Paper 4: The low-paid workforce and labour market transitions: assessing the impact of unemployment on earnings at the bottom of the labour market

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The low paid workforce and labour market transitions

Assessing the impact of unemployment on earnings at the bottom of the labour market

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Abstract

One of the most important labour market transitions a person can make is from unemployment into paid work. How does the experience of unemployment influence a person's subsequent earnings? Using longitudinal data from the HILDA Survey, this paper examines the impact on a worker's current earnings of previous experiences of unemployment, as well as a longer-term history of unemployment. The framework adopted in this paper is one of labour market segmentation, based on occupational segments. This recasts the question as: what impact does unemployment have on the low paid workforce, particularly the wages structure at the bottom of the labour market. The findings suggest that in recent times the wages floor in Australia has remained intact.

1 Introduction

Australian studies on the low paid workforce have ranged across a number of themes. Some studies have focussed on the labour market characteristics of the low paid (Buchanan and Watson, 1997; Eardley, 1998; Richardson and Harding, 1998; Healy and Richardson, 2006; Masterman-Smith and Pocock, 2008) while others have examined more closely the links between low pay and unemployment (Richardson and Harding, 1999; Borland and Woodbridge, 1999; Dunlop, 2001; Scutella and Ellis, 2007; Perkins and Scutella, 2009; Watson, 2007, 2009). One strand within this latter literature could be termed 'transition studies', research which makes use of longitudinal data to examine individual transitions between various situations at discrete points in time (for some recent examples using the HILDA data, see Buddelmeyer and Wooden (2008); Carroll and Poehl (2007); Chalmers and Waddoups (2007)).

The main econometric issue in the transition literature concerns problems of 'genuine state dependence', that is, assessing the extent to which remaining in a particular state is due to previous similar states and how much is due to (unobserved) personal characteristics (see, for example, Cappellari (2002); Stewart and Swaffield (1999); Stewart (2007); Scutella and Ellis (2007). In terms of earnings mobility or unemployment transitions, these kinds of studies grapple with the problem of deriving reliable transition probabilities of moving between low paid jobs or between low paid jobs and unemployment. Extensions to this approach often include consideration of subgroups (male and female, or disadvantaged job seekers, for example).

When it comes to the issue of earnings mobility, the main substantive problem with this approach is its artificiality. The boundaries between earnings categories are somewhat arbitrary, and it is not clear what proportion of upwardly mobile persons constitutes a 'good outcome'. Moreover, as Dickens argues, this approach picks up mobility between deciles (or quintiles, or whatever), but not within them. This has led him to prefer a more fine-grained approach of measuring mobility using changes in an individual's percentile rankings (Dickens, 2000).

Ultimately, however, the most unsettling aspect to earnings transition studies is their underlying focus on individual mobility. The class mobility studies which gained prominence in sociology from the 1960s onwards often conveyed the impression that everything was fine provided a certain proportion of people were upwardly mobile (see, for example, Jones and Davis (1986)). The same impression emerges in some earnings mobility studies, particularly those that focus on whether low paid jobs are 'stepping stones' into better jobs. From within this perspective it does not seem to matter whether the wage structure as a whole is unjust or not, provided individuals can move upward through the structure in true meritocratic fashion.

By way of contrast, studies of the labour market which focus on structural segmentation move beyond this individualistic focus and examine outcomes for large groups of workers, particularly those in the most vulnerable labour market situations. Both the more sophisticated segmentation literature, and the literature which examines the connections between wage inequality and unemployment, view labour market transitions in a very different light to these individualistic mobility studies (Fine, 1998; Botwinick, 1993; Freedman, 1976). In particular, constant transitions between unemployment and low pay are seen as one of the key dynamics of a market economy, one of the mechanisms for keeping wages low and for sustaining inequality (Botwinick, 1993; Watson, 2002).

In policy terms, what matters from a structural perspective is how far unemployment is allowed to foment a ghettoised low wage sector within the labour market. The classic studies just cited indicate that if left unchecked this dynamic is quite strong, and the United States labour market is often viewed as providing an archetypal instance of this. However, in the kind of labour market which currently prevails in Australia, it seems likely that this dynamic has been curtailed: partly because of a period of strong economic growth and partly because of institutional measures to sustain the wages floor. The SNA and Fair Pay Commission rulings over the last few years have been particularly important in this regard.

'Good outcomes' in structural terms means the reintegration of unemployed people into the wages structure in ways which do not open cracks in the floor. Their fate is a good barometer to the health of the labour market, since if anyone is likely to find those cracks, it is people made vulnerable by the experience of unemployment. In research terms, the agenda becomes one of examining the links between experiences of unemployment and subsequent earnings and the extent of the wages penalty which unemployment exacts. This agenda has, of course, been pursued within the mainstream economic literature in studies of the 'scarring effects' of unemployment (for example, Ruhm (1991), Swaim and Podgursky (1991), Jacobson et al. (1993), Stevens (1997), Gregory and Jukes (2001) and Arulampalam (2001)). While the focus is often individualistic, this kind of research agenda can also be more structurally oriented if one examines what the earnings outcomes of previously unemployed individuals mean for the wages structure as a whole. A framework of labour market segmentation helps in this regard.

Overseas studies certainly suggest that the 'scarring effect' can be substantial. Gregory and Jukes (2001, pp. F610–F611) summarised the literature and observed that studies in the United States had put the size of the wages penalty induced by unemployment at between 5 and 10 per cent, with earnings losses greatest for those workers who had longer tenure. The European experience showed a different pattern:

> ... losses on re-engagement are lower, possibly negligible and, where they exist, are more quickly overcome. Against this, however, the longer duration of the average unemployment spell causes much higher immediate forgone earnings (2001, p. F611).

In their own study of the experiences of British men between 1984 and 1994, Gregory and Jukes found that the wages penalty was between 2 per cent and 10 per cent, depending on the recency of the spell of unemployment (2001, p. F619). They also distinguished between the incidence of unemployment and its duration, and found that the impact of the latter was particularly noteworthy: a one-year spell of unemployment was associated with a wages penalty of about 11 per cent. They concluded: 'Unemployment incidence itself gives rise to an earnings penalty, but this is largely temporary, most of it being eliminated after two years of continuous re-employment. The effect of duration, on the other hand, is permanent and proportional to the length of the spell' (2001, p. F622).

While this study examined men who passed through a period of major economic restructuring and high levels of unemployment, later studies also found unemployment had a considerable impact on earnings. Looking at the period 1991 to 1997, Arulampalam (2001, p. F597) found sizeable scarring effects among his cohort of men. Compared to those men who made employment-to-employment transitions, those who reentered employment from a spell of unemployment faced a wages penalty of about 7%. If the interruption was a period of economic inactivity, the effect was 11%. Unlike Gregory and Jukes who found a diminishing wages penalty, Arulampalam found that the scarring effect persisted over time: the wages penalty was about 6% in the first year and increased to about 14% upto about 4 years later. After that it slowly diminished. Like Gregory and Jukes, Arulampalam also considered a man's prior history of unemployment and concluded that the scarring effect was 'long lasting': 'the scarring effect from his previous spell of unemployment although reduced, is still there even in his second spell of employment' (2001, p. F602).

Despite a short downturn in 2001, Australia has experienced a decade of strong economic growth, with the unemployment rate recently slipping below 4 per cent for the first time since the early 1970s.[1] In such a tight labour market do those workers who experience unemployment still face a wages penalty when they re-enter the workforce? What is the impact on wages of recent unemployment experiences as well as a longer-term history of unemployment? From a structural perspective, what is the impact on the wages structure of unemployed workers returning to employment. Do those that the bottom of the labour market experience worse outcomes? These are the core questions which this paper tackles.

2 Data and approach

This paper draws on the Australian Government/Melbourne Institute's *Household, Income and Labour Dynamics in Australia Survey* (HILDA). This is an ongoing longitudinal survey of Australian households which began in 2001 and which is representative of the Australian population.[2] The data for this paper comes from Release 6.0 and includes all adult employed persons from Wave 3 through to Wave 6. The descriptive data below, which covers the period 2003 to 2006, uses unbalanced panels and weights the observations using cross-sectional weights, thus approximating a time-series of representative slices of employed adults over this period. The data used for the modelling is unweighted and is a balanced panel, that is, the sample is restricted to the same individuals who entered the survey in Wave 1, but who were observed in the period Wave 3 to Wave 6.

There are two reasons for restricting the observations to the period from Waves 3 to 6. First, one of the key measures of unemployment

[1] It is worth noting that the 30 year comparison can be misleading. The prevalence of under-employment in the Australian labour market and major changes in how employers utilise labour make long-term comparisons somewhat dubious. Even with an unemployment rate hovering around 4 per cent, the under-utilisation rate has remained in double figures.

[2] For more information on the HILDA survey, see the HILDA Survey User Manual, (Watson, 2008).

experience used in this paper is the cumulative length of time spent unemployed in the last three years, a variable based on the calendar data in HILDA for an individual in his/her current and previous two waves. Secondly, one of the important variables of interest—access to workplace training—only became available from Wave 3 onward.

The other measure of unemployment used in this paper is an individual's history, measuring how long they have spent unemployed prior to the survey interview. This variable—based on years—is transformed into a proportion of that individual's post-school life. There are a few complications in finalising these measures, but they do appear robust. While useful for the purposes of this paper, these measures do not map exactly onto the incidence and duration measures used in some of the overseas literature. The former usually relates to 'spells' of unemployment, while I have chosen to convert the calendar data on such intervals into a cumulative measure.

In future research, it may be worth revisiting how unemployment experiences might be operationalised. The two measures used here overlap to some extent. For example, about 40 per cent of those people with 6 months or more of recent unemployment experience also belong in the long duration category when it comes to their history. Offsetting this, to some extent, about one fifth of those with no recent experience of unemployment have a history of some unemployment, while about one fifth of those with a small amount of recent unemployment have no history of unemployment prior to their recent experience. One of the questions for this paper, pursued in the modelling section, is whether these two categories of unemployment experience have independent explanatory power.

The earnings measure is hourly rates of pay, based on dividing current weekly earnings in the main job by usual weekly hours of work in the main job.[3] The latter have been top-coded to 50 hours (following the approach in Healy and Richardson (2006)), and recoding has been used for extreme outliers.[4] The hourly rates have been converted to real earnings using the CPI, with a base of 2006. Both employees and the self-employed constitute the population of interest,[5] and employed persons under 21 have been excluded because of the influence of junior rates. Finally, casuals' earnings have been deflated by 15 per cent, following the logic and strategy used in Watson (2005).[6]

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[3] For a thorough discussion on the reliability of the HILDA wage and salary data, see Wooden et al. (2007).

[4] Outliers were those adults earning \$5 per hour or below in 2001 (and then CPI indexed for subsequent waves) or those earning \$160 per hour or above (also CPI indexed). Both were recoded to either the minimum (\$5) or the maximum (\$160) as appropriate. The results in this paper were not sensitive to this recoding scheme.

[5] The latter have been retained because of the importance of transitions into and out of self-employment.

Operationalising labour market segments has never been easy, from the earliest dual-labour market theories through to the more recent and sophisticated studies (see Cain (1976) for the classic critique and the various rejoinders by Piore (1983) and Reich (1984)). Even a conceptually appealing framework like that of Richard Edwards (1979), becomes difficult to implement in contemporary Australia, particularly following several periods of de-industrialisation. For pragmatic reasons, this paper works with a simple model of occupational segmentation. (The terms 'occupational segments' and 'labour market segments' will be used interchangeably.) The top segment is reasonably straightforward: managers and professionals (a group dubbed the 'PMC'—the professional-managerial class—by Ehrenreich and Ehrenreich (1979)). The bottom segment is reasonably coherent: the low skilled occupations of labourers and those termed 'elementary clerical, sales and service workers' in ASCO Second Edition. This leaves the middle segment as a miscellany of those in-between. Except for unusual situations—such as labourers in the mining industry—there is little doubt that the bottom segment is a reasonable approach to classifying low paid jobs in structural terms.[7] As Table 1 shows, there are distinct earnings breaks in the occupational structure and these map quite well onto these occupational segments.

In what follows I introduce the data by way of descriptive tables and kernel density distributions. These allows us to examine the impact of unemployment experiences on each segment of the labour market. The overall impression appears to be that the bottom occupational segment is not particularly disadvantaged, in relative terms, by unemployment, vis-a-vis the other segments. To assess the robustness of this impression I then introduce a multivariate modelling strategy which investigates these findings more exhaustively.

3 Descriptive overview

The strong links between occupational segmentation and unemployment are evident in Table 2, which gives an overview of the key variables employed in this paper and the sample sizes involved. The association between low skilled jobs and vulnerability to unemployment is evident in this table, a result consistent with most of the literature. The very small number of persons affected by unemployment in the top segment is also notable, the implications of which will be discussed in more detail below.

[6] This takes account of the 'loadings' paid to casuals to compensate them for their lack of holiday and sick pay.

[7] From a skills-typology point of view, this classification is consistent with Cully (2003, p. 13). His Level 1 is equivalent to the 'top' segment and his Level 5 is equivalent to the 'bottom' segment here.

Table 1: Median earnings by occupational segments and occupations (real$)

	Year surveyed				
	2003	2004	2005	2006	Total
Occupational segments					
Top	26.40	26.89	27.44	28.00	27.26
Middle	18.68	19.11	19.64	20.00	19.37
Bottom	15.29	15.75	16.25	15.87	15.80
Total	19.78	20.13	20.80	21.05	20.47
Occupations					
Managers	28.85	28.96	31.19	31.35	30.02
Professionals	25.86	26.64	26.65	27.50	26.64
Assoc Professionals	21.84	20.73	22.05	23.00	21.84
Tradespersons	19.34	19.98	20.59	21.74	20.41
Adv Clerical & Serv	20.13	20.37	20.77	21.59	20.57
Inter Clerical, Sales & Serv	17.54	17.76	18.19	18.27	17.87
Inter Prod & Trans Workers	18.10	18.71	18.98	19.49	18.72
Elem Clerical, Sales & Serv	15.47	15.98	16.29	16.63	15.98
Labourers	15.20	15.42	16.18	15.51	15.53
Total	19.78	20.13	20.80	21.05	20.47

Notes: Data weighted by cross-sectional weights. Data shows median real hourly wages (CPI adjusted with a base of 2006). Occupational segments: *top* = managers, professionals; *middle*= associate professionals, tradespersons, advanced clerical/service, intermediate clerical/sales/service, intermediate production/transport; *bottom* = elementary clerical/sales/service, labourers.
Source: HILDA Release 6.0, Waves 3 to 6.
Population: All adult employed persons in each wave (unbalanced panel).

Table 2: Recent experiences of unemployment and history of unemployment by occupational segments, 2003

Cumulative time unemployed in last 3 yrs	**Occupational segment** Top	Middle	Bottom	Total
None	90	84	77	84
Under 3 mths	5	7	6	7
3 to 6 mths	3	4	5	4
6 mths or more	2	5	11	5
Total	100	100	100	100
N	2,088	3,296	932	6,316
Percentage of post-school life unemployed	**Occupational segment** Top	**Middle**	**Bottom**	**Total**
None	76	65	56	67
Under 10 percent	21	26	26	24
10 to under 20 percent	2	6	9	5
20 percent or more	1	4	9	4
Total	100	100	100	100
N	2,062	3,234	907	6,203

Notes: Data weighted by cross-sectional weights. Occupational segments: *top* = managers, professionals; *middle*= associate professionals, tradespersons, advanced clerical/service, intermediate clerical/sales/service, intermediate production/transport; *bottom* = elementary clerical/sales/service, labourers.
Source: HILDA Release 6.0, Wave 3.
Population: All adult employed persons in Wave 3.

The median earnings of persons in each unemployment category, cross-classified by labour market segment, are shown in Table 3. Earnings are shown re-indexed in each year by the 'no unemployment' category, which allows us to quickly compare across categories and segments. Looking at the top segment, for example, we see that in 2003, those whose recent experiences of unemployment lasted less than three months were earning 94 per cent of the amount earned by those without any experience of unemployment. The comparable figure for those in the middle segment was 93 per cent, and for those in the bottom segment, 95 per cent. It needs to be kept in mind that the number of observations for those in the top segment with longer experiences of unemployment is quite small. Nevertheless, the most remarkable features of Table 3 are the relatively poor showing by those in the middle segment, and the fact that the results for those in the bottom segment do not appear to be disproportionately worse off. This initial overview suggests that workers in the bottom segment, while more vulnerable to the experience of unemployment, have not been disproportionately penalised—vis-a-vis their peers in the other segments—by those experiences.

Table 3: Indexed median earnings by recent experiences of unemployment, different occupational segments

Cumulative time unemployed in last 3 yrs	Year surveyed 2003	2004	2005	2006	Total
Top segment					
None	100	100	100	100	100
Under 3 mths	94	91	83	82	87
3 to 6 mths	102	111	91	89	97
6 mths or more	86	84	81	70	80
Total	99	99	98	97	99
Middle segment					
None	100	100	100	100	100
Under 3 mths	93	88	86	87	88
3 to 6 mths	86	84	84	82	85
6 mths or more	79	78	76	77	77
Total	97	97	96	97	97
Bottom segment					
None	100	100	100	100	100
Under 3 mths	95	95	92	95	95
3 to 6 mths	96	94	83	96	93
6 mths or more	91	90	86	83	88
Total	98	99	97	97	98

Notes: Data weighted by cross-sectional weights. The index is based on the none category in each wave, and the underlying measure is median real hourly wages. Occupational segments: *top* = managers, professionals; *middle*= associate professionals, tradespersons, advanced clerical/service, intermediate clerical/sales/service, intermediate production/transport; *bottom* = elementary clerical/sales/service, labourers.
Source: HILDA Release 6.0, Waves 3 to 6.
Population: All adult employed persons in each wave (unbalanced panel).

Turning now to a person's history of unemployment, Table 4 shows the results calculated in a similar fashion, that is, using indexed median earnings. The history measure is the proportion of a person's post-school life which has been spent unemployed. There are considerable similarities between Tables 3 and 4: relatively poor outcomes for those in the middle segment of the labour market and relatively good results for those at the bottom. Again, as we saw earlier, while those in the bottom segment are much more vulnerable to having a longer history of unemployment, this legacy does not appear to be penalising them in a disproportionate fashion.

Table 4: Indexed median earnings by history of unemployment, different occupational segments

Percentage of post-school life unemployed	Year surveyed 2003	2004	2005	2006	Total
Top segment					
None	100	100	100	100	100
Under 10 percent	90	93	95	96	94
10 to under 20 percent	88	74	73	75	75
20 percent or more	84	57	85	85	80
Total	97	97	98	99	98
Middle segment					
None	100	100	100	100	100
Under 10 percent	96	96	91	92	94
10 to under 20 percent	85	92	84	84	86
20 percent or more	76	79	75	80	76
Total	97	98	95	94	97
Bottom segment					
None	100	100	100	100	100
Under 10 percent	99	99	99	97	99
10 to under 20 percent	91	94	88	95	92
20 percent or more	87	88	91	88	89
Total	98	98	98	97	98

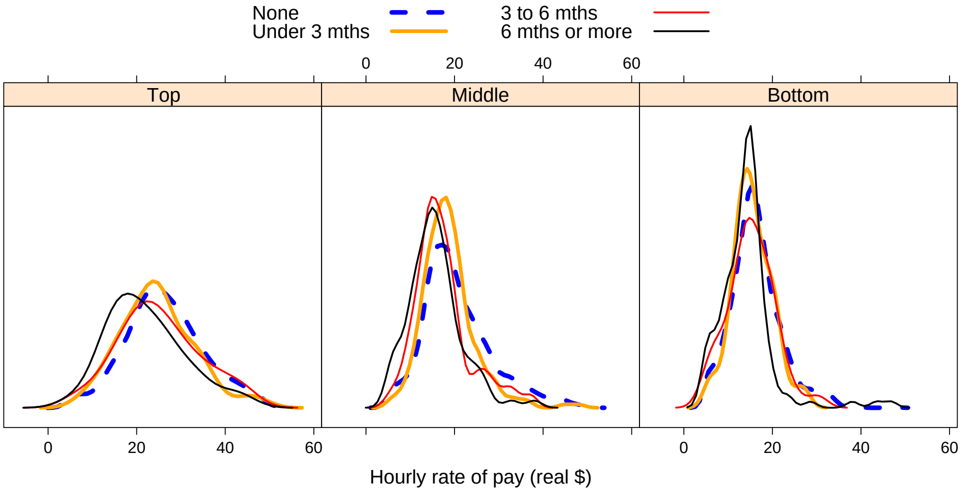
Notes: Data weighted by cross-sectional weights. The index is based on the none category in each wave, and the underlying measure is median real hourly wages. Occupational segments: *top* = managers, professionals; *middle*= associate professionals, tradespersons, advanced clerical/service, intermediate clerical/sales/service, intermediate production/transport; *bottom* = elementary clerical/sales/service, labourers.
Source: HILDA Release 6.0, Waves 3 to 6.
Population: All adult employed persons in each wave (unbalanced panel).

The density graphs for the 2003 data shown in Figures 1 and 3 reinforce these impressions. Those respondents with recent experiences of unemployment which stretched beyond 6 months appear to be 'punished' in terms of their earnings at each level of the labour market. The results for those at the top of the labour market and with the longest experience of unemployment should be treated with caution, given the small number of observations involved. Nevertheless, the similarity between those at the bottom of the labour market and those in the middle is notable. Both show a similar bulge at the bottom of the earnings distribution where those persons with longer experiences of unemployment (3 months and upward) can be found. Despite this, it is worth noting that, for both middle and bottom segments, these persons are spread reasonably well across their respective earnings distribution. In other words, those persons with recent experiences of unemployment have not been ghettoised, particularly at the bottom of the labour market.

The gender dimension to this story is shown in Figure 2. While the number of observations is obviously smaller, some conclusions can be drawn. It appears to be men in the middle segment who are contributing to the relatively poor showing among those with longer experiences of unemployment while, on the other hand, the gender differences at the bottom of the labour market are quite constrained. (Though clearly the overall male distribution is more unequal than the female distribution.)

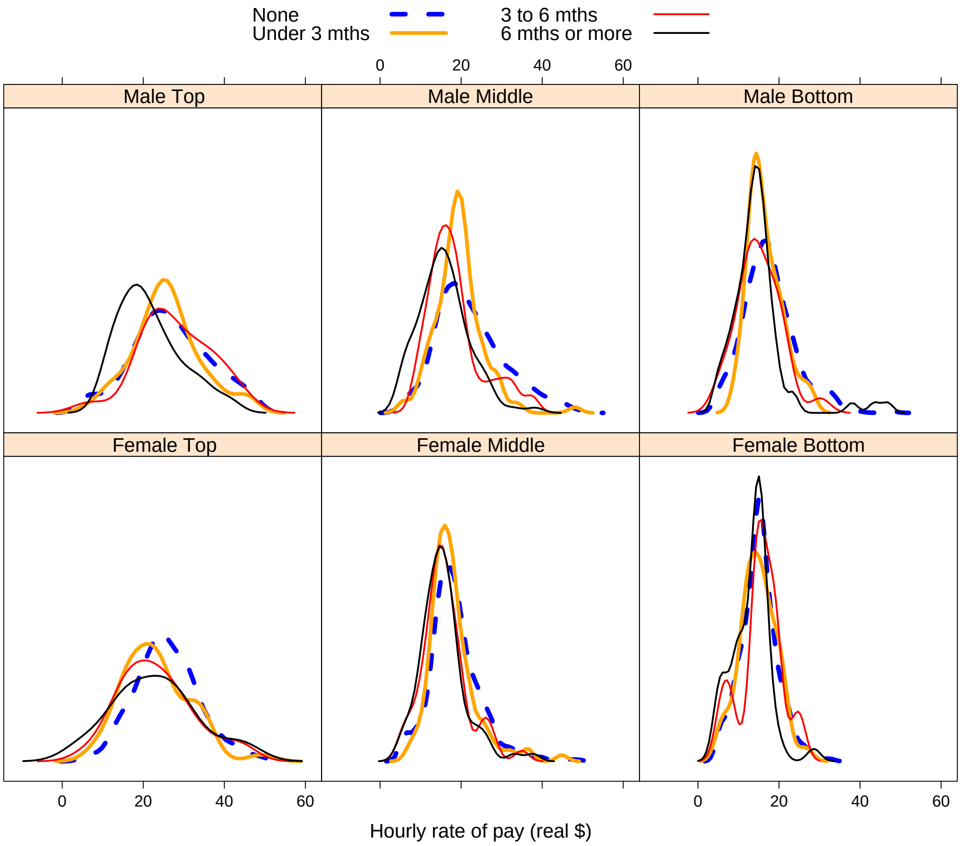
The combined results for those with a history of unemployment parallel this situation (Figure 2). Again, we can see that those in the middle of the labour market with longer histories of unemployment appear to fare worse (in relative terms). The number of observations for those in the top segment suggest caution, though clearly those with any level of unemployment history are being penalised. Turning to the gender dimension, Figure 2 suggests that it is men in the middle segment who are again responsible for the relatively poor results for those with a history of unemployment, particularly if its extends beyond 10 per cent of a person's post-school life.

Figure 1: Distribution of real hourly earnings by recent experiences of unemployment, within each occupational segment, 2003



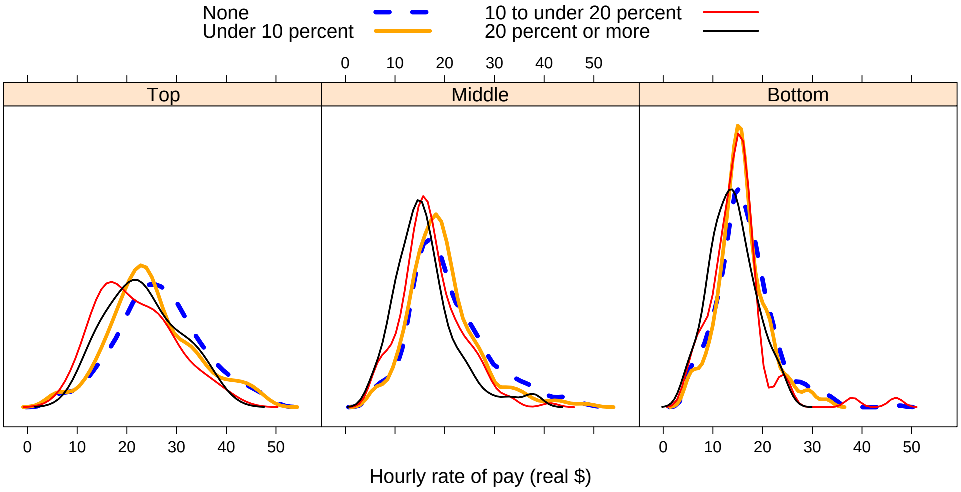
Source: HILDA Release 6.0, Wave 3. *Note*: Rates of pay indexed to 2006.

Figure 2: Distribution of real hourly earnings by recent experiences of unemployment, within each occupational segment by sex, 2003



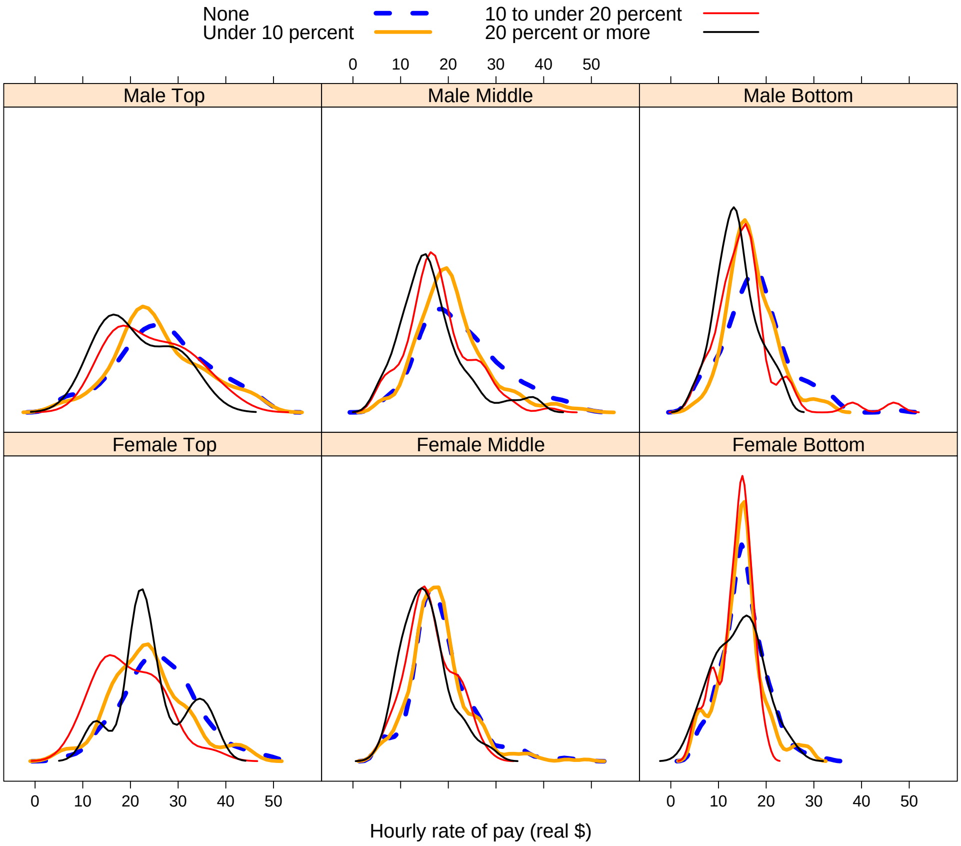
Source: HILDA Release 6.0, Wave 3. *Note*: Rates of pay indexed to 2006.

Figure 3: Distribution of real hourly earnings by history of unemployment, within each occupational segment, 2003



Source: HILDA Release 6.0, Wave 3. *Note*: Rates of pay indexed to 2006.

Figure 4: Distribution of real hourly earnings by history of unemployment, within each occupational segment by sex, 2003



Source: HILDA Release 6.0, Wave 3. *Note*: Rates of pay indexed to 2006.

4 Multivariate analysis

4.1 Model specification

As a longitudinal dataset, the HILDA survey data provides some distinct advantages for researchers. As mentioned earlier, studies which examine transitions between discrete states become feasible with this kind of data. In the case of this paper, not only does the longitudinal data allow for the construction of new work-history variables based on the calendar data (such as recent experiences of unemployment), but problems of unobserved individual heterogeneity can be addressed by recourse to various panel data modelling stragegies. By pooling the data over several waves, the researcher gains access to repeated observations on the same individuals. This lends itself to fix-effects modelling approaches, as employed by Arulampalam (2001) and Gregory and Jukes (2001), as well as other panel-data strategies.

In this paper I employ a mixed-effects or multilevel modelling strategy (see Pinheiro and Bates (2004) and Gelman and Hill (2007) for the approach taken in this paper). This means fitting a model with a fixed component—the usual set of earnings regression controls—as well a random component. In this case, it means allowing the intercept to vary for each individual in the sample. While not undertaken here, it is also possible to incorporate a random (or varying) coefficient into the model specification. This flexibility in model specification makes multilevel modelling strategies highly regarded by a number of authors (see Goldstein (1994), Gelman and Hill (2007) and Skrondal and Rabe-Hesketh (2004)).

The advantages of this approach are considerable when it comes to repeated measures data, such as panel data sets. Multilevel modelling provides a kind of 'partial pooling' of the 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 estimatesGelman and Hill (2007, pp. 7, 256). Moreover, unlike fixed-effects modelling, which removes the possibility of estimating time-invariant characteristics (such as gender or ethnicity), a mixed-effects model makes it feasible to include these. Moreover, within a multilevel framework, mixed-effects also allows one to include variables from different levels in the hierarchy within the fixed component.

Ignoring the panel structure in the data not only has implications for the standard errors, but also for the coefficients themselves. By way of illustration, the final models discussed in this paper (models 5 and 6 below) provide a set of coefficients which differ considerably from those produced by pooling the data and running an ordinary least squares (OLS) regression. OLS models produces coefficients which severely under-estimate the impact of variables such as casual status, part-time work, level of education and history of unemployment. This applies to both men and women. On the other hand, the industry coefficients for men from an OLS model are considerably exaggerated. Pooling the data ad using OLS clearly ignores the way in which some of these variables are more strongly associated with the same individuals. To think of all of these earning episodes—which is the best way to conceptualise the observations—as somehow independently observed is misleading. The grouped nature of these data matters. It also matters, of course, when it comes to the question of standard errors. As is well known, grouped data like these violate the *iid* assumption (that observations are independent and identically distributed).

Before looking more closely at the specification of the multilevel model, it is worth considering another technical complication with fitting earnings equations to the HILDA data. This is the 'sample selection problem', that fact that some individuals are never observed earning a labour-market income, and some are observed in only some years. If such selectivity were purely random this would not be an issue, but the factors which influence selection into the sample are likely to be correlated with the regressors which predict the outcome of interest, namely earnings. As a result, 'self-selection bias' may be present in the final earnings estimates.[8] This problem is dealt with using a standard two-stage Heckman approach, applied to each wave of the data (from Waves 3 to 6). The model equation is:

$$Z_i\lambda + \epsilon_{2i} > 0 \tag{1}$$

where

$$\begin{aligned} \epsilon_i &\sim N(0, \sigma) \\ \epsilon_{2i} &\sim N(0, 1) \\ \text{corr}(\epsilon, \epsilon_{2i}) &= \rho \end{aligned}$$

Z represents a matrix of characteristics likely to influence whether an individual is observed to be earning an income. If the error term for the earnings equation (ϵ_i) and the error term for the selection equation (ϵ_{2i}) are correlated (if $\rho \neq 0$), then a 'selection effect' would appear to be operating. Fitting a probit model to the full sample (in each wave) allows one to calculate the inverse of the Mills' ratio for each observation in the sample, and this term can be incorporated into the earnings equation in the second stage as a 'correction' term.[9]

[8] Self-selection bias is succinctly defined by Fishe et al. (1981, p. 172) as follows: 'The problem of selectivity bias arises when, say, a specific feature of an individual is to be examined and we ignore the decision process involved that generated the observed data.'

[9] For details on the construction of the inverse of the Mill's ratio, see Cameron and Trivedi (2005, p. 550). To ensure identification, one or more variables used in the probit model must be omitted from the earnings model. In this case, the number of dependent children in the household has been chosen for this variable. The full details of the probit models are not shown here, but are available from the author.

The second equation—the earnings equation—can take the classic longitudinal form:

$$y_{it} = \alpha + X_{it}\beta_1 + \lambda_{it}\beta_2 + \epsilon_{it} \tag{2}$$

where y_{it} is the (log) of the hourly rate of pay for each individual i in period t. The term X_{it} is a matrix of relevant demographic and labour market explanatory variables, λ_{it} is the correction term for the selection effect, and ϵ_{it} is the usual error term. As mentioned above, the *iid* assumption regarding this error term is violated, since the model contains repeated observations for the same individual.[10]

From within the perspective of multilevel modelling, this wages equation can also be recast as a 'repeated measures' model, in which the correlated error terms within individuals are not simply a nuisance to be corrected for in calculating standard errors, but also a source of additional useful information(Rabe-Hesketh and Skrondal, 2005, p. 34). Not only are the coefficients more reliable with multilevel models (as noted above), but the random intercept (and random coefficient) specification also provide information on the sources of variation in the outcome of interest. Particularly, if a number of levels are involved, one can partition this variation between these different levels and gain useful insights. For example, if one analysed individuals clustered in households clustered in geographical localities (such as local labour markets), one could draw very useful conclusions about a person's experiences of unemployment which incorporated information from each level in the hierarchy. In the case of this paper, 'earnings episodes' clustered within individuals is the extent of the multilevel modelling undertaken.

The time-series nature of the HILDA data, with annual data collected on the same individuals, also introduces issues of serial correlation when the observations are treated as repeated measures. The within-individual errors are serially correlated, and an appropriate correlation structure must be incorporated into the modelling to take account of this. The analysis in this paper uses an autoregressive correlation structure of order 1 (Pinheiro and Bates, 2004, pp. 235–36).

For a model with random, or varying, intercepts, equation 2 can be recast as:

$$\begin{gathered} y_i = \alpha j[i] + X_i\beta_1 + \lambda_i\beta_2 + \epsilon_i, \\ \text{for individual earnings episodes} \quad i = 1, \ldots, 4 \end{gathered} \tag{3}$$

[10] As well as its longitudinal dimension, 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. At this stage in the analysis, this added layer of complexity is ignored, though multilevel modelling certainly makes it feasible to explore 'household effects' on the earnings of individuals. Complications arise because of the changing composition of households across waves.

$$\alpha_j = \alpha + bu_j + \eta_j, \quad \text{for individual persons} \quad j = 1, \ldots, n \tag{4}$$

where i no longer represents the individual person, but rather the individual earnings episodes taken at time intervals from Wave 3 to Wave 6. (Though not all individual persons have all four measures taken). The j term now represents the individual person across which the episodes have been taken and η_j represents the error term at the level of the individual. The predictors for the individual episodes in equation 3 are the same as before but with the constant, α, in equation 2 allowed to vary, and modelled explicitly in equation 4. When varying coefficients are also included the multilevel structure then takes the form:

$$y_i = \alpha j[i] + X_i\beta_{j[i]} + \lambda_i\beta_2 + \epsilon_i, \quad \text{for individual earnings episodes} \quad i = 1, \ldots, 4 \tag{5}$$

$$\begin{aligned} \alpha_j &= \alpha_0 + b_0 u_j + \eta_{j1}, \\ \beta_j &= \alpha_1 + b_1 u_j + \eta_{j2}, \\ &\text{for individual persons} \quad j = 1, \ldots, n \end{aligned} \tag{6}$$

where the coefficient on (some variables within) X_i are also allowed to vary for each person, hence $\beta_{j[i]}$. While this formulation of the model is not universal, it emphasises the fact that the multilevel approach explicitly models the hyperparameters of the second-level model, and illustrates why some authors regard multilevel modelling as a such a flexible approach to model specification (Gelman and Hill, 2007). As mentioned above, in this paper only a random intercepts model is fitted to the data, though the possibilities of random coefficient models will be considered in subsequent work.

4.2 Results

A number of models were fitted to the data, with each subsequent model adding more complexity. The first two models pooled males and females, the final four split the sample by sex. All models employed a mixed effects approach, with a random intercept for each individual in the sample based on their cross-wave indentifier. All the models were fit through restricted maximum likelihood estimation (REML) using the `nlme` package in R (R Development Core Team, 2008; Pinheiro et al., 2008). Detailed results for all models are shown in the appendix.

The first two models fit each of the unemployment variables (termed 'experience' and 'history' for convenience) to the same specification, in which sex is interacted with some of the key demographic and labour market variables, as well as the occupational segment and unemployment variables. The overall results for the fixed effects are mostly what one would expect and are shown in detail in Table 8 in the appendix. Interest centres on the impact of unemployment, and its gender dimension.

Table 5: Wage penalties for employed persons by sex: experience and history (marginal effects from models 1 and 2)

Experience	**Cumulative time unemployed in last 3 years**		
	Under 3 months	*3 to 6 months*	*6 months or more*
Male	-4%	-2%	-10%
95% confidence intervals	[-7% to -1%]	[-6% to 2%]	[-14% to -7%]
Female	-4%	-3%	-8%
95% confidence intervals	[-7% to -1%]	[-7% to 1%]	[-11% to -4%]
History	**Percentage of post-school life unemployed**		
	Under 10 per cent	*10 to 20 per cent*	*20 per cent or more*
Male	-7%	-16%	-15%
95% confidence intervals	[-9% to -4%]	[-20% to -12%]	[-20% to -10%]
Female	-6%	-8%	-8%
95% confidence intervals	[-8% to -3%]	[-13% to -3%]	[-14% to -2%]

Notes: Wage penalties are marginal effects, based on models 1 and 2 in the appendix. Coefficients are converted to percentages using the formula $100 * (exp(\beta) - 1)$. The model is refit with different sex categories omitted each time, hence interaction effects are accommodated. Occupational segments: *top* = managers, professionals; *middle*= associate professionals, tradespersons, advanced clerical/service, intermediate clerical/sales/service, intermediate production/transport; *bottom* = elementary clerical/sales/service, labourers.
Source: HILDA Release 6.0, Waves 3 to 6.
Population: All adult employed persons who endured from Wave 1 to Wave 6, observed from Wave 3 onward (balanced panel).

Because of the interaction specification, the marginal main effects for unemployment and for history in Table 8 need to be interpreted as applying to males. By refitting the model with males as the omitted category, marginal main effects for unemployment can be derived for females as well. These are converted to percentages and the results for both sexes are shown in Table 5. These results are quite illuminating. The wages penalty for being unemployed for less than 6 months in the previous three years is quite modest—around 4 per cent—and differs little by gender. However, a period of unemployment which lasts for 6 months or more sees this penalty increase considerably, to around 8 to 10 per cent. Again there is little gender difference.

By way of contrast, a history of prior unemployment exacts a considerable penalty, and this is particularly so for men. While a prior history which has seen men and women spending less than 10 per cent of their post-school life unemployed reduces earnings by about 6 to 7 per cent, for men this penalty leaps to 15 to 16 per cent if they have spent more than 10 per cent of that time unemployed. For women, the extra time spent unemployed exacts a more modest decline in earnings of just 2 percentage points.

The random effects show that about 57 per cent of the variation in earnings can be attributed to characteristics which differ between individuals, and the remaining 43 per cent can be attributed to variability in each earnings episode for individuals. This applies to both models 1 and 2. The Heckman correction term, λ, is not statistically significant, suggesting that the selection effect is weak for this sample.

The next two models—models 3 and 4—are fit separately for males and females, and are shown in Table 9 in the appendix. The results are not further tabulated, since the main interest in this part of the modelling lies in the inclusion of both experience and history. This allows us to examine the net effect of each variable, to see whether recent experiences of unemployment have an impact independent of whether one had a prior history of unemployment. The answer, for both men and women, appears to be that unemployment history is more decisive in influencing future earnings than are recent experiences of unemployment. Only when that recent experience has extended beyond 6 months is the result statistically significant. By contrast, the impact of a history of unemployment remains solid, with little diminution of the marginal effects at each level of one's history.

The random effects in models 3 and 4 (and also in models 5 and 6) show considerable gender variation. Among men, the component of the variance due to differing individual characteristics makes up 64 per cent of the total, with the remaining 36 per cent due to variability within individuals, that is, variability in earnings episodes. For women, on the other hand, the between-individuals component is about 48 per cent, and the within-individuals component makes up the remaining 52 per cent. These findings are consistent with the common observation that earnings dispersion is generally greater among men than among women because men's labour market circumstances are more diverse than women's.

Again the Heckman correction term, λ, is not statistically significant, suggesting that the selection effect is weak for this sample. This applies to models 5 and 6, as well as 3 and 4. The Heckman correction term makes no difference to the coefficients in the models. This lack of statistical significance for the Heckman correction term, and the absence of a selection effect on earnings, may reflect weak identification in the probit equations or it may mean that the final earnings sample is a reasonably representative one. This could be due to the panel nature of the data—where people 'missing from work' in one wave resurface in the next—coupled with a period of strong economic growth during the life of the survey. Both (Gregory and Jukes, 2001) and (Arulampalam, 2001), for example, found that their Heckman correction terms made little difference to their earnings estimates (though their correction terms were statistically significant).

The final set of models—models 5 and 6—address the core theme of this paper, the influence of occupational segmentation. These models fit interactions between experience/history and the occupational segmentation variable, thus answering the question of whether these wage penalties we have been discussing operate differently in different segments of the labour market. The results are shown in detail in Table 10 in the appendix and can be summarised succinctly by recourse to an assessment of the interaction effects between the unemployment variables and the occupational segmentation variable (considered using joint significance tests). For men, the experience of unemployment does indeed differ by occupational segmentation (a p-value of 0.037), while the history of unemployment is not significant at the 10 per cent level (a p-value of 0.076). For women, the experience interaction is not statistically significant at the 5 per cent level, but is statistically significant at the 10 per cent level (a p-value of 0.067). The history interaction is not statistically significant for women (a p-value of 0.238).

These tests suggest occupational segmentation makes a modest difference when it comes to the wages penalty exacted by a period of unemployment. But in what ways? To assess this question, Table 6 shows the marginal effects for each occupational segment of recent experiences of unemployment. This table suggests that for men, both the middle and bottom segments appear to be more vulnerable to the experience of unemployment when it extends beyond six months. However, there is no statistically significant difference between the two segments, and when it comes to a shorter period of unemployment (3 to 6 months), the wages penalty is absent in the bottom segment. The results for women parallel this finding, again suggesting that it is only longer periods of unemployment which produce a wages penalty.

Turning to question of one's history of unemployment, the results are quite striking. As noted above, the joint significance tests for interaction effects between occupational segmentation and the history variable in models 5 and 6 are not statistically significant and Table 7 suggests why this is so. The confidence intervals for the estimates of these marginal effects are very wide. For example, the 17 per cent wages penalty for men in the top segment with an unemployment history of 20 per cent spans the interval -1 to -31 per cent. As noted at the outset, the results for the top segment need to be treated with caution, and this applies to the modelling as well as the descriptive results. Fortunately, our real interest lies in the results for the middle and bottom segments, and among these groups, there do appear to be patterns which are quite robust.

Among men, the estimates for those in the middle segment are consistently negative and of a reasonably large magnitude. By way of comparison, the estimates for men in the bottom segment are not only considerably smaller, but overlap with positive territory in some cases. A similar pattern is evident with the female results, except that the magnitude of the penalty is somewhat reduced.

Table 6: Wage penalties for experience variable, by occupational segment and sex (marginal effects)

	Cumulative time unemployed in last 3 years		
	Under 3 months	*3 to 6 months*	*6 months or more*
Male estimates			
Top segment	-4%	6%	1%
95% confidence intervals	[-9% to 2%]	[-4% to 17%]	[-8% to 10%]
Middle segment	-3%	-4%	-9%
95% confidence intervals	[-7% to 1%]	[-9% to 2%]	[-13% to -3%]
Bottom segment	-2%	6%	-12%
95% confidence intervals	[-9% to 6%]	[-3% to 16%]	[-18% to -5%]
Female estimates			
Top segment	-5%	7%	0%
95% confidence intervals	[-11% to 1%]	[-2% to 16%]	[-9% to 10%]
Middle segment	-3%	-4%	-7%
95% confidence intervals	[-7% to 2%]	[-9% to 2%]	[-12% to -2%]
Bottom segment	0%	2%	-8%
95% confidence intervals	[-7% to 8%]	[-8% to 13%]	[-14% to -1%]

Notes: Wage penalties are marginal effects, based on models 5 and 6 in the appendix. Coefficients are converted to percentages using the formula $100 * (exp(\beta) - 1)$. The model is refit with different occupational segments omitted each time, hence interaction effects are accommodated.
Source: HILDA Release 6.0, Waves 3 to 6.
Population: All adult employed persons who endured from Wave 1 to Wave 6, observed from Wave 3 onward (balanced panel).

Table 7: Wage penalties for history variable, by occupational segment and sex (marginal effects)

	Percentage of post-school life unemployed		
	Under 10 per cent	*10 to 20 per cent*	*20 per cent or more*
Male estimates			
Top segment	-6%	-21%	-16%
95% confidence intervals	[-10% to -2%]	[-29% to -11%]	[-30% to 0%]
Middle segment	-8%	-18%	-15%
95% confidence intervals	[-11% to -5%]	[-22% to -13%]	[-21% to -9%]
Bottom segment	-6%	-7%	-6%
95% confidence intervals	[-12% to -1%]	[-14% to 1%]	[-15% to 2%]
Female estimates			
Top segment	-5%	-11%	-10%
95% confidence intervals	[-10% to -1%]	[-20% to -2%]	[-22% to 4%]
Middle segment	-5%	-7%	-10%
95% confidence intervals	[-8% to -1%]	[-13% to -1%]	[-17% to -2%]
Bottom segment	1%	-1%	3%
95% confidence intervals	[-5% to 8%]	[-10% to 9%]	[-7% to 15%]

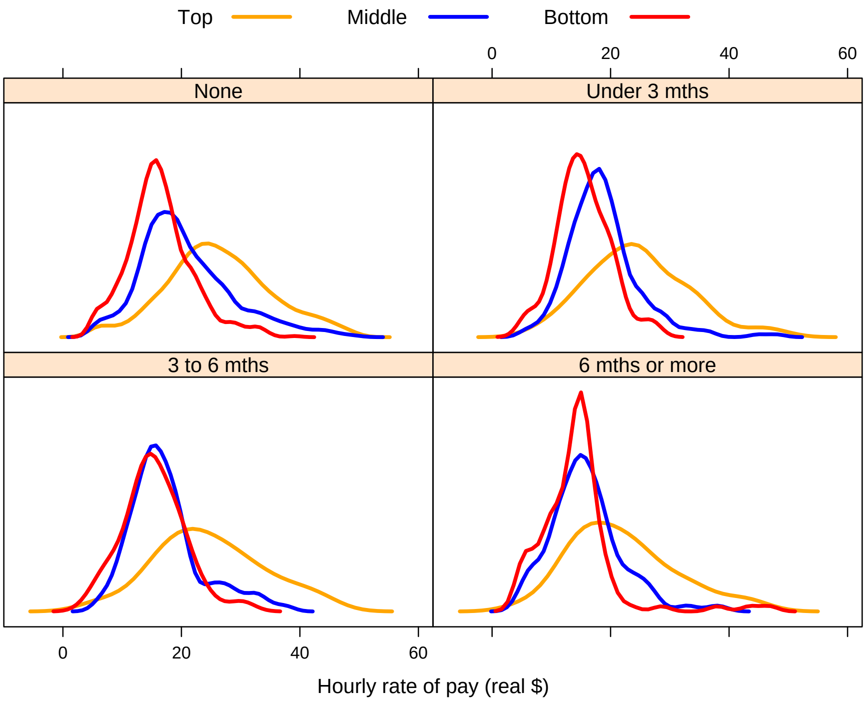
Notes: Wage penalties are marginal effects, based on models 5 and 6 in the appendix. Coefficients are converted to percentages using the formula $100 * (exp(\beta) - 1)$. The model is refit with different occupational segments omitted each time, hence interaction effects are accommodated.
Source: HILDA Release 6.0, Waves 3 to 6.
Population: All adult employed persons who endured from Wave 1 to Wave 6, observed from Wave 3 onward (balanced panel).

In summary, the key finding appears to be that the wages penalty exacted by unemployment—itself quite real and quite considerable—does not operate in a more punishing fashion at the bottom of the labour market, as one might be led to expect. Secondly, it is clear that a longer-term history of unemployment is more of a liability than a recent experience with unemployment, unless that recent experience has extended for some considerable period of time. This finding is consistent with some of the overseas literature. Gregory and Jukes (2001, p. F621), for example, found that duration of unemployment had a more severe impact than its incidence.

In conclusion, it seems that the overall impression conveyed by the descriptive data is confirmed by the multivariate analysis. Those at the bottom of the labour market have fared reasonably well over the period 2003 to 2006. However, it is important to appreciate that these results largely concern *relative effects*, that is, a wages penalty experienced by someone relative to their peers. Someone with a history of unemployment in the bottom segment will earn less than a similar person in the middle segment, but that's because those in the middle segment earn more on average than those in the bottom.

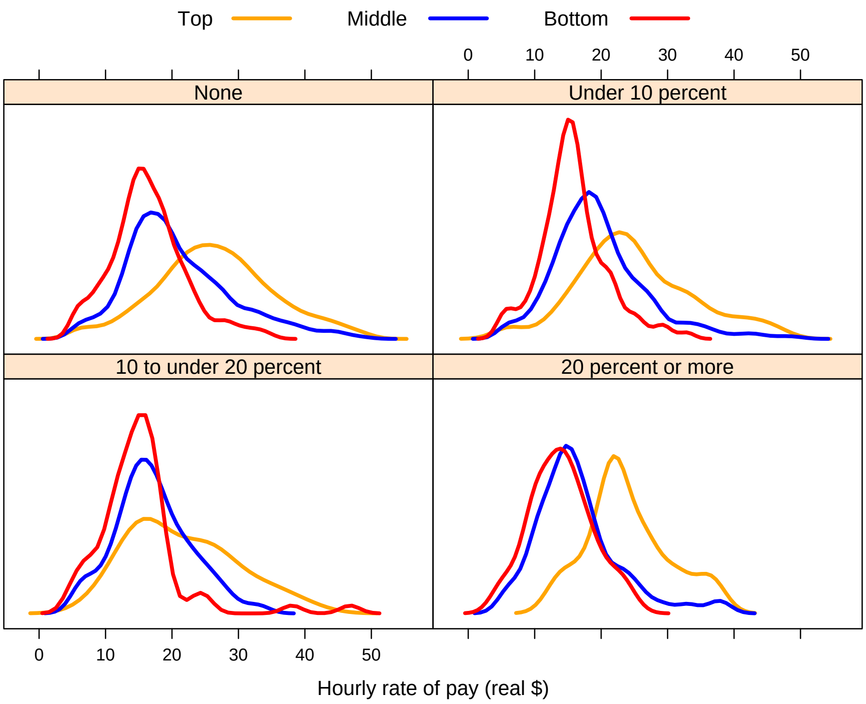
The extent to which the bottom segment has *not* been disproportionately disadvantaged by unemployment is evident in the descriptive data introduced earlier in this paper. If we recast the original density graphs in a slightly different way, this phenomenon is more readily apparent. As Figure 5 shows, the earnings of those in the bottom segment with *no* experience of unemployment are indeed below those in the middle segment, which are in turn below those in the top segment. But notice that as the period of unemployment increases, the relativities between the middle and the bottom shrink, to the point where the two distributions are identical for those in the 3 to 6 months category, and very similar for those in the 6 months or more category. A similar phenomenon is evident with the history variable, in Figure 6, except that a small amount of relative disadvantage for the bottom segment is still evident in the largest history category.

Figure 5: Distribution of real hourly earnings by occupational segment, within each category of unemployment experience, 2003



Source: HILDA Release 6.0, Wave 3. *Note*: Rates of pay indexed to 2006.

Figure 6: Distribution of real hourly earnings by occupational segment, within each category of unemployment history, 2003



Source: HILDA Release 6.0, Wave 3. *Note*: Rates of pay indexed to 2006.

5 Discussion

The usual explanations for the kind of results analysed above often have recourse to human capital theory, search theory or 'matching' theory (see Gregory and Jukes (2001, pp. F608–F609) for an example). My interest, however, lies in contextualising these findings within the structural perspective outlined in the introduction. This means returning to the concept of labour market segmentation and supplementing some insights from that literature with a recognition of some important contemporary economic developments in Australia.

One of the most sophisticated empirical studies of the operation of segmented labour markets was the pioneering work of Marcia Freedman (1976). Her concepts of labour market 'shelters', and of vulnerabilities and protections are particularly fruitful. In explaining the mechanisms which determined the wages structure, Freedman emphasised organisational factors—such as stability and continuity in employment—and factors which represented the bargaining power of workers—such as the degree of unionisation or the extent of credentialism. Each of the labour market segments which Freedman empirically identified, using statistical clustering methods, was characterised by a unique combination of these factors. Freedman showed, for example, that different workers could achieve the same earnings levels through different combinations of these characteristics. Teachers and construction craftsmen earned similar annual incomes, but the former achieved this largely through their credentials, the latter through their union (Freedman, 1976, p. 29). Workers whom dual labour market theory traditionally assigned to the secondary labour market were generally in segments which Freedman described as lacking both stability (that is, organisational permanency) and bargaining power. One of the most powerful insights to be gleaned from Freedman's work was her concept of labour market shelters, a term which signified two themes:

1. 'a retreat from competition and the sum of arrangements that give workers strong claims to their jobs';
2. 'a search for protection against adversity and the mitigation of the effects of unemployment, disability, illness and old age' (1976, p. 113).

It is worth asking whether these insights into labour market protections and vulnerabilities have played a role in the findings discussed in this paper. By fitting a series of interaction effects to the models discussed earlier, it is possible to assess the relative contribution of trade union membership, workplace training and educational credentials to the wages penalties faced by those with an unemployment background. The detailed results are not shown here.[11] They all point to the same conclusion: none of these factors has any impact on the size of the wages

[11] But are available from the author.

penalty faced by those with a recent experience of unemployment or those with a history of unemployment.

By way of testing vulnerabilities, models were fitted with interactions for the variables of casualisation and small employers. The former was not statistically significant, but the latter was, and the size of the marginal effect was considerable. For a person whose recent experience of unemployment extended beyond 6 months, the net wages penalty of working for a small employer was 31 per cent. A history of unemployment, on the other hand, had no impact. One interpretation of this finding is that workers made vulnerable by recent unemployment find their bargaining power considerably weakened by that experience when they seek employment with a small employer, the traditional setting for head-to-head bargaining.

It is important to realise that Freedman was examining the American labour market, where institutional factors, such as regulation by the State, was minimal. The American minimum wage, for example, was allowed to fall steadily (in real terms) for over two decades (Waltman, 2000). Consequently, it is useful to add to Freedman's list the importance of institutional interventions, such as minimum wage legislation, which place a floor at the bottom of the labour market and curtail unbridled competition. In the case of Australia, that floor has largely been kept intact over the last decade. In the period covered by the data in this survey, the Federal Minimum Wage increased by an annual average rate of 3.9 per cent (with a low point of 3.2 per cent and a high point of 4.3 per cent).

Finally, to this list of protections should be added tight labour markets. Much of the early research on labour market segmentation occurred during the period of economic stagnation which succeeded the long post-war boom. Hence a deep pessimism about the fortunes of workers trapped in the secondary labour market was evident in its analyses. Without overlooking the extent of exploitation prevalent in many low paid jobs, there is little doubt that the best protection a vulnerable worker has are tight labour markets, where the opportunity of a better paying job lies just around the corner. As Galbraith (1998) argued persuasively in his assessment of wage inequality in the United States labour market, it was the failure to sustain full employment which predominantly drove the growth of low paid work in that country over the past 30 years.

While sustained economic growth is a necessary condition for tight labour markets, it is not sufficient in itself. Australia's experience of 'jobless' growth during the middle 1990s provides evidence of that. Constant sources of new labour—through immigration or labour market reentry by former workers—can restrict the development of tight labour markets even during periods of economic expansion. The last twenty years has also shown us that employers can also find new ways to engage labour which result in chronic conditions of under-employment (Watson et al., 2003). As noted in the introduction, tight labour markets can co-exist with continuing unemployment, and it seems unlikely that Australia could return to the kind of full-employment which prevailed in the post-war period without decisive labour market interventions to tackle entrenched labour market disadvantage.

Despite the failure to return to genuine full-employment in Australia, its does seem to be the case that the combination of institutional interventions and tight labour markets has prevented serious cracks emerging in the floor of the labour market. If such cracks had emerged, one would certainly expect to find them among the most vulnerable job holders, namely those with a background in unemployment working in the lowest paid jobs. The findings of this paper suggest that this has not happened to any great extent in recent years.

6 Appendix

6.1 Multilevel regression results

Table 8: Models 1 and 2

	(1) Experience			(2) History		
Fixed effects	**Coef**	**SE**	**P-value**	**Coef**	**SE**	**P-value**
Intercept	2.387	0.076	0.000	2.378	0.079	0.000
Wave2004	0.008	0.005	0.114	0.012	0.005	0.022
Wave2005	0.037	0.006	0.000	0.042	0.006	0.000
Wave2006	0.054	0.006	0.000	0.062	0.006	0.000
Ind:Agric, forestry & fishing	-0.190	0.021	0.000	-0.192	0.022	0.000
Ind:Mining	0.311	0.026	0.000	0.316	0.027	0.000
Ind:Electric, gas, water	0.125	0.036	0.001	0.109	0.036	0.003
Ind:Construction	0.077	0.016	0.000	0.066	0.016	0.000
Ind:Wholesale trade	-0.017	0.015	0.254	-0.027	0.015	0.082
Ind:Retail trade	-0.086	0.014	0.000	-0.095	0.014	0.000
Ind:Accommodation etc	-0.139	0.018	0.000	-0.149	0.019	0.000
Ind:Transport & storage	0.019	0.018	0.266	0.007	0.018	0.696
Ind:Communication services	0.044	0.024	0.068	0.034	0.025	0.173
Ind:Finance & insurance	0.118	0.020	0.000	0.110	0.020	0.000
Ind:Prop & business services	0.023	0.013	0.076	0.017	0.013	0.198
Ind:Government	0.005	0.017	0.756	-0.005	0.018	0.757
Ind:Education	-0.095	0.017	0.000	-0.106	0.017	0.000
Ind:Health & comm services	-0.068	0.015	0.000	-0.078	0.015	0.000
Ind:Cultural & rec services	-0.074	0.021	0.000	-0.064	0.021	0.003
Ind:Personal & other services	-0.133	0.019	0.000	-0.142	0.020	0.000
Age/5	0.153	0.016	0.000	0.161	0.016	0.000
Age/5 squared	-0.009	0.001	0.000	-0.009	0.001	0.000
Student:No	0.009	0.018	0.622	0.014	0.019	0.472
Sex:Female	-0.143	0.015	0.000	-0.151	0.016	0.000
Married:Separated, divorced or widowed	-0.023	0.017	0.187	-0.035	0.018	0.052
Married:Never married and not de facto	-0.099	0.013	0.000	-0.101	0.014	0.000
Geog:Balance of NSW	-0.120	0.016	0.000	-0.116	0.016	0.000
Geog:Melbourne	-0.063	0.013	0.000	-0.060	0.014	0.000
Geog:Balance of Victoria	-0.182	0.019	0.000	-0.179	0.019	0.000
Geog:Brisbane	-0.107	0.016	0.000	-0.106	0.017	0.000
Geog:Balance of QLD	-0.150	0.016	0.000	-0.142	0.017	0.000
Geog:Adelaide	-0.161	0.019	0.000	-0.157	0.020	0.000
Geog:Balance of SA	-0.174	0.028	0.000	-0.176	0.029	0.000
Geog:Perth	-0.074	0.018	0.000	-0.056	0.019	0.003
Geog:Balance of WA	-0.121	0.027	0.000	-0.123	0.028	0.000
Geog:Tasmania	-0.196	0.027	0.000	-0.188	0.027	0.000
Geog:Northern Territory	-0.070	0.040	0.077	-0.066	0.041	0.107
Geog:ACT	-0.002	0.027	0.939	0.006	0.028	0.833
ESB immigrant	0.025	0.015	0.089	0.026	0.015	0.081
NESB immigrant	-0.078	0.015	0.000	-0.074	0.015	0.000
Employee	0.120	0.012	0.000	0.124	0.012	0.000
Small Employer	-0.029	0.014	0.039	-0.030	0.014	0.036
Contract: Fixed term	0.034	0.013	0.007	0.027	0.013	0.035
Contract: Casual	-0.174	0.013	0.000	-0.174	0.014	0.000
Part-time	0.148	0.013	0.000	0.151	0.014	0.000
Labour hire	0.065	0.016	0.000	0.076	0.016	0.000
Shift: Shift worker	0.047	0.009	0.000	0.051	0.009	0.000
Shift: Irregular	0.020	0.009	0.030	0.028	0.010	0.003
Edu:Degree or above	0.272	0.017	0.000	0.266	0.017	0.000
Edu:Adv diploma, diploma	0.136	0.017	0.000	0.129	0.017	0.000
Edu:Cert III or IV	0.050	0.013	0.000	0.041	0.014	0.003
Edu:Cert I or II or nd	-0.021	0.030	0.480	-0.017	0.031	0.584
Edu:Year 12	0.095	0.015	0.000	0.085	0.016	0.000
Public Sector	0.038	0.010	0.000	0.040	0.010	0.000
Trade union member	0.052	0.008	0.000	0.051	0.008	0.000
Accessed training	-0.000	0.005	0.954	0.003	0.005	0.628
Supervisor	0.029	0.006	0.000	0.027	0.006	0.000
Tenure/5	0.024	0.006	0.000	0.023	0.006	0.000
Tenure/5 squared	-0.002	0.001	0.014	-0.002	0.001	0.012
NILF:Under 3 mths	-0.003	0.011	0.822	-0.001	0.011	0.917
NILF:3 to 6 mths	-0.010	0.014	0.498	-0.021	0.015	0.146

Fixed effects	(1) Experience Coef	SE	P-value	(2) History Coef	SE	P-value
NILF:6 mths to 12 mths	-0.038	0.013	0.004	-0.038	0.014	0.005
NILF:12 mths or more	-0.063	0.013	0.000	-0.061	0.013	0.000
Occ segment:Middle	-0.103	0.010	0.000	-0.095	0.010	0.000
Occ segment:Bottom	-0.188	0.015	0.000	-0.176	0.015	0.000
(1) Unemp:<3 mths (2) Hist: <10%	-0.044	0.016	0.004	-0.069	0.013	0.000
(1) Unemp:3<6 mths (2) Hist: 10%<20%	-0.024	0.021	0.266	-0.177	0.024	0.000
(1) Unemp:6 mths+ (2) Hist: 20%+	-0.111	0.020	0.000	-0.165	0.028	0.000
λ (inverse of the Mills' ratio)	0.014	0.031	0.647	0.017	0.032	0.601
Female X Separated, divorced or widowed	0.010	0.023	0.671	0.028	0.024	0.243
Female X Never married and not de facto	0.045	0.019	0.016	0.050	0.020	0.010
Female X Fixed term	-0.021	0.018	0.233	-0.016	0.018	0.369
Female X Casual	0.022	0.017	0.192	0.020	0.017	0.255
Female X Part-time	-0.011	0.016	0.497	-0.012	0.017	0.478
Female X Middle segment	-0.033	0.014	0.021	-0.038	0.014	0.009
Female X Bottom segment	-0.021	0.021	0.316	-0.041	0.021	0.052
Female X Under 3 mths/Under 10%	-0.001	0.022	0.959	0.009	0.019	0.628
Female X 3 to 6 mths/10% to under 20%	-0.004	0.030	0.906	0.095	0.035	0.007
Female X 6 mths or more/20% or more	0.028	0.027	0.309	0.079	0.044	0.073

Random effects	(1) Experience Variance	Std Dev	(2) History Variance	Std Dev
Intercept	0.103	0.321	0.104	0.323
Residual	0.078	0.279	0.077	0.278

Statistics	(1) Experience	(2) History
Log likelihood	-8,820	-8,415
BIC	18,461	17,648
AIC	17,803	16,993
Number of observations	22,630	21,808
Number of individuals	7,713	7,353

Source: HILDA Release 6.
Population: All adult employed persons who endured from Wave 1 to Wave 6, observed from Wave 3 onward (balanced panel).

Table 9: Models 3 and 4

	(3) Male			(4) Female		
Fixed effects	**Coef**	**SE**	**P-value**	**Coef**	**SE**	**P-value**
Intercept	2.128	0.114	0.000	2.615	0.114	0.000
Wave2004	0.013	0.007	0.047	0.008	0.008	0.312
Wave2005	0.047	0.007	0.000	0.034	0.009	0.000
Wave2006	0.057	0.008	0.000	0.062	0.009	0.000
Ind:Agric, forestry & fishing	-0.169	0.026	0.000	-0.187	0.040	0.000
Ind:Mining	0.300	0.029	0.000	0.292	0.067	0.000
Ind:Electric, gas, water	0.111	0.040	0.006	0.138	0.082	0.093
Ind:Construction	0.048	0.018	0.008	0.168	0.038	0.000
Ind:Wholesale trade	-0.019	0.018	0.286	-0.025	0.028	0.374
Ind:Retail trade	-0.102	0.019	0.000	-0.078	0.023	0.001
Ind:Accommodation etc	-0.180	0.028	0.000	-0.128	0.028	0.000
Ind:Transport & storage	0.004	0.021	0.826	0.015	0.036	0.674
Ind:Communication services	0.029	0.030	0.344	0.049	0.044	0.270
Ind:Finance & insurance	0.174	0.029	0.000	0.048	0.030	0.106
Ind:Prop & business services	0.036	0.017	0.033	0.006	0.023	0.795
Ind:Government	-0.005	0.023	0.824	0.016	0.028	0.578
Ind:Education	-0.084	0.027	0.002	-0.106	0.025	0.000
Ind:Health & comm services	-0.058	0.025	0.021	-0.070	0.022	0.002
Ind:Cultural & rec services	-0.059	0.028	0.039	-0.066	0.033	0.044
Ind:Personal & other services	-0.144	0.028	0.000	-0.143	0.029	0.000
Age/5	0.205	0.023	0.000	0.103	0.022	0.000
Age/5 squared	-0.011	0.001	0.000	-0.006	0.001	0.000
Student:No	0.032	0.027	0.234	-0.006	0.027	0.828
Married:Separated, divorced or widowed	-0.025	0.018	0.165	0.002	0.015	0.891
Married:Never married and not de facto	-0.087	0.014	0.000	-0.062	0.015	0.000
Geog:Balance of NSW	-0.115	0.023	0.000	-0.114	0.022	0.000
Geog:Melbourne	-0.042	0.020	0.041	-0.081	0.018	0.000
Geog:Balance of Victoria	-0.222	0.028	0.000	-0.142	0.025	0.000
Geog:Brisbane	-0.102	0.025	0.000	-0.109	0.022	0.000
Geog:Balance of QLD	-0.155	0.024	0.000	-0.132	0.023	0.000
Geog:Adelaide	-0.173	0.029	0.000	-0.139	0.027	0.000
Geog:Balance of SA	-0.196	0.043	0.000	-0.146	0.039	0.000
Geog:Perth	-0.058	0.027	0.034	-0.057	0.025	0.024
Geog:Balance of WA	-0.129	0.040	0.001	-0.127	0.039	0.001
Geog:Tasmania	-0.235	0.042	0.000	-0.147	0.035	0.000
Geog:Northern Territory	-0.089	0.057	0.116	-0.065	0.057	0.260
Geog:ACT	-0.003	0.040	0.951	-0.007	0.039	0.847
ESB immigrant	0.039	0.021	0.070	0.017	0.020	0.400
NESB immigrant	-0.100	0.022	0.000	-0.038	0.020	0.058
Employee	0.169	0.015	0.000	0.029	0.020	0.144
Small Employer	-0.048	0.019	0.012	-0.011	0.021	0.605
Contract: Fixed term	0.013	0.013	0.294	0.020	0.013	0.129
Contract: Casual	-0.183	0.014	0.000	-0.148	0.012	0.000
Part-time	0.174	0.014	0.000	0.129	0.010	0.000
Labour hire	0.131	0.022	0.000	0.013	0.025	0.586
Shift: Shift worker	0.057	0.012	0.000	0.040	0.013	0.002
Shift: Irregular	0.021	0.013	0.106	0.034	0.014	0.014
Edu:Degree or above	0.264	0.025	0.000	0.239	0.023	0.000
Edu:Adv diploma, diploma	0.135	0.026	0.000	0.111	0.023	0.000
Edu:Cert III or IV	0.050	0.019	0.010	0.022	0.020	0.257
Edu:Cert I or II or nd	0.010	0.047	0.833	-0.023	0.039	0.551
Edu:Year 12	0.087	0.024	0.000	0.073	0.020	0.000
Public Sector	0.032	0.015	0.036	0.050	0.013	0.000
Trade union member	0.069	0.011	0.000	0.028	0.011	0.010
Accessed training	0.009	0.007	0.221	-0.005	0.008	0.524
Supervisor	0.028	0.008	0.000	0.022	0.008	0.009
Tenure/5	0.009	0.008	0.240	0.033	0.009	0.000
Tenure/5 squared	-0.001	0.001	0.200	-0.002	0.002	0.159
NILF:Under 3 mths	0.011	0.016	0.505	-0.007	0.016	0.639
NILF:3 to 6 mths	-0.048	0.023	0.036	0.002	0.019	0.910
NILF:6 mths to 12 mths	-0.045	0.024	0.056	-0.025	0.017	0.145
NILF:12 mths or more	-0.051	0.024	0.034	-0.058	0.016	0.000
Occ segment:Middle	-0.084	0.011	0.000	-0.149	0.012	0.000

Fixed effects	(3) Male Coef	SE	P-value	(4) Female Coef	SE	P-value
Occ segment:Bottom	-0.158	0.015	0.000	-0.241	0.017	0.000
Unemp:Under 3 mths	-0.029	0.017	0.077	-0.022	0.018	0.215
Unemp:3 to 6 mths	0.009	0.022	0.695	0.004	0.023	0.854
Unemp:6 mths or more	-0.071	0.022	0.001	-0.053	0.021	0.013
Hist: Under 10%	-0.074	0.015	0.000	-0.039	0.014	0.006
Hist: 10% to under 20%	-0.167	0.026	0.000	-0.068	0.026	0.009
Hist: 20% or more	-0.139	0.031	0.000	-0.069	0.034	0.042
λ (inverse of the Mills' ratio)	0.017	0.047	0.723	-0.023	0.044	0.606

Random effects	(3) Male Variance	Std Dev	(4) Female Variance	Std Dev
Intercept	0.125	0.354	0.079	0.281
Residual	0.071	0.266	0.085	0.291

Statistics	(3) Male	(4) Female
Log likelihood	-4,233	-4,194
BIC	9,155	9,072
AIC	8,613	8,535
Number of observations	11,265	10,543
Number of individuals	3,745	3,608

Source: HILDA Release 6.
Population: All adult male (model 3) and female (model 4) employed persons who endured from Wave 1 to Wave 6, observed from Wave 3 onward (balanced panel).

Table 10: Models 5 and 6

	(5) Male			(6) Female		
Fixed effects	**Coef**	**SE**	**P-value**	**Coef**	**SE**	**P-value**
Intercept	2.097	0.114	0.000	2.647	0.114	0.000
Wave2004	0.014	0.007	0.036	0.009	0.008	0.253
Wave2005	0.048	0.007	0.000	0.034	0.009	0.000
Wave2006	0.058	0.008	0.000	0.062	0.009	0.000
Ind:Agric, forestry & fishing	-0.169	0.026	0.000	-0.188	0.040	0.000
Ind:Mining	0.297	0.029	0.000	0.299	0.067	0.000
Ind:Electric, gas, water	0.110	0.040	0.007	0.128	0.082	0.118
Ind:Construction	0.046	0.018	0.011	0.167	0.038	0.000
Ind:Wholesale trade	-0.020	0.018	0.275	-0.022	0.028	0.425
Ind:Retail trade	-0.100	0.019	0.000	-0.077	0.023	0.001
Ind:Accommodation etc	-0.175	0.028	0.000	-0.122	0.028	0.000
Ind:Transport & storage	0.001	0.021	0.945	0.018	0.036	0.614
Ind:Communication services	0.030	0.030	0.325	0.058	0.045	0.194
Ind:Finance & insurance	0.172	0.029	0.000	0.050	0.030	0.092
Ind:Prop & business services	0.034	0.017	0.046	0.006	0.023	0.805
Ind:Government	-0.006	0.023	0.809	0.018	0.028	0.525
Ind:Education	-0.089	0.027	0.001	-0.108	0.025	0.000
Ind:Health & comm services	-0.056	0.025	0.026	-0.068	0.022	0.002
Ind:Cultural & rec services	-0.055	0.028	0.053	-0.063	0.033	0.056
Ind:Personal & other services	-0.145	0.028	0.000	-0.145	0.030	0.000
Age/5	0.211	0.023	0.000	0.096	0.022	0.000
Age/5 squared	-0.012	0.001	0.000	-0.005	0.001	0.000
Student:No	0.033	0.027	0.218	-0.011	0.027	0.678
Married:Separated, divorced or widowed	-0.026	0.018	0.156	0.004	0.015	0.764
Married:Never married and not de facto	-0.085	0.015	0.000	-0.060	0.015	0.000
Geog:Balance of NSW	-0.115	0.023	0.000	-0.111	0.022	0.000
Geog:Melbourne	-0.042	0.020	0.039	-0.080	0.018	0.000
Geog:Balance of Victoria	-0.223	0.028	0.000	-0.139	0.025	0.000
Geog:Brisbane	-0.100	0.025	0.000	-0.107	0.023	0.000
Geog:Balance of QLD	-0.154	0.024	0.000	-0.131	0.023	0.000
Geog:Adelaide	-0.174	0.029	0.000	-0.135	0.027	0.000
Geog:Balance of SA	-0.197	0.043	0.000	-0.138	0.039	0.000
Geog:Perth	-0.057	0.027	0.036	-0.056	0.025	0.027
Geog:Balance of WA	-0.130	0.040	0.001	-0.120	0.039	0.002
Geog:Tasmania	-0.239	0.042	0.000	-0.142	0.035	0.000
Geog:Northern Territory	-0.092	0.057	0.108	-0.071	0.057	0.216
Geog:ACT	-0.005	0.040	0.891	-0.007	0.039	0.857
ESB immigrant	0.040	0.021	0.065	0.016	0.020	0.417
NESB immigrant	-0.101	0.022	0.000	-0.034	0.020	0.090
Employee	0.169	0.015	0.000	0.030	0.020	0.125
Small Employer	-0.047	0.019	0.014	-0.013	0.021	0.540
Contract: Fixed term	0.012	0.013	0.361	0.018	0.013	0.158
Contract: Casual	-0.184	0.014	0.000	-0.153	0.012	0.000
Part-time	0.172	0.014	0.000	0.126	0.010	0.000
Labour hire	0.130	0.022	0.000	0.013	0.025	0.606
Shift: Shift worker	0.056	0.012	0.000	0.039	0.013	0.002
Shift: Irregular	0.019	0.013	0.133	0.034	0.014	0.015
Edu:Degree or above	0.262	0.025	0.000	0.232	0.023	0.000
Edu:Adv diploma, diploma	0.132	0.026	0.000	0.105	0.023	0.000
Edu:Cert III or IV	0.048	0.019	0.013	0.019	0.020	0.328
Edu:Cert I or II or nd	0.006	0.047	0.902	-0.023	0.039	0.558
Edu:Year 12	0.086	0.024	0.000	0.068	0.020	0.001
Public Sector	0.032	0.015	0.037	0.050	0.013	0.000
Trade union member	0.070	0.011	0.000	0.029	0.011	0.008
Accessed training	0.009	0.007	0.190	-0.004	0.008	0.629
Supervisor	0.028	0.008	0.000	0.023	0.008	0.006
Tenure/5	0.010	0.008	0.192	0.038	0.009	0.000
Tenure/5 squared	-0.002	0.001	0.164	-0.003	0.001	0.056
Occ segment:Middle	-0.075	0.013	0.000	-0.147	0.014	0.000

Fixed effects	Coef	(5) Male SE	P-value	Coef	(6) Female SE	P-value
Occ segment:Bottom	-0.177	0.020	0.000	-0.276	0.021	0.000
Unemp:Under 3 mths	-0.040	0.029	0.162	-0.052	0.033	0.116
Unemp:3 to 6 mths	0.057	0.050	0.256	0.065	0.044	0.136
Unemp:6 mths or more	0.006	0.044	0.897	0.002	0.049	0.966
Hist: Under 10%	-0.065	0.021	0.002	-0.056	0.022	0.012
Hist: 10% to under 20%	-0.232	0.059	0.000	-0.119	0.050	0.018
Hist: 20% or more	-0.178	0.091	0.051	-0.102	0.072	0.159
λ (inverse of the Mills' ratio)	0.018	0.047	0.706	-0.043	0.044	0.329
Occseg:Middle X unemp:Under 3 mths	0.007	0.034	0.844	0.026	0.039	0.494
Occseg:Bottom X unemp:Under 3 mths	0.025	0.047	0.600	0.053	0.049	0.275
Occseg:Middle X unemp:3 to 6 mths	-0.096	0.057	0.089	-0.101	0.051	0.049
Occseg:Bottom X unemp:3 to 6 mths	0.003	0.067	0.961	-0.043	0.069	0.530
Occseg:Middle X unemp:6 mths or more	-0.095	0.049	0.054	-0.076	0.054	0.162
Occseg:Bottom X unemp:6 mths or more	-0.128	0.057	0.024	-0.084	0.061	0.168
Occseg:Middle X hist:Under 10%	-0.018	0.023	0.439	0.007	0.026	0.775
Occseg:Bottom X hist:Under 10%	-0.002	0.034	0.964	0.069	0.037	0.059
Occseg:Middle X hist:10 to under 20%	0.036	0.061	0.553	0.045	0.056	0.420
Occseg:Bottom X hist:10 to under 20%	0.160	0.069	0.021	0.109	0.068	0.108
Occseg:Middle X hist:20% or more	0.019	0.091	0.836	0.000	0.077	0.999
Occseg:Bottom X hist:20% or more	0.111	0.099	0.260	0.133	0.088	0.130

Random effects	(5) Male		(6) Female	
	Variance	**Std Dev**	**Variance**	**Std Dev**
Intercept	0.125	0.354	0.079	0.281
Residual	0.071	0.266	0.085	0.291

Statistics	(5) Male	(6) Female
Log likelihood	-4,241	-4,205
BIC	9,246	9,168
AIC	8,646	8,573
Number of observations	11,265	10,543
Number of individuals	3,745	3,608

Source: HILDA Release 6.
Population: All adult male (model 5) and female (model 6) employed persons who endured from Wave 1 to Wave 6, observed from Wave 3 onward (balanced panel).

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