AUSTRALIAN JOURNAL OF LABOUR ECONOMICS
Volume 11 • Number 1 • 2008 • pp 71 - 96

Low Paid Jobs and Unemployment: Churning in the Australian Labour Market, 2001 to 2006

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Abstract

This article explores the links between low pay, unemployment and labour market churning over the period 2001 to 2006. The issue of churning is explored through analysis of the HILDA calendar data, in which job starts and job terminations are modelled using multinomial logit regressions. The results are further explored using multilevel binomial logit models. Predicted probabilities of moving from job to job, from unemployment into jobs, and from jobs into unemployment, are calculated and these show that low paid, low skilled workers are highly vulnerable to labour market churning. Certain demographic groups, particularly migrants from particular regions, are also shown to be vulnerable. The results reinforce the importance of labour market policies which prioritise job continuity, skills development and earnings improvement rather than simply focusing on job attainment.

1. Introduction

The literature dealing with low paid workers in Australia generally divides into those studies examining the characteristics of the low paid workforce in more general terms (Buchanan and Watson, 1997; Eardley, 1998; Richardson and Harding, 1998; Healy and Richardson, 2006; Masterman-Smith and Pocock, 2008) and those which also focus on the links between low pay and unemployment (Richardson and Harding, 1999; Borland and Woodbridge, 1999; Watson, 2002; Scutella and Ellis, 2007; Perkins and Scutella, 2008).[1] These latter studies overlap considerably with another tradition of research which has focussed on the labour market transitions of the unemployed, particularly their duration of unemployment and their success or otherwise in entering

[1] This article 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.

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Thanks to two anonymous referees for many useful suggestions. Thanks also to Paul Wray for assistance with some C programming and to Frank Harrell for statistical advice.

and retaining employment. Not surprisingly, studies such as these have exploited the potential of longitudinal data sets, the two most notable being the ABS Survey of Employment and Unemployment Patterns (SEUP) conducted in the mid-1990s (see, for example, Dunlop (2001); Le and Miller (1999); ABS (6286.0)) and the HILDA survey, which began in 2001 (see, for example, Dockery (2003); Carroll (2005); Black and Borland (2005)).

Labour market churning—where individuals cycle between unemployment and employment—has been well documented in these studies, and some evidence of a 'no pay low pay' cycle has also been found. In the mid-1990s, for example, when the Australian labour market was characterised by high levels of unemployment and sluggish employment growth, the SEUP data showed considerable churning. Over an 18 month period, some 70 per cent of the respondents who made up the 'Jobseeker' cohort in that data did manage to find work, but 90 per cent of these jobs were temporary (ABS, 6286.0, pp. 4–5). The links between churning and low paid work were also evident in these data, as Dunlop (2001) showed. By the early 2000s, in the context of a much-improved labour market, the persistence of a 'no pay low pay' cycle was still evident in the Australia labour market (Perkins and Scutella, 2008).

These Australian results have mirrored those found overseas, particularly in Britain. Stewart and Swaffield (1999, p. 40), for example, found that:

> As well as the low paid being more likely to move into non-employment, those entering employment from a spell outside are more likely to be low paid, and those who had been low paid prior to the spell of non-employment are even more likely than other entrants to be low paid again when they subsequently move back into work. There is thus evidence of a cycle of low pay and no pay.

This article is a contribution to the literature on labour market churning, with a focus on the links between low pay and unemployment. Whereas authors like Black and Borland (2005), Scutella and Ellis (2007) and Perkins and Scutella (2008) pursue this theme using a discrete time framework—in which transitions between annual states are compared— this article makes use of calendar data to analyse the continuous period from 2001 to 2006. In this respect, the analysis resembles Carroll (2005), who used the HILDA calendar data to model the duration of unemployment. However, where Carroll focussed on the unemployment episodes in the calendar data, this article analyses the employment episodes, and examines the labour market states which preceded and followed these jobs. While it would be ideal to use job duration data within a continuous time framework, this approach is not feasible at present with the HILDA data because we do not have adequate information on the duration of all jobs in the calendar. So the approach taken here represents a compromise. The unit of analysis is an employment 'episode', a unique extract from the monthly calendar data where a job is either preceded or followed by a change, for example, from unemployment into a job, or from one job into another. These employment episodes are 'clustered' within individuals and it is the characteristics of these individuals which are employed in the analysis of these episodes. The implications of the hierarchical structure of this data will be discussed shortly.

In the first part of the paper multinomial logit regression models are fit to these employment episodes, with the explanatory variables based on the various demographic and labour market characteristics of the respondents who undertook these jobs. Data on all of the employment episodes in the calendar—such as the level of earnings, the hours of work or the duration of the job—is not available in the HILDA data unless the episode matches the job held in the annual interview, but this match is not something one can be sure about.[2]

What becomes clear from the multinomial logit analysis is that certain groups have much higher predicted probabilities of entering their jobs from unemployment and leaving their jobs to enter unemployment. This analysis treats these episodes as independent, and so we do not acknowledge whether the repeated entries and re-entries into jobs which are captured in these data are happening to the same individuals. These multinomial models ignore this dependence, but the use of bootstrapping for the standard errors partly addresses the violation of the *idd* assumption.

In the second part of the paper I move beyond this assumption of independence and explicitly model the hierarchical structure of the data, namely, the fact that these episodes are clustered within individuals. By using a multilevel modelling framework, I take account of the fact that these repeated entries and re-entries into jobs are happening more often to certain individuals, than to others. This can make a considerable difference to the model estimates, and as will be shown below, these differences emphasise the concentrated nature of labour market disadvantage. By comparing conventional logistic regression models with comparable multilevel models, the extent of these differences are quantified.[3]

2. Data and Approach

The individuals observed in this analysis are a subset of all individuals in the HILDA dataset. In terms of age, the analysis is restricted to all persons aged between 21 and 65 in 2001. From a methodological point of view, the restriction which really matters are those individuals who never entered employment during this 6 year period, as well as those individuals who remained in the same job over the whole period. These groups are outside the analysis because the definition of an employment episode used in this analysis excludes them. As noted earlier, to be defined as an 'episode' requires respondents to report a change in their labour market circumstances and for this to be documented in the calendar data. In summary, in the data used for the analysis of labour market states preceding a job there are 6,018 episodes among 1,852 males, and 6,437 episodes among 2,197 females. In the case of labour markets states following a job, there are 6,095 episodes among 1,967 males, and 6,300 episodes among 2,240 females. This sample of respondents is much reduced from the full HILDA sample of

[2] At present, the absence of unique job identifiers means that one cannot reliably link the calendar data jobs with the job held at the time of the annual interview.

[3] As well as the hierarchical structure of the calendar data, the HILDA data also has additional complexity because of its sample design. Sample selection was based on households, such that some of the individuals observed in this dataset are living in the same households. Consequently, another violation of the *iid* assumption is introduced because of this clustering. In this article, this added layer of complexity is ignored, though multilevel modelling certainly makes it feasible to explore 'household effects' on labour market outcomes. Complications arise because of the changing composition of households across waves.

adult respondents with a connection to the labour market (which often numbers between 6,000 and 7,000 depending on various assumptions.) As a consequence, the regression analysis needs to deal with sample selection bias, since it is possible that the same factors which influence who comes under observation also influence the outcome under scrutiny. The potential problems of sample selection bias are dealt with using a conventional two-stage Heckman approach which estimates a probit model to derive a 'correction term' which is then entered into the subsequent models in the main part of the analysis (Cameron and Trivedi, 2005, p. 550). In this probit model, a number of household and demographic characteristics are used to estimate the probability of an individual being selected into the sample. An inverse of the Mills' ratio is derived, and this correction term is then introduced at the multinomial modelling stage and in the multilevel modelling.[4]

The second major methodological challenge is the hierarchical structure of the employment episodes, clustered as they are within individual respondents. In this article, this challenge is dealt with in two ways. In the case of the multinomial models, the standard errors are derived using bootstrapping, a long-standing method for dealing with models which violate distributional assumptions (Davison and Hinkley, 1997). While this is a useful strategy, a multilevel modelling approach is superior. The details of the multilevel models are discussed more fully below, but by way of a brief introduction, it is helpful to see multilevel modelling as a kind of 'partial pooling' of longitudinal data. In this respect, it avoids the pitfalls of *complete pooling*—which would lead us to ignore differences between individuals and suppress variation in the data—and, on the other hand, *no pooling* with its problems of unreliable estimates Gelman and Hill (2007, pp. 7, 256). The multinomial models in the first part of the article entail complete pooling, and as we shall see, they fail to capture the full extent of the variation in the data.

The jobs discussed in the annual interviews are only a subset of all the jobs in the calendar. This makes it difficult to assign work-related characteristics to all of these jobs. Lifetime stable demographic characteristics—such as age, gender and birthplace—can be mapped successfully onto all jobs; annually-stable characteristics—such as educational qualifications and geographical location—also map reasonably well. But job-specific characteristics—such as earnings and occupation— are somewhat more difficult. It is a reasonable assumption, however, that for most individuals the occupations held in any one year have skill levels in common, so assigning an annual average skill-score to every job held by them in that year is a viable strategy.[5] The same strategy can be applied to earnings quintiles, but with more caution. While somewhere between 40 per cent 60 per cent of all workers stay in the same quintile between annual interviews, the remainder do change at some point during the year. Assigning an average quintile-score to all jobs held in that year is thus less satisfactory than is the case for occupation. Nevertheless, without this strategy there is no way of exploring the unemployment-low pay nexus within this framework. The reassuring observation that between 60 and 70 per cent of all workers stay within the same two

[4] The probit results are not shown, but details are available from the author.

[5] Equating occupation with a skill-score is feasible with ASCO Major Group level data, because at this level the codes are skill-based. For reasons of clarity, the ASCO coding has been reversed for this score, so that a low number equates to a low level of skill.

quintiles between annual interviews makes it more likely that the final results, when compared across several quintiles rather than just adjacent quintiles, are reasonably sound. For this reason, the modelling reported below makes the middle quintile the reference category, and interest focusses on the results for the lowest quintile.[6]

In the first part of the analysis I fit multinomial logit models to the four labour market states which preceded job starts and those which followed job terminations.[7] These labour market states are three mutually exclusive categories: not in the labour force (NILF), unemployment and employment; and one category which can overlap with these: education.[8] This overlap is resolved in a particular fashion, such that someone employed and in education is defined as employed, someone unemployed and in education is defined as unemployed, and someone NILF and in education is defined as in education.[9]

Separate male and female models are fit, and the independent variables include demographic measures, specifically: age, education, birthplace, English language ability, indigenous status, geographical location, health status, marital status and number of dependent children. The other main variables are the skills and earnings measures mentioned above and the year in which the job started (or ended). Interactions in the model included marital status by number of dependent children and birthplace by English language ability. Finally, age is entered into the model as a quadratic (age plus age squared). This range of variables represents a combination of demographic and labour market variables which are known to be influential in determining labour market outcomes, as well as some additional variables for which the HILDA dataset is well suited (such as detailed geographical area and health status).

In the second part of the analysis, I adopt a multilevel modelling approach as a way of dealing with the hierarchical structure of the job episode data, that is, the clustering of episodes within individuals. Multilevel models have been used in educational research for a long time, as they lend themselves to the analysis of hierarchical data where students are clustered in classes which are clustered in schools (Goldstein, 1994). Not only is the complexity of the correlated error terms addressed by such models, but useful insights are provided into the amount of variation in the outcome which is due to individuals, and that which is due to the classes or the schools. Within disciplines where repeated measures data is common, such as experimental studies, multilevel models are also commonly employed. In this paper these employment episodes can be regarded as a kind of repeated measures data (Rabe-

[6] For a small number of individuals, their interviews never overlapped with holding a job, so these individuals were given imputed values for these two variables. In the case of skill, it was the ASCO average for all individuals. In the case of earnings, it was the quintile into which their household gross income fell.
[7] All of the analysis in this article was conducted using the R statistical language, see R Development Core Team (2008). The bootstrapping of standard errors made use of functions developed by Davison and Hinkley (1997) and converted to R by Angelo Canty. The multinomial logit models used the *multinom* function, part of the *net* package by Venables and Ripley (2002).
[8] Technically, education is not a 'labour market' state, but within this framework it counts as one. The main issue is the predominant activity of an individual, spread across a spectrum from employment through to NILF. Engaged in education is closer to employment than NILF, but less so than unemployment.
[9] The HILDA data records full-time and part-time educational activity, but the small numbers involved in the latter within this approach makes collapsing this distinction more fruitful for analysis.

Hesketh and Skrondal, 2005; Pinheiro and Bates, 2004), though I do not extend the analysis into the partitioning of the variance. My main concern is to use multilevel modelling to gauge the extent to which the multinomial coefficients might be misleading.[10]

When it comes to the actual task of modelling, multilevel models are able to use both random intercept and random coefficient specifications. For this reason, these models are commonly referred to as 'mixed effects' models, to distinguish them from the well-known 'random effects' and 'fixed effects' models. Some authors, such as Gelman and Hill (2007, p. 245) avoid the terminology of 'random' and 'fixed', arguing that their usage has become too complicated and inconsistent. Instead, they prefer the terminology of 'varying intercept' and 'varying coefficients'. In the case of the former (which is the specification employed in this paper), the intercepts are allowed to vary for each individual. This is analogous to a no-pooling estimation strategy, in which separate or 'local' regressions are fitted for each individual, but with the estimates augmented with additional information gained from a complete pooling estimation. In this way, a 'partial' pooling of the data, mentioned above, is conducted; the final estimates reflect the benefits of each estimation strategy while avoiding their weaknesses. In the repeated measures context, a random intercept can be regarded as representing the 'combined effect of all omitted subject-specific (time-constant) covariates' which might cause some subjects to be more prone to the outcome under scrutiny (Rabe-Hesketh and Skrondal, 2005, p. 116).

In practice, what this means in this paper is reading the coefficients in a mixed-effects model and contrasting them with an approach which uses only complete pooling. Because the latter ignores the hierarchical structure of the data, and the fact that many of these episodes are repeated for some individuals, the effect of many explanatory variables is downplayed. Further details of such comparisons will be discussed below, in the results section.

In summary, the second part of the analysis is intended as a corrective to the first part, a way of establishing whether the patterns discerned in the multinomial modelling are stronger or weaker once the hierarchical structure of the longitudinal HILDA data is acknowledged. For reasons of computational complexity, the mixed-effects models are not multinomial, but rather binomial. This means that the *direct* comparison is between a conventional logistic regression model and a mixed- effects logistic regression. Consequently, the multinomial outcomes are collapsed to a binomial outcome: whether the preceding (or following) episode was a job or a non-job. The actual estimation for the logistic regressions is done using a generalised linear model (GLM), within a mixed-effects framework. GLMs have become a standard way of fitting a large range of models (Hardin and Hilbe, 2001), and logistic regressions (such as those used here) are carried out by adopting a binomial distribution with a logit link.[11] As noted above, the intercepts are allowed to vary (a 'random' intercepts specification) and the 'fixed' effects are essentially the same as those used in the multinomial modelling (with the omission of one of the interactions).

[10] For this reason, the modelling results in the appendix do not display the random intercept findings, but rather, display the equivalent fixed effects coefficients alongside those of conventional logistic regression models.

[11] The mixed effects models were fit using the *lmer* function in the *Matrix* package (Bates and Maechler, 2008).

3. Results

Multinomial Models

The detailed results of the multinomial modelling are shown in the appendix in tables A1 and A2. It is worth keeping in mind that the coefficients in those tables refer to the unit of analysis, that is, job starts and job terminations. In the discussion which follows I extrapolate from jobs to individuals and I offer interpretations of the results which move between these levels. I do this by means of predicted probabilities. This not only makes the discussion more accessible, but it allows me to incorporate the characteristics of the individuals who held these jobs into the discussion of the labour market patterns which attach to these jobs. In other words, while the modelling shows what labour market states preceded the current job (or followed it), the discussion below talks about individuals moving between jobs and unemployment, and so forth. These predicted probabilities are presented in tables 1 and 2 and are based on various values being 'plugged' into the equations which result from the models shown in the appendix. In what follows, the values for the variable of interest are allowed to vary, while the values for all other variables are set to their median or modal value. While the choice of values (for example, Melbourne rather than Sydney, for geographical area) clearly determine the absolute size of the prediction, the important issue for discussion is the relative change in the variable of interest. For example, how does the predicted probability of being in unemployment prior to starting a job change when comparing someone with a tertiary qualification to someone who has only completed Year 12?

The core theme in this article is the connection between low paid work and unemployment, so the results for earnings quintiles are of particular interest. Table 1 shows that for men, the predicted probability of being in unemployment prior to a job rose from 29 per cent in the middle quintile to 42 per cent in the bottom quintile. For women, the rise was from 22 per cent to 29 per cent. Turning to exits from employment, table 2 shows that among men, the predicted probability of exiting into unemployment was 27 per cent for those in the middle quintile and 38 per cent for those in the bottom quintile. For women, the figures show a rise from 21 per cent to 29 per cent as one moved from the middle to the bottom quintile.

Table 1 - Predicted Probabilities for Labour Market States Preceding Current Job (%)

	Males				*Females*			
	NILF	*Educ*	*U/E*	*Employ*	*NILF*	*Educ*	*U/E*	*Employ*
Unconditional	*12.9*	*2.9*	*20.1*	*64.1*	*21.6*	*4.5*	*19.3*	*54.6*
Earning quintiles								
Bottom	9.6	0.8	42.0	47.6	10.1	2.8	29.3	57.8
Second	8.9	0.3	33.2	57.6	8.0	1.8	25.1	65.0
Middle	8.0	0.4	28.7	62.9	7.4	1.8	21.5	69.3
Fourth	8.3	0.2	26.4	65.0	10.2	1.9	19.3	68.6
Top	10.3	0.2	22.3	67.2	13.1	1.1	15.2	70.5

Table 1 (continued) - Predicted Probabilities for Labour Market States Preceding Current Job (%)

	Males				*Females*			
	NILF	*Educ*	*U/E*	*Employ*	*NILF*	*Educ*	*U/E*	*Employ*
Unconditional	*12.9*	*2.9*	*20.1*	*64.1*	*21.6*	*4.5*	*19.3*	*54.6*
Skill levels								
Low	7.4	0.5	37.5	54.6	10.3	1.1	33.2	55.4
Level 2	7.5	0.5	35.3	56.6	9.6	1.3	30.2	58.9
Level 3	7.7	0.5	33.2	58.6	8.9	1.4	27.4	62.3
Level 4	7.8	0.4	31.2	60.6	8.2	1.6	24.6	65.5
Level 5	8.0	0.4	29.2	62.5	7.6	1.7	22.1	68.6
Level 6	8.1	0.4	27.3	64.3	6.9	1.9	19.7	71.5
Level 7	8.2	0.4	25.4	66.0	6.3	2.1	17.5	74.1
Level 8	8.3	0.3	23.7	67.7	5.7	2.3	15.4	76.5
High	8.3	0.3	22.0	69.3	5.2	2.5	13.6	78.7
Educational quals								
Degree or above	8.7	3.6	28.3	59.4	8.9	4.6	23.2	63.3
Adv diploma,	5.9	3.3	30.9	59.9	8.7	4.1	17.8	69.4
Certificate	7.8	1.5	25.9	64.8	6.5	3.2	19.0	71.3
Year 12	5.7	2.2	25.4	66.7	6.6	4.3	18.3	70.7
Year 11 and below	8.0	0.4	28.7	62.9	7.4	1.8	21.5	69.3
Indigenous								
Yes	12.2	0.6	24.9	62.3	11.4	3.2	22.7	62.7
No	8.0	0.4	28.8	62.8	7.4	1.8	21.6	69.2
Birthplace								
Australia	8.0	0.4	28.7	62.9	7.4	1.8	21.5	69.3
ESB countries	9.6	0.5	30.9	59.0	7.8	2.1	18.0	72.1
Pacific	6.5	0.4	25.5	67.6	3.3	0.0	13.5	83.2
Northern Europe	5.6	2.2	25.2	67.0	6.9	2.2	17.1	73.8
Southern Europe	8.2	0.4	21.3	70.0	5.5	2.2	22.9	69.3
Eastern Europe	1.2	0.6	43.6	54.5	4.8	0.0	52.7	42.5
Middle East	4.5	0.2	48.0	47.2	3.3	0.9	30.0	65.8
South East Asia	5.5	0.6	30.9	63.0	4.5	2.5	23.6	69.4
North Asia	4.3	0.3	40.4	55.0	4.8	4.6	20.4	70.2
South-Central Asia	12.7	0.5	32.0	54.7	6.9	0.0	14.5	78.6
Latin America	3.9	0.0	43.9	52.1	2.6	2.2	13.8	81.4
Africa	7.6	1.6	47.4	43.4	4.6	0.0	21.1	74.3

Notes: Predicted probabilities from a multinomial logit model with the four labour market states as the dependent variable. A subset of independent variables are shown in the rows. Predicted probabilities are calculated with variable of interest allowed to vary while other variables are set at median or modal values. NILF stands for Not in the Labour Force. Data unweighted.
Source: HILDA Release 6.
Population: All job starts between 2001 and 2006, male n = 6,018, female n = 6,437.

Table 2 - Predicted Probabilities for Labour Market States Following Current Job (%)

	Males				Females			
	NILF	*Educ*	*U/E*	*Employ*	*NILF*	*Educ*	*U/E*	*Employ*
Unconditional	*17.9*	*3.2*	*17.6*	*61.7*	*29.3*	*4.7*	*13.8*	*52.3*
Earning quintiles								
Bottom	14.0	0.9	38.4	46.7	9.8	3.0	28.8	58.4
Second	11.9	0.4	32.9	54.7	9.9	2.2	26.4	61.5
Middle	11.6	0.5	26.8	61.1	9.0	2.1	21.3	67.6
Fourth	12.7	0.4	24.6	62.3	11.7	1.5	19.0	67.9
Top	15.4	0.3	24.1	60.2	14.4	1.1	14.0	70.5
Skill levels								
Low	10.5	0.6	34.2	54.6	12.5	1.4	29.5	56.7
Level 2	10.8	0.6	32.4	56.2	11.6	1.5	27.5	59.4
Level 3	11.1	0.6	30.6	57.8	10.8	1.7	25.5	62.0
Level 4	11.3	0.5	28.9	59.3	10.0	1.9	23.6	64.6
Level 5	11.6	0.5	27.2	60.7	9.2	2.1	21.7	67.0
Level 6	11.8	0.5	25.6	62.1	8.5	2.3	20.0	69.3
Level 7	12.0	0.5	24.1	63.5	7.8	2.5	18.3	71.5
Level 8	12.2	0.4	22.6	64.8	7.1	2.7	16.7	73.5
High	12.4	0.4	21.2	66.0	6.5	2.9	15.2	75.4
Educational quals								
Degree or above	10.1	4.0	22.7	63.2	9.3	5.6	20.6	64.5
Adv diploma,	8.4	3.1	28.8	59.7	10.2	4.1	14.2	71.5
Certificate	11.5	1.4	23.5	63.5	6.7	2.8	14.4	76.2
Year 12	8.9	2.9	21.4	66.7	7.9	4.1	17.1	70.8
Year 11 and below	11.6	0.5	26.8	61.1	9.0	2.1	21.3	67.6
Indigenous								
Yes	14.0	0.2	31.4	54.3	12.3	4.5	29.0	54.2
No	11.6	0.5	26.9	61.0	9.1	2.1	21.4	67.5
Birthplace								
Australia	11.6	0.5	26.8	61.1	9.0	2.1	21.3	67.6
ESB countries	12.7	0.6	27.6	59.1	7.8	1.8	18.4	72.0
Pacific	7.6	0.5	24.0	68.0	2.4	0.0	19.9	77.7
Northern Europe	10.9	2.5	20.0	66.6	6.9	3.2	18.8	71.2
Southern Europe	7.3	1.3	19.2	72.2	7.2	1.0	33.4	58.3
Eastern Europe	3.9	0.9	34.9	60.3	5.8	2.6	58.3	33.3
Middle East	9.8	1.0	31.9	57.4	8.0	2.6	14.0	75.5
South East Asia	14.5	0.4	21.1	64.0	8.7	2.3	21.0	68.0
North Asia	11.5	0.6	35.5	52.3	8.4	4.9	12.5	74.1
South-Central Asia	15.1	0.5	37.7	46.6	8.1	1.8	15.6	74.4
Latin America	6.7	0.0	30.4	63.0	7.9	7.4	13.4	71.3
Africa	19.9	0.3	38.4	41.4	5.5	2.7	28.5	63.3

Notes: Predicted probabilities from a multinomial logit model with the four labour market states as the dependent variable. A subset of independent variables are shown in the rows. Predicted probabilities are calculated with variable of interest allowed to vary while other variables are set at median or modal values. NILF stands for Not in the Labour Force. Data unweighted.
Source: HILDA Release 6.
Population: All job terminations between 2001 and 2006, male n = 6,095, female n = 6,300.

Low wage work is strongly associated with low skilled work so we should expect to find similar outcomes when we look at the occupational results. For men the rise in the predicted probability of being unemployed prior to a job as one moves from the middle of the skill range to the lowest skill level was from 29 per cent to 38 per cent. For women the equivalent figures were a rise from 22 per cent to 33 per cent. Job exits show a similar pattern: for men the rise was from 27 per cent to 34 per cent and, for women, a rise from 22 per cent to 30 per cent.

Research suggests that non-English speaking background (NESB) migrants have often been disadvantaged in the labour market (O'Loughlin and Watson, 1997) and the results in tables 1 and 2 reinforce this impression. As table 1 shows, the profile of migrants from English speaking background (ESB) countries differed hardly at all from that of the Australia-born. Yet for some NESB migrants, the differences were stark. Men from the Middle East, for example, had a predicted probability of being in unemployment prior to their job of 48 per cent, a figure some 20 percentage points higher than for the Australia-born. Other male birthplace groups with high levels of relative disadvantage included migrants from Latin America, North Asia and Africa. Among women, migrants from Eastern Europe had a very high predicted probability of entering their jobs from unemployment: 53 per cent. The Australia-born figure was just 22 per cent: a difference of 31 percentage points. The next most disadvantaged group of women were migrants from the Middle East. In terms of exits to unemployment, Eastern European women were again the most disadvantaged, with a predicted probability of 58 per cent.

By way of contrast, men from Northern and Southern Europe had a vulnerability to unemployment which was not very different to those of the Australia-born.[12] Among women, the figures for migrants from the Pacific, Northern Europe, South-Central Asia and Latin America were not dissimilar to those for the Australia-born. This considerable variability in the vulnerability to unemployment among different birthplace groups is symptomatic of the Australian labour market. Research conducted into long-term unemployment in the mid-1990s showed similar variability, with Middle Eastern men also notable for their high levels of unemployment (O'Loughlin and Watson, 1997). The relative improvement in the fortunes of some birthplace groups might reflect the more buoyant labour market conditions of the period since 2001. When it comes to birthplace, it is interesting to note that exits to unemployment show a different pattern to recruitments from unemployment. The figures shown in table 2, for example, are all of smaller magnitude than those shown in table 1. It would appear that the relative disadvantage of some NESB migrant groups, vis-a-vis the Australia-born, has been reduced when it comes to labour market episodes which are subsequent to employment. Overall, the predicted probabilities analysed here suggest that labour market churning is certainly evident at the bottom of the labour market. Those working for low pay, and those with lower skills, appear to be most vulnerable to churning, whilst some of those migrant groups traditionally disadvantaged in the labour market also appear to be vulnerable.

The analysis just discussed concentrated on the net effects of particular

[12] 'Vulnerability' is used here in the sense of 'highly likely to be unemployed prior to or following a job'. It is not equivalent to 'vulnerability' in the broader sense, where some individuals may spend years unemployed without ever gaining entry into jobs.

variables, with all other variables held constant. In this respect, the absolute values of the predicted probabilities were not relevant; rather, the relative changes for the variables of interest were what mattered. However, the absolute values can also provide insights, highlighting to some extent the polarised nature of the Australian labour market and the way in which advantage and disadvantage accumulate for different demographic groups. To illustrate this phenomenon, several 'cameos' are constructed and their predicted probabilities calculated. In the first two cameos, the attributes of two men are contrasted. The first is someone disadvantaged in the labour market: an early school leaver with low skill levels, located in the bottom earnings quintile, single and without children, and aged in their early 50s. This cameo is contrasted with a university graduate, working at a professional level, located in the top earnings quintile, married with two children, and aged in their early 40s. For the women, the first of the contrasting cameos are: an early school leaver with low skill skills, separated from her husband and with two children (ie. a sole parent), in the bottom earnings quintile and aged in her early 30s. This woman is contrasted with: a university graduate, working at a professional level, located in the top earnings quintile, never married, with no children, and aged in her late 20s. In each cameo, all other attributes are set at their modal values.

Table 3 shows the predicted probabilities for these four cameos. For men with the classic set of labour market disadvantages, the predicted probability of having a job prior to the current job was just 39 per cent. They were far more likely to have moved into that job from unemployment (43 per cent) and about half as likely to have moved into that job from the NILF state (17 per cent). By contrast, the man with the favourable set of labour market characteristics was highly likely to have moved from an existing job into their current job, with a predicted probability of 76 per cent. By contrast, other states—such as NILF and unemployment—were very low, at just 10 and 14 per cent respectively.

Table 3 - Cameos of Poor and Good Outcomes, Predicted Probabilities for Labour Market States Preceding the Current Job (%)

	Male		*Female*	
	Poor	*Good*	*Poor*	*Good*
NILF	16.6	9.6	27.2	16.2
Education	1.1	0.7	1.0	4.0
Unemployment	43.0	13.5	46.2	11.4
Employment	39.2	76.2	25.7	68.3

Notes: Predicted probabilities from a multinomial logit model with the four labour market states as the dependent variable. Cameos are described in the text, with those characteristics not mentioned set at modal values. NILF stands for Not in the Labour Force. Data unweighted.
Source: HILDA Release 6
Population: All job starts between 2001 and 2006, male n = 6,018, female n = 6,437.

Among women, the results are also quite striking. Women with labour market disadvantages were more likely to have entered their job from outside the labour market (27 per cent) than was the case for the men. Entry from unemployment, however, was still dominant (at 46 per cent), whilst the probability that this person entered her job from another job was just 26 per cent. By way of contrast, the woman with favourable labour market characteristics had a 68 per cent probability of having been in a job prior to the current one. Her likelihood of having moved from NILF or unemployment into her job was very low (11 and 16 per cent).

In summary, while these cameos are somewhat stark, they are symptomatic of how the labour market works. People whose background characteristics are favoured by the labour market are likely to have a three in four chance of maintaining continuity in their employment experiences. By contrast, those with unfavourable characteristics have just a two in five chance (men) or a one in four chance (women). For people with these kinds of characteristics, labour market churning is the order of the day.

Multilevel Models

The results for the multilevel models are shown in the appendix as tables A3 and A4, the former modelling whether jobs (rather than non-jobs) preceded current jobs and the latter whether jobs (rather than non-jobs) followed current jobs. As noted earlier, this binomial outcome collapses the former set of categories (NILF, education and unemployment) into one category: non-job. The models shown as I and III are for male and female models in which the estimation is carried out by conventional logistic regression (with jobs coded 1, non-jobs coded 0). As with the multinomial modelling, this approach ignores the hierarchical structure in the data and implements a complete pooling of observations. By comparing the coefficients for these models with those from the multilevel logistic models (shown as II and IV), we can assess how much the assumption of complete pooling suppresses variation in the data and provides misleading estimates.

It is clear from tables A3 and A4 that for many of the variables in these models, the multilevel estimates are considerably larger than the conventional estimates. To illustrate this, and to pursue the theme of low pay, the estimates relevant to earnings quintiles have been extracted from the tables in the appendices and are shown below in tables 4 and 5. Looking first at estimates for holding a job prior to the current job, Table 4 shows that the coefficient for jobs in the bottom earnings quintile among males was -0.606 (with the middle quintile as the reference category). This coefficient is considerably below that estimated by the multilevel logistic regression, which puts the figure at -0.821. For the female models, the comparable figures are also considerably apart: the conventional logistic model puts the coefficient at -0.530 and the multi-level model puts it at -0.780. These results can be interpreted as showing that jobs in the bottom quintile were much less likely to have been preceded by a job (compared with a 'non-job') than those jobs located in the middle quintile.

These results are all highly significant, even with the increased standard errors evident for the multilevel models (not shown here, but shown in the appendix tables). Similarly, the results for the second earnings quintile (compared with the middle quintile) also show larger effects when modelled using the multilevel approach. The magnitude of these coefficients, as one would expect, are less than those for the bottom quintile, though the results are still statistically significant. On the other hand, in the case of the two upper quintiles, their differences from the middle quintile are positive and not statistically significant. There is one exception to this, which is something of an anomaly. For females in the top two quintiles, the coefficients are negative, though the results are small in magnitude and not statistically significant.

Table 4 - Comparison of Conventional and Multilevel Models: Logit Estimates for Earnings Categories (being in a job prior to current job)

	Males				*Females*			
	Conventional		*Multilevel*		*Conventional*		*Multilevel*	
Earnings quintiles	*Coef*	*Pr*	*Coef*	*Pr*	*Coef*	*Pr*	*Coef*	*Pr*
Bottom	-0.606	0.000	-0.821	0.000	-0.530	0.000	-0.780	0.000
Second	-0.178	0.024	-0.306	0.021	-0.180	0.012	-0.260	0.015
Fourth	0.117	0.190	0.123	0.394	-0.130	0.118	-0.120	0.339
Top	0.136	0.147	0.228	0.133	-0.130	0.232	-0.170	0.251

Notes: Coefficients and p-values from models shown in appendix in table A3. Note that middle earnings quintile is the reference category.

Table 5 - Comparison of Conventional and Multilevel Models: Logit Estimates for Earnings Categories (being in a job subsequent to current job)

	Males				*Females*			
	Conventional		*Multilevel*		*Conventional*		*Multilevel*	
Earnings quintiles	*Coef*	*Pr*	*Coef*	*Pr*	*Coef*	*Pr*	*Coef*	*Pr*
Bottom	-0.558	0.000	-0.814	0.000	-0.345	0.000	-0.512	0.000
Second	-0.209	0.009	-0.298	0.022	-0.219	0.003	-0.330	0.003
Fourth	0.049	0.570	0.091	0.507	-0.087	0.297	-0.125	0.318
Top	-0.056	0.542	-0.039	0.788	-0.100	0.335	-0.264	0.082

Notes: Coefficients and p-values from models shown in appendix in table A4. Note that middle earnings quintile is the reference category.

Turning now to the estimates for jobs following the current job, table 5 shows that jobs in the bottom quintile had a coefficient of -0.814 when estimated using multilevel modelling, and an estimate of -0.558 when using conventional logistic regression (males). The comparable results for the female data show a similar difference: -0.512 and -0.345. Again, the multilevel estimates are considerably larger. The same applies to jobs in the second quintile. The anomaly noted above re-appears here, with some negative coefficients evident in the top quintiles, though again these results are not statistically significant. One interpretation of these anomalies are that there is little to distinguish jobs in the top three quintiles when it comes to this phenomena of churning, which as this article argues (and other research reinforces) is much more common at the bottom of the labour market. Because these models have also collapsed NILF and education into the unemployment category (for the purpose of dichotomising the outcome variable), these results can also reflect arrivals from (and departures to) states other than unemployment. Among women, for example, absences from employment are likely to include episodes of child bearing or rearing. Being able to draw such distinctions was one of the main reasons for adopting a multinomial logit approach in the first part of this article.

These results can be extrapolated to the individuals holding these jobs as follows. In assessing whether someone in a job is likely to have occupied a job prior to their current job, the association with low paid work is very strong. The association is also strong (but somewhat weaker) when it comes to holding a job subsequent to the current job. This is particularly so for those in the bottom earnings quintile, but also extends into the second quintile though the methodological cautions mentioned earlier need to be kept in mind (that is, comparisons between the middle and the bottom quintile are more reliable).

It is important to note that the implications of the multilevel modelling are that the somewhat gloomy findings in this research are even stronger when we acknowledge the repeated observations in the data, that is, when we recognise that it is a smaller subgroup of people to whom these experiences are happening more often. In this respect, one could argue that the results in the first part of this article, where the multinomial models are discussed, are likely to under-estimate the extent of labour market churning amongst the low paid.

4. Conclusion

The results from the analysis reported in this article are quite sobering. The first part of this article highlighted the vulnerability to labour market churning for particular disadvantaged demographic groups, particularly the low paid and those with low skills and particular migrant backgrounds. The second part of the paper dealt with some methodological complexities, but essentially reinforced these findings. Indeed, the results in the second part of the paper are even more sobering.

What makes these results of considerable concern is the recognition that the HILDA data used in this analysis was collected during a period of sustained economic growth, with aggregate labour market conditions the best seen in Australia since the early 1970s. This observation reinforces the view that good economic growth is a necessary condition for tackling unemployment, but it is not sufficient in itself. It is instructive to consider the plight of the long-term unemployed in the early-to-mid 1990s, in the wake of the severe 1991 recession. Integrating these individuals into productive labour market activity entailed considerable policy innovation and a real commitment of resources. The detailed case management plans, developed as part of *Working Nation*, aimed to tackle issues of poor health, disability, drug or alcohol dependence, low levels of literacy, and so forth, and they could be seen as part of a *facilitative* employment strategy.[13] For contemporary policy innovations, looking backwards in this way also needs to be complemented by learning from strategies at work in other countries, with the important insights offered by Perkins and Scutella (2008) being a case in point.

By contrast, in more recent times, case management for the unemployed has often been experienced as a punitive strategy, with little in the way of effective facilitation. Indeed, it could be argued that the Jobs Network, by virtue of its commercial imperatives, has focussed on attaining job outcomes amongst those most suited to rapid re-employment. Whether these people are still employed in subsequent years, and whether those individuals with more entrenched labour market disadvantages make it into ongoing jobs, remains unknown. Yet it is clear from the analysis in this article

[13] These comments are not intended as an uncritical endorsement of *Working Nation*, which was not without its faults.

that tackling labour market churning is essential for achieving positive long-term labour market outcomes. Continuity of employment, coupled with skills development and earnings improvement, need to be the central planks for labour market programs. Case management approaches which emphasise facilitative employment strategies and which recognise the cumulative nature of labour market disadvantage are essential. Promoting policies which simply 'privileg[e] . . . the initial transition into employment' (Perkins and Scutella, 2008) does little to address real problems of labour market churning and the 'no pay low pay' cycle for which the HILDA data has provided considerable evidence. A policy agenda which puts a priority on labour market interventions to improve wages, skill development and job tenure within the ranks of the low paid workforce is long overdue.

Appendix

Table A1 - Multinomial Logit Estimates for Labour Market States Preceding Jobs

	Males			*Females*		
Independent variables	*Educ*	*U/E*	*Employ*	*Educ*	*U/E*	*Employ*
Intercept	-1.035	-2.995	0.129	-5.454	-4.527	-5.443
	(2.092)	(1.174)	(1.075)	(1.746)	(1.362)	(1.418)
Education: Adv diploma, diploma	0.311	0.473	0.393	-0.098	-0.245	0.111
	(0.316)	(0.205)	(0.171)	(0.240)	(0.175)	(0.131)
Education: Certificate	-0.731	0.028	0.202	-0.058	0.111	0.430
	(0.291)	(0.156)	(0.132)	(0.253)	(0.148)	(0.126)
Education: Year 11 and below	-2.101	0.098	0.141	-0.774	0.106	0.274
	(0.468)	(0.181)	(0.154)	(0.281)	(0.148)	(0.126)
Education: Year 12	-0.055	0.307	0.531	0.221	0.056	0.402
	(0.324)	(0.209)	(0.180)	(0.255)	(0.146)	(0.124)
Age/10	0.473	2.662	2.117	1.814	2.015	2.320
	(0.606)	(0.349)	(0.283)	(0.535)	(0.321)	(0.273)
Age/10 squared	-0.090	-0.357	-0.281	-0.211	-0.259	-0.279
	(0.073)	(0.040)	(0.032)	(0.066)	(0.038)	(0.033)
Separated, divorced or widowed	0.123	0.363	-0.130	0.252	0.551	0.158
	(0.533)	(0.185)	(0.174)	(0.289)	(0.152)	(0.135)
Never married and not de facto	0.831	-0.085	-0.267	0.790	0.467	0.376
	(0.280)	(0.148)	(0.129)	(0.247)	(0.159)	(0.141)
One child	0.433	-0.305	-0.192	-0.674	-0.816	-0.845
	(0.383)	(0.188)	(0.151)	(0.273)	(0.155)	(0.125)
Two children	0.426	-0.050	0.079	-0.892	-0.651	-1.000
	(0.528)	(0.212)	(0.180)	(0.312)	(0.163)	(0.130)
Three or more children	0.651	-0.070	0.041	-0.627	-0.818	-0.810
	(0.385)	(0.194)	(0.170)	(0.255)	(0.130)	(0.106)
Bottom earnings quintile	0.461	0.195	-0.465	0.142	0.003	-0.489
	(0.316)	(0.182)	(0.160)	(0.248)	(0.139)	(0.108)
Second earnings quintile	-0.386	0.038	-0.197	-0.051	0.077	-0.143
	(0.255)	(0.141)	(0.119)	(0.199)	(0.114)	(0.094)
Fourth earnings quintile	-0.712	-0.124	-0.010	-0.275	-0.419	-0.326
	(0.326)	(0.168)	(0.146)	(0.201)	(0.145)	(0.113)
Top earnings quintile	-0.945	-0.503	-0.187	-1.032	-0.914	-0.554
	(0.324)	(0.169)	(0.150)	(0.292)	(0.182)	(0.126)
2002	-0.537	0.183	-0.058	-0.369	0.131	-0.136
	(0.313)	(0.193)	(0.174)	(0.253)	(0.163)	(0.138)

Table A1 (continued) - Multinomial Logit Estimates for Labour Market States Preceding Jobs

	Males			*Females*		
Independent variables	*Educ*	*U/E*	*Employ*	*Educ*	*U/E*	*Employ*
2003	-0.070	0.220	0.063	-0.285	0.109	-0.155
	(0.287)	(0.196)	(0.178)	(0.261)	(0.175)	(0.134)
2004	-0.735	-0.169	-0.228	-0.671	0.066	-0.350
	(0.315)	(0.192)	(0.168)	(0.277)	(0.173)	(0.137)
2005	-1.409	-0.294	-0.068	-0.190	0.156	-0.183
	(0.362)	(0.194)	(0.174)	(0.257)	(0.175)	(0.137)
2006	-0.725	-0.147	-0.451	-0.281	0.315	-0.227
	(0.419)	(0.230)	(0.204)	(0.290)	(0.193)	(0.154)
Balance of NSW	-0.221	-0.339	-0.335	-0.086	-0.311	0.097
	(0.337)	(0.192)	(0.166)	(0.274)	(0.172)	(0.142)
Melbourne	-0.862	-0.190	-0.305	-0.533	-0.225	-0.077
	(0.358)	(0.181)	(0.161)	(0.236)	(0.145)	(0.124)
Balance of Victoria	-0.327	-0.311	-0.215	-0.858	0.275	0.438
	(0.488)	(0.244)	(0.224)	(0.497)	(0.194)	(0.172)
Brisbane	0.148	-0.216	-0.090	-0.075	-0.062	0.004
	(0.315)	(0.212)	(0.187)	(0.265)	(0.162)	(0.136)
Balance of QLD	-0.907	-0.577	-0.502	-0.262	-0.541	-0.278
	(0.395)	(0.190)	(0.173)	(0.260)	(0.171)	(0.132)
Adelaide	-0.741	-0.223	-0.303	0.297	-0.252	-0.020
	(0.568)	(0.233)	(0.206)	(0.302)	(0.226)	(0.177)
Balance of SA	0.303	-0.419	-0.171	-0.274	-0.597	-0.173
	(0.526)	(0.320)	(0.272)	(0.579)	(0.278)	(0.222)
Perth	-0.131	-0.187	-0.070	-0.192	-0.579	-0.164
	(0.384)	(0.239)	(0.206)	(0.292)	(0.185)	(0.153)
Balance of WA	0.036	-0.929	-0.089	0.006	-0.815	-0.187
	(0.772)	(0.387)	(0.295)	(0.395)	(0.296)	(0.202)
Tasmania	0.436	-0.514	-0.894	0.895	0.026	0.403
	(0.676)	(0.351)	(0.308)	(0.394)	(0.302)	(0.258)
Northern Territory	-1.114	-0.857	-0.734	-0.020	-0.542	-0.060
	(2.896)	(0.678)	(0.468)	(1.094)	(0.386)	(0.318)
ACT	-1.409	0.196	0.559	-0.903	-0.721	-0.451
	(2.677)	(0.643)	(0.604)	(0.474)	(0.289)	(0.217)
Skill level	-0.085	-0.082	0.015	0.184	-0.026	0.129
	(0.052)	(0.027)	(0.023)	(0.050)	(0.029)	(0.024)
Not indigenous	0.039	0.570	0.433	-0.171	0.374	0.521
	(0.604)	(0.406)	(0.365)	(0.337)	(0.258)	(0.213)
Good health (no disability)	0.323	0.317	0.481	0.162	0.072	0.254
	(0.263)	(0.115)	(0.099)	(0.214)	(0.108)	(0.098)
Birthplace: ESB countries	0.053	-0.057	-0.126	0.056	-0.113	-0.006
	(0.149)	(0.082)	(0.065)	(0.110)	(0.073)	(0.057)
Birthplace: Pacific	0.126	0.044	0.138	-2.651	0.175	0.496
	(0.581)	(0.336)	(0.304)	(0.450)	(0.225)	(0.214)
Birthplace: Northern Europe	1.035	0.116	0.212	0.133	-0.077	0.066
	(0.423)	(0.388)	(0.356)	(0.372)	(0.176)	(0.140)
Birthplace: Southern Europe	-0.355	3.249	1.463	-2.227	-5.412	-4.927
	(1.299)	(1.558)	(1.043)	(0.905)	(1.151)	(1.053)
Birthplace: Eastern Europe	1.144	1.138	0.856	-2.731	0.665	-0.029
	(1.950)	(1.258)	(1.241)	(0.598)	(0.194)	(0.208)
Birthplace: Middle East	-0.648	2.857	0.722	0.085	0.579	0.384
	(1.410)	(1.110)	(1.631)	(1.412)	(0.379)	(0.326)
Birthplace: South East Asia	-1.586	-2.802	-3.899	-4.476	1.238	1.642
	(1.245)	(2.070)	(2.138)	(0.996)	(1.349)	(1.604)

able A1 (continued) - Multinomial Logit Estimates for Labour Market States Preceding Jobs

	Males			*Females*		
Independent variables	*Educ*	*U/E*	*Employ*	*Educ*	*U/E*	*Employ*
Birthplace: North Asia	2.515	-2.023	-1.928	7.004	-2.707	6.255
	(3.083)	(2.556)	(2.200)	(2.611)	(0.637)	(1.526)
Birthplace: South-Central Asia	-0.411	-1.435	1.757	-2.909	6.570	-1.886
	(0.803)	(0.870)	(1.489)	(0.280)	(3.426)	(0.991)
Birthplace: Latin America	-2.601	2.591	1.018	0.626	0.298	0.600
	(0.878)	(1.207)	(1.235)	(1.215)	(0.765)	(0.614)
Birthplace: Africa	0.613	-1.542	2.344	-2.483	0.228	0.271
	(0.471)	(1.138)	(1.703)	(0.384)	(0.390)	(0.365)
English speaking ability good	1.240	-1.292	-2.015	1.179	1.410	2.414
	(1.474)	(0.882)	(0.795)	(1.267)	(1.116)	(1.245)
Inverse of the Mills' ratio	-1.228	0.204	-0.719	-1.459	-0.718	-1.952
	(0.538)	(0.275)	(0.251)	(0.443)	(0.251)	(0.207)
Sep, divorced or widow by 1 child	-4.411	-0.803	-0.728	0.828	0.485	0.708
	(1.040)	(0.649)	(0.521)	(0.552)	(0.345)	(0.291)
Never mar& not de facto by 1 child	0.586	0.770	0.123	0.272	-0.101	-0.523
	(0.989)	(0.820)	(0.787)	(0.537)	(0.362)	(0.288)
Sep, divorced or widowed by 2 child	-3.680	-0.569	-0.802	0.308	-0.005	0.111
	(1.457)	(1.193)	(1.115)	(0.831)	(0.371)	(0.323)
Never mar& not de facto by 2 child	-3.676	1.108	-1.649	-0.399	1.181	0.520
	(1.872)	(2.815)	(3.592)	(2.577)	(0.449)	(0.452)
Sep, divorced or widowed by 3+ child	1.302	-0.123	-1.199	0.325	-0.011	-0.275
	(1.420)	(1.020)	(0.943)	(0.473)	(0.274)	(0.250)
Never mar& not de facto by 3+ child	1.292	0.312	0.575	0.571	0.539	-0.181
	(3.189)	(2.882)	(2.549)	(0.915)	(0.450)	(0.447)
ESB countries by good English	0.053	-0.057	-0.126	0.056	-0.113	-0.006
	(0.149)	(0.082)	(0.065)	(0.110)	(0.073)	(0.057)
Pacific by good English	0.126	0.044	0.138	-2.651	0.175	0.496
	(0.581)	(0.336)	(0.304)	(0.450)	(0.225)	(0.214)
Northern Europe by good English	1.035	0.116	0.212	0.133	-0.077	0.066
	(0.423)	(0.388)	(0.356)	(0.372)	(0.176)	(0.140)
Southern Europe by good English	0.349	-3.571	-1.382	2.741	5.775	5.223
	(1.618)	(1.617)	(1.109)	(1.260)	(1.202)	(1.097)
Eastern Europe by good English	1.144	1.138	0.856	-2.731	0.665	-0.029
	(1.950)	(1.258)	(1.241)	(0.598)	(0.194)	(0.208)
Middle East by good English	0.545	-1.774	-0.442	0.085	0.579	0.384
	(1.796)	(1.443)	(1.798)	(1.412)	(0.379)	(0.326)
South East Asia by good English	2.261	3.244	4.268	5.321	-0.643	-1.139
	(1.435)	(2.161)	(2.236)	(1.074)	(1.383)	(1.616)
North Asia by good English	-2.271	2.987	2.416	-5.624	3.100	-5.800
	(3.438)	(2.816)	(2.511)	(2.707)	(0.727)	(1.581)
South-Central Asia by good English	0.197	1.079	-2.362	-2.737	-6.885	2.085
	(0.910)	(0.885)	(1.477)	(0.273)	(3.480)	(1.013)
Latin America by good English	-2.098	-1.457	-0.498	0.626	0.298	0.600
	(0.868)	(1.770)	(1.793)	(1.215)	(0.765)	(0.614)
Africa by good English	0.818	2.091	-2.668	-2.483	0.228	0.271
	(0.513)	(1.215)	(1.682)	(0.384)	(0.390)	(0.365)
Log-likelihood	5,354			6,669		
Log-likelihood (0)	5,863			7,199		
AIC	11,075			13,692		
N	6,018			6,437		

Table A2 - Multinomial Logit Estimates for Labour Market States following Jobs

	Males			*Females*		
Independent variables	*Educ*	*U/E*	*Employ*	*Educ*	*U/E*	*Employ*
Intercept	-1.493	-4.559	-1.401	-5.988	-6.421	-3.873
	(2.551)	(2.473)	(1.395)	(1.040)	(0.828)	(0.875)
Education: Adv diploma, diploma	-0.052	0.427	0.131	-0.413	-0.464	0.011
	(0.302)	(0.186)	(0.168)	(0.257)	(0.187)	(0.116)
Education: Certificate	-1.146	-0.096	-0.129	-0.366	-0.028	0.498
	(0.247)	(0.151)	(0.120)	(0.253)	(0.166)	(0.121)
Education: Year 11 and below	-2.206	0.031	-0.173	-0.949	0.063	0.078
	(0.400)	(0.166)	(0.139)	(0.281)	(0.154)	(0.113)
Education: Year 12	-0.177	0.071	0.179	-0.145	-0.027	0.253
	(0.274)	(0.193)	(0.157)	(0.245)	(0.154)	(0.109)
Age/10	0.185	2.574	2.124	1.400	2.240	2.327
	(0.557)	(0.319)	(0.270)	(0.495)	(0.316)	(0.221)
Age/10 squared	-0.119	-0.348	-0.293	-0.172	-0.290	-0.291
	(0.066)	(0.036)	(0.031)	(0.062)	(0.037)	(0.026)
Separated, divorced or widowed	0.159	0.457	-0.216	0.190	1.134	0.446
	(0.390)	(0.176)	(0.154)	(0.283)	(0.149)	(0.127)
Never married and not de facto	-0.253	0.035	-0.219	0.819	0.999	0.656
	(0.212)	(0.144)	(0.120)	(0.228)	(0.173)	(0.129)
One child	-0.331	0.033	0.080	-0.973	-0.906	-0.964
	(0.389)	(0.190)	(0.162)	(0.280)	(0.178)	(0.113)
Two children	-0.090	-0.227	-0.033	-0.727	-0.317	-0.639
	(0.360)	(0.195)	(0.160)	(0.301)	(0.190)	(0.130)
Three or more children	-0.262	-0.062	-0.059	-0.503	-0.540	-0.421
	(0.338)	(0.175)	(0.142)	(0.239)	(0.162)	(0.101)
Bottom earnings quintile	0.351	0.172	-0.458	0.265	0.219	-0.229
	(0.293)	(0.163)	(0.145)	(0.231)	(0.150)	(0.109)
Second earnings quintile	-0.216	0.176	-0.138	-0.064	0.120	-0.192
	(0.234)	(0.135)	(0.115)	(0.200)	(0.126)	(0.087)
Fourth earnings quintile	-0.418	-0.173	-0.069	-0.593	-0.372	-0.253
	(0.249)	(0.159)	(0.128)	(0.207)	(0.147)	(0.098)
Top earnings quintile	-0.871	-0.386	-0.294	-1.153	-0.890	-0.429
	(0.285)	(0.165)	(0.119)	(0.273)	(0.196)	(0.114)
2002	0.198	0.132	0.073	0.290	0.033	0.067
	(0.306)	(0.174)	(0.143)	(0.229)	(0.173)	(0.116)
2003	0.598	0.099	0.204	0.136	-0.096	-0.008
	(0.284)	(0.175)	(0.147)	(0.243)	(0.170)	(0.112)
2004	0.014	0.044	0.132	-0.185	-0.257	-0.143
	(0.315)	(0.184)	(0.145)	(0.258)	(0.172)	(0.112)
2005	-0.128	-0.110	0.316	0.002	-0.020	-0.016
	(0.354)	(0.176)	(0.137)	(0.255)	(0.177)	(0.119)
2006	-0.138	-0.080	-0.218	0.253	0.040	-0.106
	(0.383)	(0.204)	(0.159)	(0.293)	(0.196)	(0.133)
Balance of NSW	-0.647	-0.607	-0.407	0.294	0.062	0.077
	(0.321)	(0.180)	(0.143)	(0.249)	(0.182)	(0.124)
Melbourne	-0.855	-0.514	-0.511	-0.801	-0.113	0.009
	(0.293)	(0.173)	(0.146)	(0.241)	(0.158)	(0.112)
Balance of Victoria	0.035	-0.493	-0.198	-0.258	0.225	0.316
	(0.385)	(0.236)	(0.205)	(0.371)	(0.220)	(0.159)
Brisbane	-0.506	-0.561	-0.243	-0.235	0.087	0.112
	(0.318)	(0.205)	(0.173)	(0.252)	(0.178)	(0.129)
Balance of QLD	-1.116	-0.693	-0.549	-0.590	-0.411	-0.245
	(0.359)	(0.197)	(0.160)	(0.279)	(0.169)	(0.123)

Table A2 (continued) - Multinomial Logit Estimates for Labour Market States following Jobs

	Males			*Females*		
Independent variables	*Educ*	*U/E*	*Employ*	*Educ*	*U/E*	*Employ*
Adelaide	-0.808	-0.283	-0.304	-0.028	-0.614	-0.168
	(0.424)	(0.226)	(0.197)	(0.298)	(0.235)	(0.154)
Balance of SA	-0.401	-0.539	-0.087	-0.213	-0.377	-0.031
	(1.696)	(0.294)	(0.221)	(0.622)	(0.321)	(0.210)
Perth	-0.223	-0.327	-0.183	-1.051	-0.705	-0.368
	(0.351)	(0.229)	(0.191)	(0.323)	(0.215)	(0.136)
Balance of WA	-0.257	-0.694	0.110	-0.527	-0.897	-0.249
	(1.410)	(0.364)	(0.270)	(0.449)	(0.345)	(0.191)
Tasmania	-0.173	-0.767	-0.998	0.562	-0.264	0.287
	(0.658)	(0.350)	(0.287)	(0.388)	(0.328)	(0.221)
Northern Territory	-1.980	-1.386	-1.417	-0.730	-0.151	-0.054
	(2.732)	(0.531)	(0.404)	(1.902)	(0.422)	(0.335)
ACT	-0.868	-0.523	0.143	-0.843	-0.481	-0.233
	(1.563)	(0.401)	(0.309)	(0.566)	(0.316)	(0.211)
Skill level	-0.060	-0.080	0.004	0.178	-0.001	0.118
	(0.051)	(0.026)	(0.022)	(0.047)	(0.027)	(0.021)
Not indigenous	1.000	0.034	0.306	-0.464	0.003	0.527
	(2.136)	(0.360)	(0.359)	(0.329)	(0.274)	(0.194)
Good health (no disability)	0.330	0.639	0.694	0.343	0.284	0.381
	(0.227)	(0.114)	(0.091)	(0.192)	(0.112)	(0.083)
Birthplace: ESB countries	0.050	-0.029	-0.060	-0.014	-0.003	0.102
	(0.156)	(0.073)	(0.057)	(0.119)	(0.077)	(0.052)
Birthplace: Pacific	0.150	4.190	-2.151	-2.521	0.637	0.741
	(0.715)	(2.526)	(1.334)	(0.348)	(0.419)	(0.396)
Birthplace: Northern Europe	0.830	-0.117	0.074	0.335	0.069	0.157
	(0.247)	(0.228)	(0.163)	(0.370)	(0.187)	(0.141)
Birthplace: Southern Europe	-0.729	1.833	-0.195	-1.456	-3.488	-0.314
	(1.303)	(2.875)	(1.904)	(1.229)	(0.522)	(1.342)
Birthplace: Eastern Europe	0.844	0.683	0.544	0.328	0.727	-0.132
	(1.541)	(1.040)	(0.998)	(1.145)	(0.222)	(0.238)
Birthplace: Middle East	-0.489	4.620	2.259	0.157	-0.149	0.116
	(0.764)	(2.110)	(1.666)	(1.364)	(1.090)	(0.237)
Birthplace: South East Asia	-0.938	0.361	-0.901	-2.584	2.279	-0.872
	(0.804)	(3.257)	(2.301)	(0.489)	(0.716)	(0.973)
Birthplace: North Asia	2.206	-0.542	-0.329	0.259	-1.402	3.391
	(2.544)	(3.498)	(1.841)	(0.289)	(0.569)	(0.975)
Birthplace: South-Central Asia	-0.214	-1.833	2.319	-0.257	-1.573	-3.890
	(0.751)	(1.025)	(1.542)	(1.224)	(1.180)	(2.204)
Birthplace: Latin America	-3.228	3.837	1.209	0.691	-0.168	0.091
	(0.559)	(1.957)	(1.876)	(0.332)	(0.759)	(0.209)
Birthplace: Africa	-0.666	3.270	1.445	0.377	0.394	0.216
	(1.550)	(3.179)	(2.603)	(1.393)	(0.267)	(0.244)
English speaking ability good	1.722	0.776	-0.413	2.610	1.976	-0.034
	(1.339)	(2.341)	(1.193)	(0.511)	(0.532)	(0.766)
Inverse of the Mills' ratio	-0.241	-0.090	-0.730	-1.496	-0.378	-1.456
	(0.508)	(0.262)	(0.209)	(0.435)	(0.266)	(0.199)
Sep, divorced or widow by 1 child	-4.477	-0.722	-0.932	0.997	0.107	0.543
	(1.098)	(0.642)	(0.534)	(0.603)	(0.339)	(0.243)
Never mar & not de facto by 1 child	1.428	0.618	-0.628	0.442	0.306	-0.070
	(0.803)	(0.564)	(0.576)	(0.594)	(0.352)	(0.279)
Sep, divorced or widowed by 2 child	-2.905	0.709	0.340	-0.921	-0.052	-0.029
	(1.241)	(1.821)	(1.684)	(2.402)	(0.444)	(0.348)

Table A2 (continued) - Multinomial Logit Estimates for Labour Market States following Jobs

	Males			*Females*		
Independent variables	*Educ*	*U/E*	*Employ*	*Educ*	*U/E*	*Employ*
Never mar & not de facto by 2 child	-4.474	-0.804	-1.388	0.284	0.659	0.121
	(2.137)	(3.749)	(3.016)	(1.926)	(0.509)	(0.465)
Sep, divorced or widowed by 3+ child	-4.856	-0.041	-0.811	-0.048	-0.453	-0.453
	(1.226)	(0.882)	(0.799)	(0.549)	(0.310)	(0.251)
Never mar & not de facto by 3+ child	1.460	0.751	0.906	-0.058	-0.158	-1.319
	(3.573)	(2.749)	(2.643)	(1.162)	(0.479)	(0.494)
ESB countries by good English	0.050	-0.029	0.060	-0.014	-0.003	0.102
	(0.156)	(0.073)	(0.057)	(0.119)	(0.077)	(0.052)
Pacific by good English	0.243	-3.876	2.685	-2.521	0.637	0.741
	(0.728)	(2.572)	(1.368)	(0.348)	(0.419)	(0.396)
Northern Europe by good English	0.830	-0.117	0.074	0.335	0.069	0.157
	(0.247)	(0.228)	(0.163)	(0.370)	(0.187)	(0.141)
Southern Europe by good English	2.159	-1.699	0.829	0.967	4.160	0.385
	(1.657)	(2.924)	(1.943)	(1.986)	(0.582)	(1.376)
Eastern Europe by good English	0.844	0.683	0.544	0.328	0.727	-0.132
	(1.541)	(1.040)	(0.998)	(1.145)	(0.222)	(0.238)
Middle East by good English	1.294	-4.282	-2.156	0.157	-0.149	0.116
	(1.000)	(2.292)	(1.806)	(1.364)	(1.090)	(0.237)
South East Asia by good English	0.548	-0.823	0.727	2.702	-2.257	0.912
	(0.968)	(3.308)	(2.346)	(0.747)	(0.770)	(0.978)
North Asia by good English	-1.981	0.833	0.184	0.658	0.940	-3.233
	(2.953)	(3.731)	(2.287)	(0.333)	(0.839)	(1.031)
South-Central Asia by good English	0.029	1.910	-2.853	0.232	1.369	4.091
	(0.802)	(1.064)	(1.538)	(1.523)	(1.486)	(2.226)
Latin America by good English	-2.793	-3.157	-0.622	0.691	-0.168	0.091
	(0.527)	(2.433)	(2.251)	(0.332)	(0.759)	(0.209)
Africa by good English	-0.273	-3.449	-2.372	0.377	0.394	0.216
	(1.688)	(3.216)	(2.632)	(1.393)	(0.267)	(0.244)
Log-likelihood	5,584			6,430		
Log-likelihood (0)	6,217			7,022		
AIC	11,545			13,208		
N	6,095			6,300		

Table A3 - Comparison of Conventional and Multilevel Models: Logit Estimates for Being in a Job Prior to Current Job

	Males		*Females*	
Independent variables	*I*	*II*	*III*	*IV*
Intercept	-1.438	-2.161	-3.024	-4.289
	(0.612)	(0.956)	(0.634)	(0.885)
Education: Adv diploma, diploma	0.106	0.220	0.224	0.246
	(0.114)	(0.185)	(0.100)	(0.146)
Education: Certificate	0.262	0.319	0.407	0.504
	(0.088)	(0.144)	(0.096)	(0.139)
Education: Year 11 and below	0.198	0.257	0.285	0.273
	(0.103)	(0.172)	(0.093)	(0.136)
Education: Year 12	0.359	0.395	0.379	0.336
	(0.113)	(0.180)	(0.092)	(0.133)

Table A3 (continued) - Comparison of Conventional and Multilevel Models: Logit Estimates for Being in a Job Prior to Current Job

	Males		*Females*	
Independent variables	*I*	*II*	*III*	*IV*
Age/10	0.929	1.565	1.327	1.967
	(0.205)	(0.338)	(0.205)	(0.305)
Age/10 squared	-0.121	-0.205	-0.154	-0.226
	(0.024)	(0.040)	(0.025)	(0.037)
Separated, divorced or widowed	-0.349	-0.357	-0.119	-0.182
	(0.113)	(0.171)	(0.100)	(0.143)
Never married and not de facto	-0.293	-0.430	0.048	0.053
	(0.084)	(0.128)	(0.094)	(0.134)
One child	-0.050	-0.131	-0.432	-0.641
	(0.109)	(0.154)	(0.100)	(0.132)
Two children	0.073	-0.078	-0.627	-0.813
	(0.117)	(0.164)	(0.106)	(0.142)
Three or more children	0.033	-0.057	-0.396	-0.581
	(0.099)	(0.148)	(0.085)	(0.121)
Bottom earnings quintile	-0.606	-0.821	-0.526	-0.780
	(0.105)	(0.174)	(0.094)	(0.138)
Second earnings quintile	-0.178	-0.306	-0.184	-0.260
	(0.079)	(0.133)	(0.073)	(0.107)
Fourth earnings quintile	0.117	0.123	-0.131	-0.117
	(0.089)	(0.144)	(0.084)	(0.123)
Top earnings quintile	0.136	0.228	-0.126	-0.173
	(0.094)	(0.152)	(0.105)	(0.151)
2002	-0.105	-0.128	-0.144	-0.245
	(0.104)	(0.128)	(0.101)	(0.119)
2003	-0.043	-0.096	-0.165	-0.271
	(0.107)	(0.133)	(0.103)	(0.122)
2004	-0.070	-0.054	-0.306	-0.337
	(0.109)	(0.137)	(0.104)	(0.124)
2005	0.194	0.282	-0.219	-0.299
	(0.111)	(0.139)	(0.104)	(0.125)
2006	-0.314	-0.372	-0.321	-0.386
	(0.129)	(0.158)	(0.121)	(0.142)
Balance of NSW	-0.130	-0.235	0.234	0.229
	(0.109)	(0.173)	(0.109)	(0.153)
Melbourne	-0.123	-0.161	0.081	0.066
	(0.102)	(0.163)	(0.092)	(0.132)
Balance of Victoria	-0.034	0.060	0.358	0.522
	(0.139)	(0.226)	(0.129)	(0.185)
Brisbane	0.001	0.056	0.032	-0.034
	(0.116)	(0.187)	(0.104)	(0.149)
Balance of QLD	-0.114	-0.120	-0.021	-0.119
	(0.113)	(0.181)	(0.103)	(0.148)
Adelaide	-0.146	-0.102	0.030	0.072
	(0.131)	(0.213)	(0.135)	(0.195)
Balance of SA	0.050	0.083	0.100	0.100
	(0.191)	(0.328)	(0.185)	(0.264)
Perth	0.046	0.018	0.090	0.013
	(0.131)	(0.207)	(0.121)	(0.172)
Balance of WA	0.392	0.563	0.133	0.053
	(0.192)	(0.298)	(0.169)	(0.250)
Tasmania	-0.653	-0.926	0.247	0.287
	(0.206)	(0.324)	(0.182)	(0.254)
Northern Territory	-0.189	-0.439	0.186	0.018
	(0.312)	(0.437)	(0.238)	(0.366)
ACT	0.450	0.633	-0.076	0.029
	(0.222)	(0.349)	(0.176)	(0.267)

Table A3 (continued) - Comparison of Conventional and Multilevel Models:Logit Estimates for Being in a Job Prior to Current Job

	Males		*Females*	
Independent variables	*I*	*II*	*III*	*IV*
Skill level	0.067	0.094	0.122	0.138
	(0.016)	(0.027)	(0.017)	(0.025)
Not indigenous	0.214	0.275	0.411	0.496
	(0.244)	(0.400)	(0.161)	(0.247)
Good health (no disability)	0.287	0.316	0.203	0.262
	(0.072)	(0.101)	(0.073)	(0.096)
Birthplace: ESB countries	-0.187	-0.294	0.064	0.120
	(0.092)	(0.150)	(0.088)	(0.131)
Birthplace: Pacific	0.174	0.049	0.879	1.154
	(0.257)	(0.428)	(0.299)	(0.449)
Birthplace: Northern Europe	0.028	0.158	0.153	0.140
	(0.251)	(0.408)	(0.212)	(0.319)
Birthplace: Southern Europe	0.189	0.077	0.003	-0.061
	(0.240)	(0.376)	(0.249)	(0.348)
Birthplace: Eastern Europe	0.035	0.083	-0.673	-0.726
	(0.377)	(0.586)	(0.318)	(0.436)
Birthplace: Middle East	-0.607	-0.900	0.229	0.292
	(0.302)	(0.437)	(0.350)	(0.499)
Birthplace: South East Asia	-0.071	-0.050	0.121	0.185
	(0.217)	(0.361)	(0.180)	(0.265)
Birthplace: North Asia	-0.035	-0.049	0.157	0.266
	(0.327)	(0.490)	(0.243)	(0.363)
Birthplace: South-Central Asia	-0.373	-0.407	0.384	0.441
	(0.266)	(0.389)	(0.346)	(0.459)
Birthplace: Latin America	-0.264	-0.401	0.756	0.897
	(0.374)	(0.609)	(0.416)	(0.565)
Birthplace: Africa	-0.773	-0.985	0.311	0.500
	(0.259)	(0.442)	(0.364)	(0.535)
English speaking ability good	0.275	0.179	0.628	0.820
	(0.357)	(0.500)	(0.430)	(0.563)
Inverse of the Mills' ratio	-0.734	-1.024	-1.489	-1.885
	(0.157)	(0.259)	(0.156)	(0.228)
Sep, divorced or widow by 1 child	-0.225	-0.337	0.431	0.690
	(0.363)	(0.556)	(0.205)	(0.280)
Never mar & not de facto by 1 child	-0.512	-0.572	-0.440	-0.223
	(0.303)	(0.436)	(0.233)	(0.317)
Sep, divorced or widowed by 2 child	-0.384	0.215	0.115	0.123
	(0.464)	(0.600)	(0.250)	(0.325)
Never mar & not de facto by 2 child	-2.238	-2.910	-0.112	-0.036
	(1.099)	(1.415)	(0.287)	(0.382)
Sep, divorced or widowed by 3+ child				
	-1.330	-0.765	-0.274	-0.254
	(0.482)	(0.654)	(0.186)	(0.265)
Never mar & not de facto by 3+ child				
	0.089	-0.251	-0.442	-0.684
	(0.573)	(0.754)	(0.313)	(0.427)
Number of observations	6,018		6,437	
AIC	7,524		8,480	
Deviance	7,414		8,370	
Number of observations	6,018		6,437	
Number of individuals	1,852		2,197	
AIC	7,089		8,160	
BIC	7,464		8,540	
Log likelihood	-3,488		-4,024	
Deviance	6,977		8,048	

Table A4 - Comparison of Conventional and Multilevel Models: Logit Estimates for Being in a Job Subsequent to Current Job

	Males		*Females*	
Independent variables	*I*	*II*	*III*	*IV*
Intercept	-2.341	-3.341	-3.721	-5.169
	(0.587)	(0.893)	(0.611)	(0.856)
Education: Adv diploma, diploma	-0.034	0.058	0.190	0.122
	(0.112)	(0.177)	(0.099)	(0.149)
Education: Certificate	0.041	0.075	0.565	0.711
	(0.086)	(0.139)	(0.097)	(0.144)
Education: Year 11 and below	-0.057	-0.024	0.137	0.065
	(0.101)	(0.166)	(0.093)	(0.139)
Education: Year 12	0.150	0.139	0.298	0.225
	(0.111)	(0.173)	(0.091)	(0.136)
Age/10	1.362	2.188	1.601	2.317
	(0.195)	(0.313)	(0.198)	(0.296)
Age/10 squared	-0.181	-0.292	-0.197	-0.284
	(0.023)	(0.036)	(0.024)	(0.035)
Separated, divorced or widowed	-0.448	-0.509	0.041	0.040
	(0.113)	(0.168)	(0.098)	(0.140)
Never married and not de facto	-0.219	-0.322	0.191	0.217
	(0.084)	(0.127)	(0.094)	(0.137)
One child	0.077	-0.021	-0.643	-0.765
	(0.110)	(0.151)	(0.100)	(0.131)
Two children	0.087	-0.044	-0.458	-0.569
	(0.114)	(0.160)	(0.105)	(0.140)
Three or more children	-0.017	-0.175	-0.204	-0.314
	(0.098)	(0.144)	(0.089)	(0.127)
Bottom earnings quintile	-0.558	-0.814	-0.345	-0.512
	(0.105)	(0.172)	(0.095)	(0.145)
Second earnings quintile	-0.209	-0.298	-0.219	-0.330
	(0.079)	(0.130)	(0.074)	(0.112)
Fourth earnings quintile	0.049	0.091	-0.087	-0.125
	(0.086)	(0.137)	(0.083)	(0.125)
Top earnings quintile	-0.056	-0.039	-0.100	-0.264
	(0.091)	(0.145)	(0.103)	(0.152)
2002	-0.013	0.055	0.022	-0.153
	(0.101)	(0.124)	(0.099)	(0.118)
2003	0.090	0.157	0.004	-0.139
	(0.102)	(0.127)	(0.101)	(0.121)
2004	0.092	0.237	-0.050	-0.155
	(0.106)	(0.131)	(0.101)	(0.122)
2005	0.355	0.515	-0.006	-0.126
	(0.107)	(0.133)	(0.103)	(0.125)
2006	-0.188	-0.168	-0.135	-0.270
	(0.123)	(0.150)	(0.118)	(0.141)
Balance of NSW	-0.052	-0.132	0.026	-0.029
	(0.107)	(0.167)	(0.109)	(0.155)
Melbourne	-0.162	-0.264	0.141	0.113
	(0.101)	(0.157)	(0.093)	(0.136)
Balance of Victoria	0.030	0.069	0.270	0.348
	(0.137)	(0.217)	(0.131)	(0.190)
Brisbane	0.079	0.082	0.116	0.023
	(0.116)	(0.180)	(0.106)	(0.157)
Balance of QLD	-0.118	-0.131	-0.065	-0.145
	(0.111)	(0.174)	(0.105)	(0.154)
Adelaide	-0.096	-0.070	-0.007	-0.066
	(0.129)	(0.206)	(0.131)	(0.195)

Table A4 (continued) - Comparison of Conventional and Multilevel Models: Logit Estimates for Being in a Job Subsequent to Current Job

	Males		*Females*	
Independent variables	*I*	*II*	*III*	*IV*
Balance of SA	0.275	0.439	0.107	-0.030
	(0.189)	(0.317)	(0.183)	(0.270)
Perth	0.001	-0.015	-0.071	-0.222
	(0.128)	(0.198)	(0.120)	(0.175)
Balance of WA	0.476	0.725	0.032	-0.052
	(0.186)	(0.288)	(0.173)	(0.256)
Tasmania	-0.630	-0.979	0.282	0.290
	(0.207)	(0.323)	(0.180)	(0.254)
Northern Territory	-0.604	-0.839	0.076	-0.202
	(0.309)	(0.441)	(0.249)	(0.389)
ACT	0.449	0.608	-0.008	0.133
	(0.216)	(0.340)	(0.180)	(0.274)
Skill level	0.045	0.083	0.099	0.124
	(0.016)	(0.026)	(0.017)	(0.026)
Not indigenous	0.280	0.143	0.596	0.818
	(0.246)	(0.391)	(0.175)	(0.267)
Good health (no disability)	0.388	0.480	0.259	0.355
	(0.071)	(0.098)	(0.072)	(0.097)
Birthplace: ESB countries	-0.098	-0.210	0.203	0.287
	(0.091)	(0.145)	(0.090)	(0.135)
Birthplace: Pacific	0.191	0.304	0.933	1.471
	(0.264)	(0.431)	(0.337)	(0.518)
Birthplace: Northern Europe	-0.025	0.352	0.155	0.064
	(0.236)	(0.364)	(0.212)	(0.315)
Birthplace: Southern Europe	0.386	0.284	-0.129	0.025
	(0.231)	(0.348)	(0.242)	(0.347)
Birthplace: Eastern Europe	0.099	-0.059	-0.911	-1.093
	(0.394)	(0.586)	(0.369)	(0.522)
Birthplace: Middle East	-0.335	-0.401	0.245	0.355
	(0.304)	(0.444)	(0.401)	(0.554)
Birthplace: South East Asia	0.056	0.210	-0.067	-0.023
	(0.221)	(0.348)	(0.192)	(0.279)
Birthplace: North Asia	-0.042	-0.193	0.162	0.100
	(0.357)	(0.500)	(0.265)	(0.375)
Birthplace: South-Central Asia	-0.556	-0.574	0.215	0.434
	(0.261)	(0.400)	(0.383)	(0.499)
Birthplace: Latin America	0.086	0.070	-0.044	-0.003
	(0.364)	(0.579)	(0.338)	(0.501)
Birthplace: Africa	-0.752	-0.899	0.029	0.246
	(0.286)	(0.447)	(0.373)	(0.543)
English speaking ability good	0.337	0.182	0.349	0.444
	(0.335)	(0.444)	(0.404)	(0.526)
Inverse of the Mills' ratio	-0.633	-0.947	-1.192	-1.522
	(0.155)	(0.250)	(0.156)	(0.234)
Sep, divorced or widow by 1 child	-0.564	-0.946	0.519	0.682
	(0.402)	(0.569)	(0.205)	(0.284)
Never mar & not de facto by 1 child	-1.131	-1.316	-0.056	-0.026
	(0.339)	(0.462)	(0.240)	(0.328)
Sep, divorced or widowed by 2 child	-0.045	0.382	0.009	0.013
	(0.512)	(0.707)	(0.267)	(0.346)
Never mar & not de facto by 2 child	-0.862	-1.576	-0.230	-0.194
	(0.942)	(1.323)	(0.313)	(0.420)

Table A4 (continued) - Comparison of Conventional and Multilevel Models: Logit Estimates for Being in a Job Subsequent to Current Job

	Males		*Females*	
Independent variables	*I*	*II*	*III*	*IV*
Sep, divorced or widowed by 3+ child	-0.726	-0.462	-0.262	-0.246
	(0.461)	(0.606)	(0.197)	(0.284)
Never mar & not de facto by 3+ child	0.352	0.068	-1.195	-1.509
	(0.559)	(0.735)	(0.373)	(0.499)
Number of observations	6,095		6,300	
AIC	7,664		8,314	
Deviance	7,554		8,204	
Number of observations	6,095		6,300	
Number of individuals	1,967		2,240	
AIC	7,238		7,959	
BIC	7,614		8,337	
Log likelihood	-3,563		-3,924	
Deviance	7,126		7,847	

References

ABS (6286.0), *Australia's Employment and Unemployment Patterns 1994-1996*, Australian Bureau of Statistics, 1997.

Bates, D. and Maechler, M. (2008), *Matrix: Sparse and Dense Matrix Classes and Methods*. R package version 0.999375-16.

Black, D. and Borland, J. (2005), 'Workforce Transitions Following Unemployment', *HILDA Survey Research Conference,* University of Melbourne.

Borland, J. and Woodbridge, G. (1999), 'Wage Regulation, Low-wage Workers, and Employment', in S. Richardson, (ed.), *Reshaping the Labour Market: Reguation, Efficiency and Equality in Australia*, Cambridge University Press, Melbourne, 86-121.

Buchanan, J. and Watson, I. (1997), 'The Living Wage and the Working Poor', in M. Bittman, ed., *Poverty in Australia: Dimensions and Policies, Reports and Proceedings No. 135*, Social Policy Research Centre, UNSW, Kensington, NSW.

Cameron, A.C. and Trivedi, P.K. (2005), *Microeconometrics: Methods and Applications*, Cambridge University Press.

Carroll, N. (2005), 'Explaining Unemployment Duration in Australia', *HILDA Survey Research Conference* University of Melbourne.

Davison, A. and Hinkley, D. (1997), *Bootstrap Methods and their Application*, Cambridge University Press, New York.

Dockery, A.M. (2003), 'Looking Inside the Unemployment Spell', *HILDA Survey Research Conference* University of Melbourne.

Dunlop, Y. (2001), 'Low-paid Employment in the Australian Labour Market, 1995 97', in J. Borland, B. Gregory and P. Sheehan, (eds.), *Work Rich: Work Poor: Inequality and Economic Change in Australia*, Centre for Strategic Economic Studies, Victoria University, Melbourne.

Eardley, T. (1998), *Working But Poor? Low Pay and Poverty in Australia*, Discussion Paper No. 91, Social Policy Research Centre, University of NSW.

Gelman, A. and Hill, J. (2007), *Data analysis using regression and multilevel hierarchical models*, Cambridge University Press, Cambridge.

Goldstein, H. (1994), *Multilevel Statistical Models*, Second (ed.), E. Arnold, London.

Hardin, J.W. and Hilbe, J. (2001), *Generalized Linear Models and Extensions*, State Press, College Station, Texas.

Healy, J. and Richardson, S. (2006), *An Updated profile of the minimum wage workforce in Australia*, Report Commissioned by the Australian Fair Pay Commission, Adelaide: National Institute of Labour Studies.

Le, A.T. and Miller, P.W. (1999), *Job Quality and Churning of the Pool of the Unemployed*, Occasional Paper Cat. 6293.0.00.003, Australian Bureau of Statistics.

Masterman-Smith, H. and Pocock, B. (2008), *Living Low Paid: The Dark Side of Prosperous Australia*, Allen & Unwin, Crows Nest.

O'Loughlin, T. and Watson, I. (1997), *Loyalty is a One Way Street: NESB Immigrants and Long-Term Unemployment*, ACIRRT, Sydney.

Perkins, D. and Scutella, R. (2008), 'Improving Employment Retention and Advancement of Low Paid Workers', *Australian Journal of Labour Economics,* 11(1).

Pinheiro, J.C. and Bates, D.M. (2004), *Mixed-Effects Models in S and S- Plus*, Springer, New York.

R Development Core Team (2008), *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0.

URL: *http://www.R-project.org* Rabe-Hesketh, S. and Skrondal, A. (2005), *Multilevel and Longitudinal Modeling Using Stata*, Stata Press, College Station, Texas.

Richardson, S. and Harding, A. (1998), Low wages and the distribution of family income in Australia., Conference paper presented at '25th General Conference of International Assocation for Research in Income and Wealth', Cambridge, England.

Richardson, S. and Harding, A. (1999), 'Poor Workers? The Link between Low Wages, Low Family Income and the Tax and Transfer Systems', in S. Richardson, (ed.), *Reshaping the Labour Market, Regulation, Efficiency and Equality in Australia*, Cambridge University Press, Melbourne.

Scutella, R. and Ellis, L. (2007), Employment retention and advancement of disadvantaged jobseekers, Conference paper presented at 'Australian Social Policy Conference', 11-13 July 2007, UNSW, Sydney, Australia.

Stewart, M.B. and Swaffield, J.K. (1999), 'Low Pay Dynamics and Transition Probabilities', *Economica* 66, 23-42.

Venables, W.N. and Ripley, B.D. (2002), *Modern Applied Statistics with S*, Fourth edn, Springer, New York. ISBN 0-387-95457-0.

Watson, I. (2002), 'Wage inequality and Underemployment: Australia in the 1990s', *Journal of Industrial Relations* 44, 88-107.