	(0.388)	-3.737	(0.561)	-4.506	(0.704)	-2.752	(0.321)
SD random effects	0.989	(0.107)	1.248	(0.363)	1.751	(0.312)	1.523	(0.935)	0.951	(0.439)
Correlations*	Fixed	Self	Un	NILF						
Permanent by	-0.51	-0.22	-0.04	-0.39						
Fixed-term by		0.86	0.23	0.88						
Self-emp by			-0.16	0.77						
Unemp by				0.03						
No. observations†	4,725									
No. 'groups'‡	2,192									
Log likelihood	-5710									
LR chi-squared	5512									
McFadden Pseudo $R^2\star$	0.33									

Notes: Random intercept multinomial logit model with estimation by maximum simulated likelihood (MSL) estimation using 250 Halton draws.

SD random effects = standard deviation of the random effects.

∗ correlations of the random intercepts.

† 'occasions', that is, individuals by years. ‡ separate individuals.

⋆ See note to Table 1.

Omitted categories: Aged 40–44; Married/defacto; No children 0–4 years old; Year 12; Born in Australia; No long-term health condition; Full-time hours; Middle earnings quintile; Industry: low density; Large organisation.

Source: HILDA Release 9.

Population: Female casuals aged 15 to 64, excluding full-time students.

Table 3: Model estimates and standard errors (in parentheses) for male fixed-term

	Outcome in following year (base: fixed-term)									
Variable	Casual		Permanent		Self-employed		Unemployed		NILF	
Aged 15-24	0.547	(0.863)	-0.175	(0.417)	-1.238	(0.850)	-0.106	(1.362)	3.461	(11.644)
Aged 25-29	1.022	(0.740)	0.520	(0.376)	-0.479	(0.755)	1.159	(1.273)	11.706	(11.895)
Aged 30-34	-0.489	(0.691)	0.321	(0.324)	-0.130	(0.609)	0.716	(1.278)	11.428	(12.514)
Aged 35-39	-0.169	(0.593)	0.601	(0.293)	0.480	(0.512)	1.706	(1.172)	3.050	(8.888)
Aged 45-49	-1.207	(0.779)	0.320	(0.299)	-0.113	(0.562)	2.386	(1.189)	5.038	(9.329)
Aged 50-54	-0.592	(0.739)	-0.291	(0.355)	-1.130	(0.757)	1.293	(1.393)	27.115	(22.325)
Aged 55-59	-0.933	(0.904)	-0.334	(0.421)	-0.411	(0.819)	1.061	(1.634)	49.166	(37.844)
Aged 60-64	-2.002	(1.233)	-0.821	(0.596)	-1.041	(1.113)	1.759	(1.855)	42.284	(36.055)
Degree or above	-0.012	(0.538)	-1.045	(0.262)	-0.162	(0.561)	-1.032	(0.736)	-16.570	(14.737)
Adv dip/diploma	0.823	(0.675)	-0.383	(0.336)	0.420	(0.677)	0.097	(0.907)	15.910	(12.901)
Cert III/IV	0.679	(0.509)	0.011	(0.254)	0.130	(0.538)	0.051	(0.672)	-0.880	(4.971)
Cert I/II, Year 11 <	1.495	(0.530)	0.002	(0.281)	0.486	(0.575)	-0.080	(0.788)	20.039	(11.621)
Years in paid employment	0.433	(0.883)	0.050	(0.396)	0.342	(0.782)	-1.313	(0.916)	-9.165	(8.925)
Years of job tenure	-0.125	(0.364)	0.579	(0.168)	-0.010	(0.334)	0.141	(0.521)	-3.604	(4.787)
Long-term health prob	0.549	(0.378)	0.079	(0.208)	0.842	(0.375)	0.800	(0.549)	16.367	(9.079)
SEIFA of local area	-0.395	(0.315)	-0.057	(0.163)	0.040	(0.331)	0.305	(0.483)	-9.279	(7.443)
Local unemployment rate	-0.285	(0.293)	-0.198	(0.145)	0.271	(0.294)	0.068	(0.445)	2.052	(2.379)
Level of social support	0.157	(0.286)	-0.007	(0.143)	-0.623	(0.290)	-0.877	(0.386)	-12.220	(6.561)
Learn new skills in job	-0.178	(0.297)	-0.133	(0.160)	-0.401	(0.309)	-0.164	(0.489)	-1.874	(3.132)
Part-time hours	1.887	(0.452)	-0.506	(0.294)	1.434	(0.473)	1.740	(0.649)	3.862	(3.165)
Bottom earnings quintile	-0.254	(0.482)	-0.297	(0.278)	0.908	(0.598)	0.268	(0.816)	11.271	(7.196)
Second earnings quintile	-0.563	(0.467)	0.037	(0.242)	0.737	(0.542)	0.372	(0.684)	-14.937	(10.465)
Fourth earnings quintile	-0.688	(0.469)	-0.000	(0.221)	0.370	(0.546)	-0.343	(0.722)	6.308	(6.344)
Top earnings quintile	-0.499	(0.426)	-0.331	(0.219)	0.729	(0.515)	-0.333	(0.673)	12.452	(11.098)
Industry: mod density	0.123	(0.385)	-0.467	(0.191)	-0.463	(0.378)	-0.201	(0.528)	7.385	(6.064)
Industry: high density	0.266	(0.439)	-0.402	(0.220)	-1.274	(0.517)	-0.434	(0.655)	3.809	(8.927)
Small organisation	0.991	(0.364)	0.257	(0.213)	1.139	(0.365)	-1.656	(1.081)	-6.018	(5.645)
Intercept	-3.410	(1.017)	1.182	(0.365)	-3.148	(0.962)	-4.495	(1.587)	-106.572	(66.904)
SD random effects	1.269	(0.506)	1.301	(0.144)	1.448	(0.652)	1.647	(0.861)	41.451	(20.460)
Correlations*	Perm	Self	Un	NILF						
Casual by	-0.07	0.52	0.80	-0.01						
Permanent by		-0.20	-0.38	0.32						
Self-emp by			0.09	-0.67						
Unemp by				0.12						
No. observations†	1,849									
No. 'groups'‡	1,104									
Log likelihood	-1891									
LR chi-squared	2843									
McFadden Pseudo $R^2\star$	0.43									

Notes: Random intercept multinomial logit model with estimation by maximum simulated likelihood (MSL) estimation using 250 Halton draws.

SD random effects = standard deviation of the random effects.

$*$ correlations of the random intercepts.

† 'occasions', that is, individuals by years. ‡ separate individuals.

$\star$ See note to Table 1.

Omitted categories: Aged 40–44; Year 12; No long-term health condition; Full-time hours; Middle earnings quintile; Industry: low density; Large organisation.

Source: HILDA Release 9.

Population: Male fixed-term employees aged 15 to 64, excluding full-time students.

Table 4: Model estimates and standard errors (in parentheses) for female fixed-term

Variable	Casual		Permanent		Self-employed		Unemployed		NILF	
	Outcome in following year (base: fixed-term)									
Aged 15-24	1.312	(0.595)	0.937	(0.367)	-0.619	(0.998)	3.122	(1.263)	1.024	(0.661)
Aged 25-29	1.035	(0.525)	0.284	(0.314)	-0.667	(0.810)	0.257	(1.523)	0.695	(0.555)
Aged 30-34	-0.335	(0.575)	0.022	(0.293)	-0.525	(0.761)	1.964	(1.206)	0.956	(0.501)
Aged 35-39	0.048	(0.459)	0.257	(0.250)	-0.727	(0.714)	1.043	(1.267)	0.645	(0.462)
Aged 45-49	0.706	(0.410)	-0.182	(0.245)	0.298	(0.632)	1.666	(1.147)	0.195	(0.492)
Aged 50-54	0.196	(0.508)	-0.622	(0.303)	-0.300	(0.784)	2.278	(1.160)	0.248	(0.557)
Aged 55-59	0.516	(0.641)	-0.221	(0.392)	1.289	(0.857)	2.544	(1.326)	0.864	(0.682)
Aged 60-64	2.020	(0.831)	0.217	(0.588)	1.598	(1.268)	2.805	(1.675)	1.771	(0.858)
Sep/div/widowed	0.309	(0.356)	0.080	(0.221)	-1.048	(0.667)	1.076	(0.529)	-0.037	(0.388)
Never married	0.662	(0.335)	0.081	(0.203)	-1.309	(0.669)	-0.059	(0.538)	-0.899	(0.428)
One child 0-4 years old	-0.727	(0.555)	0.390	(0.272)	1.617	(0.617)	0.207	(0.829)	0.776	(0.394)
Two or more child 0-4	-49.855	(0.000)	0.446	(0.465)	-0.228	(1.292)	0.780	(1.246)	1.178	(0.601)
Degree or above	-0.362	(0.410)	-0.491	(0.246)	-0.079	(0.646)	-0.487	(0.614)	-0.365	(0.423)
Adv dip/diploma	0.419	(0.496)	-0.056	(0.312)	0.427	(0.755)	0.335	(0.740)	-0.015	(0.539)
Cert III/IV	0.045	(0.459)	-0.152	(0.283)	0.092	(0.725)	-0.133	(0.633)	-0.547	(0.527)
Cert I/II, Year 11 <	0.195	(0.451)	-0.166	(0.280)	-0.408	(0.727)	-0.470	(0.664)	0.339	(0.455)
Born ESB	-0.419	(0.410)	-0.333	(0.240)	-1.121	(0.686)	-0.343	(0.638)	-0.224	(0.401)
Born NESB	0.247	(0.467)	0.324	(0.285)	0.212	(0.623)	-0.775	(1.087)	0.524	(0.449)
Years in paid employment	-0.211	(0.464)	0.109	(0.290)	-0.501	(0.637)	-0.378	(0.716)	-0.517	(0.466)
Years of job tenure	-0.067	(0.267)	0.435	(0.161)	-0.189	(0.494)	-0.710	(0.620)	0.146	(0.287)
Long-term health prob	0.424	(0.295)	0.182	(0.192)	-0.422	(0.600)	0.409	(0.469)	0.794	(0.310)
SEIFA of local area	-0.399	(0.252)	-0.002	(0.155)	0.211	(0.408)	0.096	(0.430)	-0.032	(0.265)
Local unemployment rate	0.139	(0.251)	-0.415	(0.145)	-0.257	(0.399)	-0.533	(0.409)	-0.430	(0.260)
Level of social support	-0.350	(0.212)	-0.015	(0.137)	-0.746	(0.322)	-0.150	(0.348)	0.034	(0.254)
Learn new skills in job	-0.061	(0.246)	-0.248	(0.147)	-1.102	(0.374)	0.211	(0.412)	-0.486	(0.249)
Part-time hours	1.136	(0.273)	-0.203	(0.161)	-0.120	(0.414)	0.383	(0.420)	0.378	(0.270)
Bottom earnings quintile	0.205	(0.397)	0.281	(0.252)	0.616	(0.665)	1.749	(0.711)	0.320	(0.479)
Second earnings quintile	0.028	(0.343)	0.570	(0.198)	0.486	(0.620)	1.438	(0.666)	0.479	(0.381)
Fourth earnings quintile	-0.111	(0.329)	-0.062	(0.185)	0.226	(0.614)	0.994	(0.667)	0.425	(0.353)
Top earnings quintile	0.433	(0.362)	-0.082	(0.216)	1.348	(0.567)	0.987	(0.747)	0.613	(0.378)
Industry: mod density	-0.020	(0.331)	0.093	(0.200)	-0.308	(0.482)	-0.273	(0.477)	0.049	(0.361)
Industry: high density	-0.100	(0.350)	-0.682	(0.211)	-1.357	(0.556)	-1.342	(0.564)	-0.291	(0.368)
Small organisation	0.609	(0.320)	-0.135	(0.209)	1.628	(0.424)	-0.786	(0.617)	-0.381	(0.389)
Intercept	-3.313	(0.780)	0.875	(0.344)	-3.147	(1.058)	-5.623	(1.444)	-2.996	(0.699)
SD random effects	1.604	(0.358)	1.322	(0.274)	2.156	(0.512)	1.234	(0.572)	1.209	(0.372)
Correlations*	Perm	Self	Un	NILF						
Casual by	-0.33	0.17	0.62	0.52						
Permanent by		0.86	0.52	0.63						
Self-emp by			0.87	0.93						
Unemp by				0.99						
No. observations†	2,008									
No. 'groups'‡	1,205									
Log likelihood	-2297									
LR chi-squared	2885									
McFadden Pseudo $R^2\star$	0.39									

Notes: Random intercept multinomial logit model with estimation by maximum simulated likelihood (MSL) estimation using 250 Halton draws.

SD random effects = standard deviation of the random effects.

∗ correlations of the random intercepts.

† 'occasions', that is, individuals by years. ‡ separate individuals.

⋆ See note to Table 1.

Omitted categories: Aged 40–44; Married/defacto; No children 0–4 years old; Year 12; Born in Australia; No long-term health condition; Full-time hours; Middle earnings quintile; Industry: low density; Large organisation.

Source: HILDA Release 9.

Population: Female fixed-term employees aged 15 to 64, excluding full-time students.

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