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Hielke Buddelmeyer, Wang-Sheng Lee and Mark Wooden

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Hielke Buddelmeyer, Wang-Sheng Lee and Mark Wooden
Melbourne Institute of Applied Economic and Social Research,
The University of Melbourne

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Melbourne Institute of Applied Economic and Social Research
The University of Melbourne
Victoria 3010 Australia
***Telephone* (03) 8344 2100**
***Fax* (03) 8344 2111**
***Email* melb-inst@unimelb.edu.au**
***WWW Address* http://www.melbourneinstitute.com**

Abstract

This paper uses longitudinal data from the Household, Income and Labour Dynamics in Australia (or HILDA) Survey to examine the extent to which the relatively high rates of transition from low-paid employment into unemployment are the result of disadvantageous personal characteristics or are instead a function of low-paid work itself. Dynamic random effects probit models of the likelihood of unemployment are estimated. After controlling for unobserved heterogeneity and initial conditions, we find that, relative to high-paid employment, low-paid employment is associated with a higher risk of unemployment, but this effect is only significant among women. We also find only weak evidence that low-wage employment is a conduit for repeat unemployment.

I Introduction

Like many other countries, and notably the UK and the US, recent government policy in Australia, especially under the Howard Coalition Government, has emphasised the importance of getting people into work in order to reduce long-term welfare dependence and increase workforce participation (e.g., DEWR, 2003). The guiding philosophy behind this approach rests on the twin claims that employment is the best protection against poverty and financial hardship, and that a low-paid job, even if it is not long lasting, can act as a bridge to more sustained and more attractive employment opportunities. In contrast, critics of this 'jobs first' approach argue that many low-paid jobs are both temporary and provide little in the way of employment enhancing skills. As a result, many labour force participants cycle between joblessness and low quality employment; what has been described as a 'no pay, low pay cycle' (Dunlop, 2001; Perkins & Scutella, 2008).

While there is convincing descriptive evidence indicating that low-paid workers in Australia are at much greater risk of experiencing future unemployment than workers in more highly paid jobs (Perkins & Scutella, 2008), what is still unknown is the extent to which this is the result of disadvantageous worker characteristics, either observed or unobserved, or a function of low-paid work itself. In this paper we shed light on this question by using longitudinal data from the Household, Income and Labour Dynamics in Australia (or HILDA) Survey to model annual rates of transition between employment, distinguishing between low-paid and high-paid jobs, and unemployment. More specifically, we estimate dynamic random effects probit models of the likelihood of labour force participants experiencing unemployment. In contrast to most previous research, we find little evidence to support the conclusion that low-paid employment *per se*, at least during the period under investigation (2001 to 2007), markedly increased the risk of men experiencing a spell of unemployment in the future. In contrast, among women a sizeable and statistically significant effect is found.

The paper is structured into seven sections. Following this introduction, we review previous empirical studies that have examined the relationship between low-paid employment and unemployment (or in some cases, joblessness). Section III then provides a short introduction to the data, and especially the earnings and hours data that are used in defining low pay. That definition is then set out in Section IV, along with a discussion of some of the issues surrounding that definition. Section V provides some descriptive statistics on low pay transitions. The centrepiece of the paper is the multivariate analyses of low pay transitions, which are described, and for which results are presented, in Section VI. Some brief conclusions are provided in Section VII.

II Previous Research

The issue of low pay dynamics and earnings mobility has been much studied in overseas countries, especially in the UK. Gregory and Elias (1994), for example, used longitudinal data collected from employers in the UK New Earnings Survey (NES) and found considerable mobility out of the bottom of the wage distribution, especially by younger workers. With the emergence of data from the British Household Panel Survey (BHPS), which commenced in 1991, UK studies on this issue proliferated, all of which were largely concerned with estimating the probability of exiting low-paid employment or, conversely, the extent of persistence of the low pay state (Sloane & Theodossiou 1996, 1998; Gosling *et al.*, 1997; Stewart & Swaffield, 1997). In contrast to the earlier work based on the NES, these studies emphasised the evidence on persistence of low pay. More recent studies, both in the UK and elsewhere in Europe, have further advanced our understanding of low pay dynamics by employing statistical techniques that take into account the endogeneity of the initial wage state (Stewart & Swaffield, 1999; Cappellari, 2002; Sousa-Poza, 2004) and in, some cases, panel attrition as well (Uhlendorf, 2006; Cappellari & Jenkins, 2008a).

One of the themes to emerge from this body of research is that the experience of low pay is closely associated with subsequent episodes of joblessness. Gosling *et al.* (1997), for example, reported from their analysis of the first four waves of the BHPS that men in the bottom quartile of the earnings distribution were "almost three times as likely to move out of employment in the 12 months following the first-wave interview as men in the top quartile" (p. 35). This interdependence between low pay and joblessness, and the role of state dependence, has been explored in a number of studies, though we are only aware of two – Stewart (2007) and Cappellari and Jenkins (2008b) – that have focussed specifically on unemployment (as distinct from all joblessness), both of which again used data from the BHPS collected during the 1990s.

Stewart (2007) estimated probabilities of both unemployment and low-paid employment using dynamic random effects probit models that controlled for endogenous initial conditions and unobserved heterogeneity. He reached the striking conclusion that low-paid employment (defined as earnings of less than £3.50 per hours in 1997 terms) has almost as large an adverse impact on future employment prospects as current unemployment. This conclusion appears to be based on the finding that the coefficients on the indicator variables for unemployment conditional on being unemployed in the previous period and for unemployment conditional on being in a low-wage state in the previous period were not significantly different from each other. This result, however, was only obtained once spells of continuing non-employment were excluded. Further, in Stewart's preferred equation, the estimated effect of past unemployment is still almost 1.4 times that of past low-wage employment. The strong conclusion of Stewart (2007) appears to be driven by a pre-occupation with statistical significance. If we focus simply on the estimated magnitudes from his research we can just as reasonably draw the conclusion that the protective effects of high-wage employment are only marginally greater than that of low-wage employment – the predicted probability of unemployment is only 1.5 percentage points (or 28%) lower.

A different estimation approach was employed by Cappellari and Jenkins (2008b). They modelled annual transitions between unemployment and low-paid and high-paid employment states using a multivariate probit model that accounted for three potentially endogenous selection processes – the initial wage state, selection into employment, and panel attrition – and allowed for correlations between the unobserved factors in these different processes. They restricted their sample to men, but like Stewart (2007) concluded that low-paid employment is associated with a higher probability of future unemployment than high-wage employment. The size of the effect, however, could still be argued to be relatively small; about one percentage point in the full model, which holds constant observed and unobserved personal attributes. And unlike the finding of Stewart, the relevant coefficient was not statistically significant.

Research in Australia is both far less prevalent and far less well developed, in part reflecting the paucity of longitudinal data in this country. The first significant Australian longitudinal survey to track labour market behaviour, for example, only commenced in 1985 and only followed young people. Known as the Australian Longitudinal Survey (and surviving today under the name, Longitudinal Surveys of Australian Youth), it formed the basis of the first empirical investigation of low-wage dynamics in Australia. That study, by Miller (1989), however, was only concerned with employment, and not with the interaction with unemployment.

It would be another decade before serious empirical evidence on the relationship between low-wage employment and unemployment, or more strictly joblessness, in Australia would be presented. This research, by Dunlop (2000, 2001), used longitudinal survey data from the Survey of Employment and Unemployment Patterns collected by the Australian Bureau of Statistics (ABS) in 1995, 1996 and 1997. Based on results from the construction of simple transition matrices, she concluded that for about half of the low paid (defined as workers earning less than $10 per hour in September 1994 and then indexed to growth in average weekly earnings), low-paid employment is a temporary state. For the remaining half, however, low-paid employment appears to be relatively persistent or involves churning in and out of joblessness. Indeed, and echoing the results typically reported for the UK, she concluded that "low-paid adults are about twice as likely as the higher paid to face spells of joblessness during the two-year transition period" covered by the data (Dunlop, 2001, p. 105). Very similar conclusions are drawn by Perkins and Scutella (2008) from their analysis of HILDA Survey data for the period 2001 to 2005. They reported annual transition rates that indicate that the probability of workers in low-paid employment being jobless a year later is around twice that of workers in higher paid work.

Both of these studies report descriptive data, and make no serious attempt to account for individual heterogeneity. They also do not distinguish unemployment from other forms of joblessness. Watson (2008), on the other hand, used the calendar data from the first six waves of the HILDA Survey to estimate a variety of statistical models of labour market states that control for individual heterogeneity to varying degrees, while also attempting to deal with other statistical issues such as correlated error structures. He also explicitly separates unemployment from other non-employment states, though not in the models that control for unobserved heterogeneity. His key findings are twofold. First, among the sample of persons who change jobs or enter employment over the sample period, those in the lowest earnings quintile are, as we would expect, much more likely to have experienced a preceding spell of non-employment. Second, and more importantly, the next transition among this group is more likely to be a move into non-employment rather than into employment.

Unfortunately, the HILDA Survey data provide no information on earnings in jobs held between interview dates, and the central conclusions of Watson (2008) are closely linked to the assumption he makes about the earnings of between-interview jobs. In particular, Watson uses earnings reported during the annual interview to impute earnings for between-interview jobs. Although Watson's attempt to use detailed job spell information from the calendar data is commendable, the assumption he makes of assigning an average quintile score to all jobs held in a year can induce a serious bias that accounts for his findings.[1] Further, we suspect the earnings measure is based on either weekly or annual earnings and thus will itself be a function of the number of hours worked.

III Data

The data used in this study come from the first seven waves of the HILDA Survey, a longitudinal survey with a focus on work, income and family that has been following a sample of Australians every year since 2001. Described in more detail in Wooden and Watson (2007), the survey commenced in 2001 with a nationally representative sample of Australian households. Personal interviews were completed at 7682 of the 11 693 households identified as in scope for wave 1 (providing an initial responding sample comprising 13 969 people), and while non-response is considerable, the characteristics of the responding sample appear to match the broader population quite well. The members of these participating households form the basis of the panel pursued in the subsequent waves of interviews, which are conducted approximately one year apart. Interviews are conducted with all adults (defined

[1] Consider an individual who is not employed at two consecutive waves, but who has a job spell in the interim. Under an average quintile score assignment strategy this job will automatically be assigned to the lowest quintile due to the absence of earnings at the time of interview preceding and following the job spell. This then biases the result towards finding that a job with low earnings is preceded (and followed) by an episode of non-employment precisely because non-employment at both waves results in low earnings being assigned to the job in between two interviews. Conversely, had the person been employed with high earnings at both waves the result would have been biased towards finding that a high earning interim job is more likely to be preceded (and followed) by employment because employment at both waves preceding and following the current job is a necessary condition for the current job to be assigned high earnings.

as persons aged 15 years or older on the 30th June preceding the interview date) who are members of the original sample, as well as any other adults who, in later waves, are residing with an original sample member. Annual re-interview rates (the proportion of respondents from one wave who are successfully interviewed the next) are reasonably high, rising from 87% in wave 2 to over 94% in waves 5, 6 and 7.

Following Stewart (2007), the sample used here is restricted to those persons who were in the labour force (i.e., either employed or unemployed) at the time of interview. But in contrast to Stewart (but like Cappellari and Jenkins, 2008b), we also remove from the sample all persons who are self-employed at the time of interview, including owner managers that might otherwise be defined as employees of their own business. Concerns about both the general quality of income information provided by the self-employed and the way incomes are apportioned to earnings by owner-managers argues strongly in favour of their exclusion. We also exclude all persons under the age of 21 years and any other full-time students. The exclusion of persons under the age of 21 years was deemed necessary given wages structures in many jobs (and in most awards) provide for junior rates of pay which are below those that apply to adult employees. Certainly the inclusion of juniors would cause the low-pay threshold (defined in Section IV) to fall and reduce the number of adults defined as low paid.[2] The working sample thus commenced with 43 262 observations on 11 152 individuals. Only 2458 of these people, however, are observed in the labour force in all seven waves.

The unemployment indicator is constructed from questions which were intended to produce a measure that accords with ABS / ILO definitions. Thus to be defined as unemployed a respondent had to meet one of the following conditions: (i) not had a paid job during the preceding 7 days; (ii) been actively looking for paid work during the previous 4

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2 An alternative approach would be to follow Richardson and Harding (1999) and define a separate low-pay threshold for juniors, and indeed for each year of age up to and including 20 years. Relatively small sample

weeks; and (iii) been available to start work in the previous week (or was waiting to start a new job that was expected to commence within the next 4 weeks).

The low pay and high pay indicators are based on a measure of the hourly wage in the main job, which is in turn obtained by dividing usual gross weekly earnings by usual weekly hours worked. The earnings measure used here is usual current gross weekly pay in the main job. It is derived from a sequence of questions that asks respondents to provide the gross amount of their most recent pay, the length of that pay period, and then to indicate whether that is their usual pay. If it is not their usual pay, details of their usual pay are then collected. The relevant questions are based quite closely on a similar set of questions included in the ABS Survey of Income and Housing Costs. A particular problem for many household surveys collecting economic data is high rates of item non-response. The earnings data in the HILDA Survey, however, do not seem to be seriously affected by this problem, with the proportion of cases where no information on current earnings (in the main job) is provided averaging just 2.9 per cent over the seven waves.

Hours of work is represented by the number of total hours usually worked per week in the main job, where total hours includes any paid or unpaid overtime as well as any work undertaken outside the workplace. While non-response is minimal, measurement error is very likely. It is, for example, often claimed that survey-based data will tend to overstate hours of work at the upper end of the distribution (see Robinson & Bostrom, 1994). In large part this will simply be the result of over-reporting, a phenomenon which is especially likely in societies where long hours of work is seen as 'badge of courage'. It could also arise as a result of other measurement problems, including the inclusion of time that we would not generally consider to be work (e.g., meal breaks, time on-call, and commuting time), and in

sizes, especially after exclusion of the full-time students, however, will almost certainly mean that the estimation of such thresholds using the approach adopted in this analysis will be highly imprecise.

the way some respondents interpret what is meant by 'usual'. However, there is no *a priori* reason to assume that the hours data for employees from the HILDA Survey are any more (or less) biased than hours data from any other survey-based data set, an assumption that has been confirmed by comparisons of the HILDA Survey estimates with estimates from ABS household surveys (Wooden *et al*., 2007).

IV Defining Low Pay

All investigations into the concept of low pay are confronted by the question of how to define it, and more specifically how to define the low-pay threshold. If the focus is on the relationship between earnings and income poverty then it makes sense to define low pay in terms of adequacy, and historically it has been this perspective that has dominated thinking about low pay in Australia. A needs-based approach, however, is not appropriate for examining questions relating to earnings mobility and labour market transitions. In the needs-based approach, transitions into and out of low pay can occur because of changes in family circumstances and relocation. In contrast, analyses of earnings mobility are not concerned with whether earnings are adequate to support some pre-defined lifestyle. Previous research into the dynamics of low-paid employment has thus not defined low pay by reference to some standard of need, but relative either to the distribution of earnings or to some administrative standard (such as a legislated minimum wage).

The choice of threshold is highly variable across studies. Some (e.g., Gregory & Elias, 1994; Gosling *et al*., 1997; Watson, 2008) have simply defined the low paid as those in the bottom decile or quintile in the wage distribution, which fixes the low paid to be a predetermined proportion of the working population. More usual, however, is to set the threshold as a proportion of either median or mean hourly earnings, with the proportion chosen varying from 50 to 75 per cent, but with two-thirds being most commonly used. In this analysis we adopt this widely used benchmark and so define a person as low paid if their rate of pay is less than two-thirds of the median gross hourly wage.

The usual rationale for employing a threshold based on hourly rates of pay is that the alternative – a cut-off based on weekly pay – will see some individuals defined as low paid simply because they work relatively few hours. This is usually judged problematic, especially when those part-time hours are the preferred working arrangement of the individual.[3] On the other hand, using hourly pay will see some people defined as low paid because of the large numbers of hours they report usually working. According to the data set used here, for example, around 21 per cent of all employed persons in Australia report usual weekly hours of at least 50.[4] This in itself is not necessarily a problem provided both that hours are measured accurately and that one working hour is much like another. Neither assumption is likely to be realistic, suggesting consideration should be given to capping working hours. Experimentation with different caps, however, suggested that a cap made little difference to the estimated threshold.

We also need to decide how to deal with multiple job-holders. Most studies ignore this distinction; the hourly earnings measure is based on earnings in all jobs. Again this seems a reasonable decision if the focus of the research is on the adequacy of incomes, but not where the focus is on labour market transitions. Thus, and as previously noted, we only use the earnings and hours from the main job, defined in the HILDA Survey as that which provides the most pay each week.

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[3] It is well established that the majority of part-time workers do not have preferences for more hours. According to Labour Force Survey data for September 2008 (ABS, 2009), only 23 per cent of persons defined as being employed on a part-time basis indicated a preference for longer working hours.

[4] Compared with the Labour Force Survey, the HILDA Survey overstates the incidence of long working hours. Estimates from the Labour Force Survey indicate that the proportion of the employed workforce that usually work 50 hours or more per week during September to November – the period of peak interviewing for the HILDA Survey – has, over the period covered in this analysis, varied from 18.6 per cent in 2001 to 17.3 per cent in 2007.

A final issue concerns the treatment of casual employees. Since the rates of pay of casual employees typically include a pay loading, usually assumed to be around 20%, to compensate for their ineligibility for annual leave, paid sick leave and other entitlements, it is often argued that the measured hourly pay rates of casual employees needs to be discounted by 20%. This, for example, was the approach used by Dunlop (2000, 2001). Alternatively, it could be argued that the casual pay loading is conceptually no different than the pay loading (implicit or explicit) that is attached to any job as compensation for some undesirable characteristic. Casuals get a higher rate of pay to compensate for lack of access to leave entitlements in the same way that, say, underground miners attract a pay loading to compensate for dangerous working conditions. In this paper we take the latter approach and do not discount casual pay.

We next need to decide from which data source to draw the benchmark. Most convenient is to use the HILDA sample itself (as compared with some external benchmark). Given the HILDA Survey is designed to provide a representative sample of all Australian residents living in private households this seems a reasonable step. Further, it provides a simple mechanism for automatically updating the low-pay threshold over time; we simply tie the threshold to the observed changes in the distribution of hourly earnings within the HILDA sample. To be more specific, we derive a median hourly wage for each survey wave based on the weighted distribution of hourly earnings of all adult employees (aged 21 years or older) with both positive earnings and positive working hours, but excluding full-time students. Cases where earnings have to be imputed are excluded.

Our estimated low-pay thresholds for each survey wave are reported in Table 1. As can be seen, the low-pay threshold has increased steadily over time, and by wave 7 was almost 30% higher than the level in wave 1. By comparison, consumer prices over this period rose by only 18%. This real growth in the level of the low-pay threshold reflects the growth in average and median real earnings over this same period. As we would also expect, the weekly equivalents of our low-pay thresholds all lie above the level of the Federal Minimum Wage that applied at the time, though the size of this differential is not large, averaging around 7%.

TABLE 1

Estimated Low-Pay Thresholds (Adults)

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Wave 7
Low-pay threshold							
Hourly earnings ($)	11.67	12.04	12.50	13.04	13.56	14.38	15.16
Weekly equivalent ($)	443.46	457.52	475.0	495.5	515.28	546.44	576.08
Sample size	6043	5760	5724	5616	5891	6039	6007

Note: Weekly equivalents are based on a 38 hour week.

We also checked the sensitivity of our estimates to different assumptions (using earnings from all jobs instead of main jobs, capping weekly hours worked at 60, using imputed earnings when not reported, and applying a discount to the earnings of casual employees). For the most part the thresholds are robust, and varying the assumptions makes little difference to the estimated threshold. The one exception here is the treatment of casual pay, the discounting of which has a noticeable impact on the level of low-paid employment, drawing as it does many more casual employees into the low pay category. However, and as discussed at length in Buddelmeyer *et al*. (2007), discounting casual pay did not appear to substantially affect employment dynamics and thus would have little bearing on the conclusions reached in the analysis that follows.

V Descriptive Statistics

We begin by presenting, in Table 2, distributions of the sample by labour market state, where we distinguish between persons who are: (i) unemployed; (ii) low paid (earning less than 2/3 median earnings); and (iii) high paid (earning more than 2/3 median). Thus we see from the first row in this table that the unweighted unemployment rate has fallen from 6.3% at the start of the period to just 3.6% by 2007. Note, however, that our exclusion of the self-employed means that these rates are not directly comparable with those produced by the ABS from the Labour Force Survey. Nevertheless, we are very confident that the composition of the sample is broadly in line with Labour Force Survey estimates. There is certainly no evidence that sample attrition is more concentrated among the unemployed than among the employed (see Watson & Wooden, 2009).

TABLE 2

Employment and Pay Status by Wave and Sex (Adults)

Labour market state	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Wave 7
Persons							
Unemployed	6.3	5.5	4.6	4.0	4.1	4.0	3.6
Low paid	11.7	11.3	11.7	11.1	11.4	11.9	12.1
High paid	82.0	83.2	83.7	84.9	84.5	84.2	84.5
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Sample size	6477	6127	6037	5879	6169	6318	6255
Males							
Unemployed	7.4	5.6	4.8	3.4	4.1	3.7	3.3
Low paid	10.9	10.6	11.3	10.4	10.4	11.3	11.1
High paid	81.7	83.8	83.9	86.2	85.5	85.0	85.6
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Sample size	3384	3215	3152	3038	3159	3206	3147
Females							
Unemployed	5.1	5.4	4.4	4.5	4.2	4.2	3.9
Low paid	12.5	12.0	12.1	12.0	12.5	12.4	13.1
High paid	82.4	82.6	83.5	83.5	83.3	83.4	83.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Sample size	3093	2912	2885	2841	3010	3112	3108

Estimates of the proportion of adult employees that would be defined as low paid in our analysis sample are presented in the second row of Table 2. As can be seen, the proportion of the adult labour force defined as having low-paid jobs is relatively stable over the period covered, averaging around 11 to 12%. Further, we can see that this proportion is slightly higher among women (averaging 12.4%) than among men (10.9%).

Even though the proportion of low-paid workers at any point in time is reasonably stable, there is considerable movement between labour market states. This is shown in Table 3, which reports average rates of transition over both a one-period interval and a two-period interval (with, on average, each period being about one year). Thus, of those in the low-paid category at time $t-1$, just 44% can be expected to still be low-paid by time *t*. The majority of low-paid workers (53%) will instead be classified as high-paid workers by the next survey date, leaving a small fraction (less than 2%) seeking jobs. Similarly, of those in the low-paid category at time $t-2$, only 38% will be in that same state by time *t*, with 59% having moved into a high-paid state.

Table 3 also reveals that the probabilities of unemployment are higher for persons who were in low-paid employment in the past than whose were in high-paid employment. Indeed, the one-period conditional probability of unemployment is, among all persons, exactly twice as great for those who were in low-paid employment last period relative to those in high-paid employment. The comparable two-period conditional probabilities are close to identical to the one-period probabilities. We can also see that this difference is characteristic of both men and women, though the size of the differential is greater among women.

Overall, the descriptive data from the HILDA Survey suggest little has changed since the 1990s when the data used by Dunlop (2000, 2001) were collected. The data presented here seem entirely consistent with her conclusion that low-paid employment is a temporary

TABLE 3

Transitions between Labour Market States by Sex (Adults)

	Labour force status at time *t*			
	Unemployed	Low paid	High paid	Total
All persons				
Status at time *t*-1				
Unemployed	36.8	14.0	49.3	100.0
Low paid	2.6	44.1	53.3	100.0
High paid	1.3	5.8	92.8	100.0
Status at time *t*-2				
Unemployed	28.5	16.5	55.0	100.0
Low paid	2.6	38.2	59.2	100.0
High paid	1.4	6.0	92.7	100.0
Males				
Status at time *t*-1				
Unemployed	39.3	13.2	47.6	100.0
Low paid	2.2	47.6	50.2	100.0
High paid	1.4	4.9	93.7	100.0
Status at time *t*-2				
Unemployed	30.8	16.4	52.8	100.0
Low paid	2.6	41.9	55.6	100.0
High paid	1.5	5.0	93.6	100.0
Females				
Status at time *t*-1				
Unemployed	33.9	14.9	51.2	100.0
Low paid	2.9	40.7	56.4	100.0
High paid	1.3	6.9	91.8	100.0
Status at time *t*-2				
Unemployed	25.8	16.6	57.6	100.0
Low paid	2.7	34.4	62.9	100.0
High paid	1.3	7.1	91.6	100.0

state for about half the low-paid workforce, and is either persistent or involves churning in and out of employment for the other half. We will now test the conclusions from the descriptive statistics within a multivariate framework that controls for personal attributes, other characteristics, and unobserved heterogeneity.

VI Multivariate Analysis of Low Pay Dynamics

(i) Model Specification

Following Stewart (2007), we employ a dynamic random effects probit framework. The latent equation for the dynamic random effects panel probit model can be written as:

$$y_{it}^{*} = \gamma y_{it-1} + x_{it}'\beta + \alpha_i + u_{it} \qquad (1)$$

where the subscript *i* = 1, 2, …, N indexes individuals, the subscript *t* = 2, …, T indexes time periods, y_{it}^{*} is the latent dependent variable for being low paid, x_{it} is a vector of exogenous characteristics, α_i are unobserved individual-specific random effects, and the u_{it} are assumed to be distributed $N(0,\sigma_u^2)$. The observed binary outcome is:

$$y_{it} = \begin{cases} 1 & \text{if } y_{it}^{*} \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

The standard random effects model assumes that α_i is uncorrelated with x_{it}. As this is potentially restrictive, we adopt the Mundlak-Chamberlain approach and allow a correlation between α_i and the observed characteristics in the model by assuming a relationship between α_i and the means of the time-varying *x*-variables:

$$\alpha_i = \overline{x_i}'a + v_i$$

where v_i is distributed $N(0,\sigma_v^2)$.

An important issue that needs to be addressed is the so-called initial conditions problem. This problem arises because the start of the observation period (wave 1 in 2001) does not coincide with the start of the stochastic process generating low-paid employment experiences. Estimation of the model therefore requires a further assumption about the relationship between y_{i1} and α_i. If the initial conditions are correlated with α_i, as is likely in our context, not addressing the initial conditions problem will lead to overstating the level of state dependence (i.e., the estimate of γ in (1) will be larger than it actually should be).

One possible approach to solve the initial conditions problems is based on a suggestion by Wooldridge (2005). In the Wooldridge approach, the relationship between y_{i1} and α_i is accounted for by modelling the distribution of α_i given y_{i1}. The assumption in Wooldridge's approach is that the distribution of the individual specific effects conditional on the exogenous individual characteristics is correctly specified.

This model is most appropriate for addressing the issue of whether prior unemployment or low pay employment experiences exacerbate the likelihood of experiencing unemployment in the future. It does so by decomposing the state dependence of unemployment into true state dependence (i.e., the scarring effect of unemployment) and the component that is due to unobserved heterogeneity across the units (i.e., differences in individuals).

The issue of whether prior unemployment and low-paid employment experiences exacerbate the likelihood of experiencing unemployment in the future is further examined using a second-order dynamic random effects probit model so that employment states in both $t-1$ and $t-2$ are allowed to impact on unemployment at *t*. Eight dummy variables are included as explanatory variables to account for the nine possible combination of states in periods $t-1$ and $t-2$ in place of the lagged dependent variable. The advantage of such an approach is that interactions of employment states in periods $t-1$ and $t-2$ can be used to help understand the effect of certain pathways or sequences. For example, unemployment followed by low-paid employment might be expected to be associated with a higher probability of unemployment at period t than unemployment followed by high-paid employment. Specifically, the model takes the following form:

$$y_{it}^{*} = \sum_{k} \gamma_k (s_{it-1})(s_{it-2}) + x_{it}'\beta + \alpha_i + u_{it} \qquad (1)$$

$$y_{it} = \begin{cases} 1 & \text{if } y_{it}^{*} \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

where s_{it-1} is a dummy variable denoting one of the three states (low pay, high pay and unemployed) in time $t-1$ and s_{it-2} is a dummy variable denoting one of the same three states in time $t-2$. The subscript i = 1, 2, … , N indexes individuals and the subscript t = 3, …, T indexes time periods. In this model, the data are restricted to those persons in the labour force in all seven waves.[5]

The observable characteristics that comprise x_{it} are listed in Table 4, along with their summary statistics (means and standard deviations). They are intended to capture the effects of age, education, marital status (or more strictly, partnership status), the number of dependent children, ethnic origin (reflected in two crude dummy variables identifying whether the respondent is of indigenous origin or was born overseas but not in one of the major English-speaking countries[6]), the presence of a long-term health condition that is work limiting, and geographic location.[7]

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5 Scaling is done by multiplying coefficient of panel estimates by $\sqrt{(1-\hat{\sigma}_u^2)}$. See Arulampalam (1999) for a detailed discussion.

6 These are the UK, New Zealand, Ireland, Canada, USA and South Africa.

7 We include dummy variables identifying States (with the largest State, New South Wales, being the omitted reference group), and distinguishing between inner regional and outer regional parts of Australia (which, in turn, are based on a categorical measure of remoteness of Australian localities developed by the Australian Bureau of Statistics).

TABLE 4

Means and Standard Deviations of Variables

Variable	Mean	Standard Deviation
Unemployed at *t*	0.046	0.209
Low paid at *t*	0.116	0.320
High paid at *t*	0.838	0.368
Control variables		
Year 11 and below	0.237	0.425
Year 12 or more	0.763	0.425
Male	0.515	0.500
Age 21 to 24	0.092	0.289
Age 25 to 34	0.254	0.435
Age 35 to 44	0.291	0.454
Age 45 to 54	0.246	0.431
Age 55 plus	0.117	0.321
Number of dependent children	0.172	0.464
Married (including de facto unions)	0.704	0.456
Aboriginal or Torres Straits Islander	0.016	0.127
Not born in English-speaking country	0.115	0.318
Long-term health condition (limits work)	0.087	0.282
Major city	0.655	0.475
Inner regional	0.225	0.418
Outer regional (and remote locations)	0.120	0.325
NSW	0.302	0.459
VIC	0.254	0.435
QLD	0.207	0.405
SA	0.086	0.280
WA	0.092	0.288
TAS	0.029	0.169
ACT / NT	0.031	0.173

Note: Pooled data from HILDA Survey waves 1-7 (2001-2008); N = 43 257.

(ii) Results

Results from the first-order dynamic model are reported in Tables 5 and 6. For completeness we report results from both the simple pooled dynamic probits (Table 5) and from the panel data (i.e., random effects) models (Table 6). We focus most of our attention, however, on the latter given the strong evidence of unobserved heterogeneity, reflected most obviously in the marked difference in the magnitude of the coefficients on the lagged employment states. As discussed above, the panel data models are estimated using the Wooldridge method, but where coefficient estimates have been rescaled in order to provide comparability with the pooled probit estimates. The variables in the tables denoted by m(.) are the means over time of the variable in parentheses, or in other words, the Mundlak-Chamberlain time averages that control to some extent for the correlation between the exogenous variables and α_i. In all cases, we report results for all persons (in line with Stewart, 2007) as well as for men and women separately. It turns out that this distinction is non-trivial, with our results suggesting quite different conclusions depending on which sex is under consideration.

From the table of results presented in Tables 5 and 6, two comparisons are worth highlighting: the average partial effects (APE) and the predicted probability ratios (PPR). These are both defined relative to the high-paid employment state at $t-1$, with the former being defined as a difference and the latter a ratio. The APEs of interest are given in the bottom of these Tables. Thus, the pooled probit (Table 5) gives an APE of unemployment at $t-1$ for all persons of 0.301. After allowing for initial conditions and controlling for heterogeneity (Table 6), the APE declines to just 0.078, indicating that the Wooldridge estimator reduces the degree of measured persistence considerably. The PPR from the random effects model, however, suggests that an individual unemployed at $t-1$ is still 7.8 times more likely to be unemployed at t than an equivalent person in high-paid employment at $t-1$. But even more interesting, our results suggest that the difference with respect to people in low-paid jobs is not that much smaller – the PPR is 5.6. This stands in marked contrast to the results obtained for the UK by Stewart (2007).

TABLE 5

Dynamic Pooled Probit Model for Unemployment Probability

	Pooled probit (Persons)	P-value	Pooled probit (Males)	P-value	Pooled probit (Females)	P-value
Unemployed at *t*-1	1.729	0.000	1.749	0.000	1.684	0.000
Low paid at *t*-1	0.190	0.001	0.093	0.275	0.287	0.000
Year 11 and below	0.065	0.811	0.160	0.652	0.006	0.986
Male	0.043	0.239				
Age 21 to 24	0.135	0.098	-0.051	0.642	0.335	0.008
Age 25 to 34	0.083	0.187	-0.055	0.486	0.236	0.024
Age 35 to 44	0.020	0.743	-0.071	0.359	0.118	0.252
Age 45 to 54	0.040	0.530	-0.052	0.522	0.157	0.132
Number of dependent children	-0.040	0.571	0.025	0.809	-0.094	0.329
Married	-0.065	0.511	-0.024	0.861	-0.132	0.351
Aboriginal or Torres Straits Islander	0.461	0.000	0.333	0.055	0.581	0.000
Not born in English-speaking country	0.188	0.001	0.142	0.067	0.232	0.002
Long-term health condition	0.366	0.000	0.322	0.001	0.412	0.000
Inner regional	0.201	0.298	0.174	0.503	0.222	0.435
Outer regional	0.087	0.710	0.003	0.992	0.212	0.480
VIC	0.003	0.957	-0.049	0.448	0.058	0.407
QLD	-0.068	0.195	-0.151	0.047	0.028	0.709
SA	-0.116	0.103	-0.109	0.254	-0.150	0.151
WA	-0.220	0.003	-0.263	0.006	-0.169	0.151
TAS	-0.075	0.481	-0.003	0.984	-0.191	0.193
ACT / NT	-0.166	0.227	-0.313	0.104	-0.006	0.975
m(Number of dependent children)	-0.123	0.225	-0.162	0.229	-0.084	0.565
m(Year 11 and below)	0.127	0.645	0.107	0.766	0.101	0.787
m(Married)	-0.199	0.068	-0.308	0.041	-0.078	0.616
m(Long-term health condition)	0.109	0.316	0.188	0.196	0.028	0.862
m(Inner regional)	-0.206	0.310	-0.225	0.409	-0.169	0.573
m(Outer regional)	-0.086	0.723	0.039	0.911	-0.273	0.379
Constant	-2.169	0.000	-1.957	0.000	-2.347	0.000
N	29432		15408		14024	
Log likelihood	-2689.47		-1408.26		-1265.79	
Prob(U_t | U_{t-1})	0.301		0.310		0.280	
Prob(U_t | L_{t-1})	0.022		0.018		0.026	
Prob(U_t | H_{t-1})	0.014		0.015		0.013	
APE: Prob(U_t | U_{t-1}) - Prob(U_t | H_{t-1})	0.287		0.295		0.267	
APE: Prob(U_t | L_{t-1}) - Prob(U_t | H_{t-1})	0.008		0.003		0.013	
PPR: Prob(U_t | U_{t-1}) / Prob(U_t | H_{t-1})	21.5		20.67		21.54	
PPR: Prob(U_t | L_{t-1}) / Prob(U_t | H_{t-1})	1.57		1.20		2.00	
PPR: Prob(U_t | U_{t-1}) / Prob(U_t | L_{t-1})	13.68		17.22		10.77	

Note: Omitted reference groups are high paid at *t*-1, aged 55 plus, 12 or more years of education, major city, State (NSW), and female (for the All persons specification).

TABLE 6

Dynamic Panel Probit Model for Unemployment Probability

	RE probit (Persons, rescaled)	P-value	RE probit (Males, rescaled)	P-value	RE probit (Females, rescaled)	P-value
Unemployed at *t*-1	0.872	0.000	0.908	0.000	0.832	0.000
Low paid at *t*-1	0.139	0.009	0.051	0.519	0.227	0.002
Year 11 and below	0.073	0.717	0.233	0.540	-0.002	0.994
Male	0.029	0.427				
Age 21 to 24	0.139	0.090	-0.082	0.474	0.379	0.002
Age 25 to 34	0.062	0.333	-0.089	0.291	0.236	0.022
Age 35 to 44	-0.005	0.939	-0.097	0.237	0.102	0.319
Age 45 to 54	0.008	0.897	-0.093	0.285	0.138	0.174
Number of dependent children	-0.027	0.695	0.045	0.647	-0.094	0.353
Married	-0.029	0.737	0.010	0.930	-0.088	0.516
Aboriginal or Torres Straits Islander	0.442	0.000	0.287	0.085	0.577	0.000
Not born in English-speaking country	0.158	0.005	0.114	0.144	0.202	0.013
Long-term health condition	0.375	0.000	0.323	0.002	0.426	0.000
Inner regional	0.183	0.165	0.197	0.274	0.160	0.421
Outer regional	0.113	0.529	0.075	0.744	0.181	0.540
VIC	0.014	0.779	-0.045	0.497	0.077	0.278
QLD	-0.083	0.119	-0.162	0.031	0.009	0.908
SA	-0.111	0.121	-0.119	0.218	-0.120	0.272
WA	-0.208	0.008	-0.260	0.014	-0.148	0.209
TAS	-0.086	0.467	-0.014	0.929	-0.189	0.294
ACT / NT	-0.192	0.122	-0.315	0.089	-0.048	0.778
m(Number of dependent children)	-0.111	0.237	-0.146	0.296	-0.069	0.594
m(Year 11 and below)	0.077	0.708	-0.016	0.966	0.085	0.736
m(Married)	-0.210	0.033	-0.333	0.013	-0.090	0.548
m(Long-term health condition)	0.062	0.578	0.139	0.372	-0.008	0.961
m(Inner regional)	-0.196	0.167	-0.259	0.183	-0.108	0.611
m(Outer regional)	-0.124	0.519	-0.046	0.851	-0.251	0.423
Initial unemployment	0.830	0.000	0.781	0.000	0.884	0.000
Constant	-2.032	0.000	-1.776	0.000	-2.350	0.000
N	29432		15408		14024	
Log likelihood	-2601.73		-1367.44		-1217.91	
Prob(U_t | U_{t-1})	0.078		0.087		0.069	
Prob(U_t | L_{t-1})	0.014		0.012		0.017	
Prob(U_t | H_{t-1})	0.010		0.010		0.010	
APE: Prob(U_t | U_{t-1}) - Prob(U_t | H_{t-1})	0.068		0.077		0.059	
APE: Prob(U_t | L_{t-1}) - Prob(U_t | H_{t-1})	0.004		0.002		0.007	
PPR: Prob(U_t | U_{t-1}) / Prob(U_t | H_{t-1})	7.80		8.70		6.90	
PPR: Prob(U_t | L_{t-1}) / Prob(U_t | H_{t-1})	1.40		1.20		1.70	
PPR: Prob(U_t | U_{t-1}) / Prob(U_t | L_{t-1})	5.57		7.25		4.06	

Note: Omitted reference groups are high paid at *t*-1, aged 55 plus, 12 or more years of education, major city, State (NSW), and female (for the All persons specification).

Even more interesting is the relativity between the indicator variables for being in high-paid employment at $t-1$ and being in low-paid employment at $t-1$. The relevant APE is just 0.004 while the PPR is 1.4. That is, a person in low-paid employment is 1.4 times more likely, compared with a person in high-paid employment, to be unemployed next period. Somewhat surprisingly, this result for the relativity between the effects of low-paid and high-paid employment at $t-1$ is very similar to the results reported by Stewart (2007). These results do, therefore, suggest that low-paid employment (relative to high paid employment) enhances the likelihood of experiencing unemployment. The magnitude of this effect, however, is only statistically significant and of any economic significance for women. Among men the effect of low-paid employment is both quite small (a PPR of 1.2) and a long way from statistical significance (p-value = 0.52). In contrast, for women the PPR is quite large (1.7) and the estimated coefficient is highly significant (p-value = .002).

As noted by Stewart (2007), the first-order model results still do not enable us to get a good handle on whether low pay is a conduit to repeat unemployment. To get at this we turn to our second-order model results. Again the results from the simple pooled probit (Table 7) are reported mainly for completeness, and we focus here on the results from the panel data models (Table 8).

As we would expect, the results indicate that an individual unemployed at both $t-1$ and $t-2$ is much more likely (by 25 percentage points) to be unemployed at time *t* relative to an individual who is high paid in both $t-1$ and $t-2$. But are employed people who have escaped unemployment recently no longer at risk of unemployment? The answer is clearly no, with the probability of future unemployment significantly higher among employed persons with a recent unemployment experiences than among employed persons who have not been scarred. Nevertheless, the relative size of these effects still suggests that the scarring

TABLE 7

Second Order Dynamic Pooled Probit Model for Unemployment Probability

	Pooled probit (Persons)	P-value	Pooled probit (Males)	P-value	Pooled probit (Females)	P-value
Unemployed at *t*-1, Unemployed at *t*-2	2.299	0.000	2.262	0.000	2.324	0.000
Unemployed at *t*-1, Low paid at *t*-2	1.411	0.000	1.603	0.000	1.228	0.000
Unemployed at *t*-1, High paid at *t*-2	1.240	0.000	1.343	0.000	1.084	0.000
Low paid at *t*-1, Unemployed at *t*-2	1.085	0.000	1.066	0.000	1.194	0.000
High paid at *t*-1, Unemployed at *t*-2	0.927	0.000	0.833	0.000	1.030	0.000
Low paid at *t*-1, Low paid at *t*-2	0.164	0.147	-0.046	0.792	0.409	0.007
Low paid at *t*-1, High paid at *t*-2	0.185	0.091	0.021	0.908	0.317	0.023
High paid at *t*-1, Low paid at *t*-2	0.207	0.041	0.278	0.039	0.114	0.462
Year 11 and below	0.131	0.721	0.143	0.574	0.177	0.744
Male	0.060	0.223				
Age 21 to 24	0.011	0.929	-0.050	0.748	0.092	0.667
Age 25 to 34	0.016	0.837	-0.096	0.346	0.135	0.295
Age 35 to 44	-0.092	0.237	-0.142	0.148	-0.045	0.733
Age 45 to 54	0.021	0.783	-0.039	0.692	0.120	0.339
Number of dependent children	-0.044	0.636	0.026	0.842	-0.112	0.411
Married	0.036	0.798	0.180	0.336	-0.180	0.378
Aboriginal or Torres Straits Islander	0.528	0.000	0.157	0.489	0.813	0.000
Not born in English-speaking country	0.142	0.052	0.091	0.374	0.200	0.051
Long-term health condition	0.430	0.000	0.304	0.017	0.573	0.000
Inner regional	0.072	0.787	0.278	0.389	-0.195	0.633
Outer regional	0.465	0.098	0.518	0.191	0.425	0.238
VIC	-0.067	0.283	-0.126	0.126	0.013	0.891
QLD	-0.157	0.024	-0.220	0.020	-0.064	0.539
SA	-0.247	0.014	-0.281	0.034	-0.230	0.140
WA	-0.324	0.003	-0.409	0.005	-0.198	0.205
TAS	-0.212	0.155	-0.063	0.732	-0.532	0.041
ACT / NT	-0.193	0.243	-0.479	0.067	0.067	0.743
m(Number of dependent children)	-0.031	0.818	-0.078	0.660	0.009	0.961
m(Year 11 and below)	-0.018	0.960	0.084	0.751	-0.222	0.684
m(Married)	-0.272	0.077	-0.443	0.031	-0.034	0.878
m(Long-term health condition)	-0.044	0.753	0.137	0.493	-0.270	0.156
m(Inner regional)	-0.057	0.838	-0.313	0.354	0.288	0.495
m(Outer regional)	-0.472	0.115	-0.476	0.263	-0.498	0.194
Constant	-2.207	0.000	-2.039	0.000	-2.347	0.000
N	20556		10927		9629	
Log likelihood	-1425.99		-775.26		-632.64	
Prob(U_t | H_{t-1}, H_{t-2})	0.009		0.010		0.009	
Prob(U_t | U_{t-1}, U_{t-2})	0.457		0.449		0.445	
Prob(U_t | U_{t-1}, L_{t-2})	0.165		0.221		0.115	
Prob(U_t | U_{t-1}, H_{t-2})	0.127		0.154		0.091	
Prob(U_t | L_{t-1}, U_{t-2})	0.098		0.098		0.109	
Prob(U_t | H_{t-1}, U_{t-2})	0.074		0.065		0.082	
Prob(U_t | L_{t-1}, L_{t-2})	0.014		0.009		0.023	
Prob(U_t | L_{t-1}, H_{t-2})	0.015		0.011		0.019	
Prob(U_t | H_{t-1}, L_{t-2})	0.016		0.020		0.012	
APE: Prob(U_t | U_{t-1}, U_{t-2}) - Prob(U_t | H_{t-1}, H_{t-2})	0.45		0.44		0.44	
APE: Prob(U_t | L_{t-1}, U_{t-2}) - Prob(U_t | H_{t-1}, H_{t-2})	0.09		0.09		0.10	
APE: Prob(U_t | H_{t-1}, U_{t-2}) - Prob(U_t | H_{t-1}, H_{t-2})	0.07		0.06		0.07	
PPR: Prob(U_t | U_{t-1}, U_{t-2}) / Prob(U_t | H_{t-1}, H_{t-2})	50.78		44.90		49.44	
PPR: Prob(U_t | L_{t-1}, U_{t-2}) / Prob(U_t | H_{t-1}, H_{t-2})	10.89		9.80		12.11	
PPR: Prob(U_t | H_{t-1}, U_{t-2}) / Prob(U_t | H_{t-1}, H_{t-2})	8.22		6.50		9.11	

Note: Omitted reference groups are high paid at *t*-1 and high paid at *t*-2, aged 55 plus, 12 or more years of education, major city, State (NSW), and female (for the All persons specification).

TABLE 8

Second Order Dynamic Panel Probit Model for Unemployment Probability

	RE probit (Persons, rescaled)	P-value	RE probit (Males, rescaled)	P-value	RE probit (Females, rescaled)	P-value
Unemployed at *t*-1, Unemployed at *t*-2	1.719	0.000	1.832	0.000	1.462	0.000
Unemployed at *t*-1, Low paid at *t*-2	1.187	0.000	1.448	0.000	0.871	0.016
Unemployed at *t*-1, High paid at *t*-2	1.040	0.000	1.249	0.000	0.665	0.002
Low paid at *t*-1, Unemployed at *t*-2	0.660	0.000	0.777	0.002	0.547	0.052
High paid at *t*-1, Unemployed at *t*-2	0.514	0.000	0.494	0.007	0.486	0.006
Low paid at *t*-1, Low paid at *t*-2	0.128	0.259	-0.057	0.734	0.337	0.031
Low paid at *t*-1, High paid at *t*-2	0.164	0.132	0.014	0.939	0.276	0.047
High paid at *t*-1, Low paid at *t*-2	0.203	0.044	0.273	0.043	0.101	0.517
Year 11 and below	0.087	0.768	0.090	0.868	0.145	0.682
Male	0.058	0.253				
Age 21 to 24	0.007	0.957	-0.075	0.673	0.138	0.495
Age 25 to 34	-0.011	0.891	-0.136	0.222	0.148	0.266
Age 35 to 44	-0.116	0.156	-0.170	0.114	-0.042	0.753
Age 45 to 54	-0.005	0.955	-0.059	0.588	0.101	0.431
Number of dependent children	-0.036	0.693	0.043	0.745	-0.118	0.368
Married	0.066	0.603	0.220	0.181	-0.131	0.512
Aboriginal or Torres Straits Islander	0.518	0.000	0.115	0.636	0.798	0.000
Not born in English-speaking country	0.128	0.091	0.070	0.500	0.193	0.086
Long-term health condition	0.435	0.000	0.313	0.030	0.551	0.000
Inner regional	0.054	0.774	0.303	0.227	-0.262	0.343
Outer regional	0.488	0.062	0.627	0.064	0.262	0.537
VIC	-0.059	0.349	-0.121	0.155	0.021	0.828
QLD	-0.168	0.019	-0.220	0.022	-0.087	0.418
SA	-0.251	0.014	-0.301	0.028	-0.208	0.190
WA	-0.320	0.004	-0.410	0.007	-0.205	0.226
TAS	-0.205	0.225	-0.042	0.844	-0.524	0.103
ACT / NT	-0.222	0.184	-0.506	0.076	0.021	0.924
m(Number of dependent children)	-0.027	0.825	-0.083	0.645	0.027	0.870
m(Year 11 and below)	-0.001	0.998	0.108	0.844	-0.207	0.570
m(Married)	-0.296	0.036	-0.488	0.009	-0.066	0.766
m(Long-term health condition)	-0.071	0.654	0.083	0.704	-0.218	0.351
m(Inner regional)	-0.057	0.774	-0.367	0.173	0.351	0.227
m(Outer regional)	-0.504	0.075	-0.600	0.102	-0.330	0.468
Initial unemployment	0.595	0.000	0.477	0.001	0.754	0.000
Constant	-2.153	0.000	-1.950	0.000	-2.324	0.000
N	20556		10927		9629	
Log likelihood	-1405.99		-766.11		-617.82	
$Prob(U_t \mid H_{t-1}, H_{t-2})$	0.008		0.010		0.006	
$Prob(U_t \mid U_{t-1}, U_{t-2})$	0.248		0.291		0.159	
$Prob(U_t \mid U_{t-1}, L_{t-2})$	0.112		0.178		0.053	
$Prob(U_t \mid U_{t-1}, H_{t-2})$	0.087		0.132		0.034	
$Prob(U_t \mid L_{t-1}, U_{t-2})$	0.041		0.058		0.025	
$Prob(U_t \mid H_{t-1}, U_{t-2})$	0.030		0.032		0.022	
$Prob(U_t \mid L_{t-1}, L_{t-2})$	0.012		0.009		0.015	
$Prob(U_t \mid L_{t-1}, H_{t-2})$	0.013		0.010		0.013	
$Prob(U_t \mid H_{t-1}, L_{t-2})$	0.014		0.020		0.008	
APE: $Prob(U_t \mid U_{t-1}, U_{t-2}) - Prob(U_t \mid H_{t-1}, H_{t-2})$	0.24		0.28		0.15	
APE: $Prob(U_t \mid L_{t-1}, U_{t-2}) - Prob(U_t \mid H_{t-1}, H_{t-2})$	0.03		0.05		0.02	
APE: $Prob(U_t \mid H_{t-1}, U_{t-2}) - Prob(U_t \mid H_{t-1}, H_{t-2})$	0.02		0.02		0.02	
PPR: $Prob(U_t \mid U_{t-1}, U_{t-2}) / Prob(U_t \mid H_{t-1}, H_{t-2})$	31.00		29.10		26.50	
PPR: $Prob(U_t \mid L_{t-1}, U_{t-2}) / Prob(U_t \mid H_{t-1}, H_{t-2})$	5.13		5.80		4.17	
PPR: $Prob(U_t \mid H_{t-1}, U_{t-2}) / Prob(U_t \mid H_{t-1}, H_{t-2})$	3.75		3.20		3.67	

Note: Omitted reference groups are high paid at *t*-1 and high paid at *t*-2, aged 55 plus, 12 or more years of education, major city, State (NSW), and female (for the All persons specification).

effect of unemployment is much reduced by an episode of employment. But most telling, it does not appear to matter that much whether the job is low paid or high paid; the size of the estimated unemployment effect are much the same – the relevant APEs are .03 compared with .02, while the relevant PPRs are 5.1 compared with 3.8.[8]

Again our conclusions differ somewhat when we focus on women and men separately. We find that among men, low-paid employment is more likely to be a channel to repeat unemployment – low-paid men with a recent history of unemployment are 5.8 times more likely to be unemployed than men in high-paid jobs in both past periods, whereas men in high-paid jobs with a history of unemployment are only 3.2 times more likely. That said, this difference, while seemingly quite large, was not statistically significant (p-value = .32). Among women the differences between low-paid employment and high-paid employment are much smaller, and also statistically insignificant.

VII Conclusion

The aim of this paper was to examine in detail, using the first seven waves of the HILDA Survey data, whether low-paid jobs in Australia reduce or exacerbate the likelihood of experiencing unemployment in the future. First and second-order dynamic random effects probit models predicting the probability of a labour force participant experiencing unemployment, after controlling for both unobserved heterogeneity and initial conditions, were estimated. The results indicate that prior low-paid employment experiences have at most, only a modest effect on the probability of experiencing unemployment in the future. Indeed, among men there appears to be no significant difference between low-paid employment and high-paid employment in terms of the risk of experiencing unemployment in the future. We did, however, uncover some weak evidence that men were more likely to

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8 A test of significance could not reject the hypothesis that the estimated coefficients are not equal (p-value = .47).

experience repeat unemployment if the intervening employment was low-paid. For women we find essentially the reverse results. Women in low-paid jobs are at much greater risk (1.7 times more likely) of experiencing future unemployment than women in high-paid jobs, but they are no more likely than women in high-paid jobs to experience repeat unemployment. Ultimately, however, the main feature of our analysis is the mainly weak scarring effects exerted by low-paid employment. Instead, by far the best predictor of whether someone is unemployed at time *t* is whether they have experienced unemployment in the past. Our findings are thus generally supportive of the jobs-first approach to workforce participation.

An interesting question is why our results seem so different from the results obtained in UK studies. Part of the explanation we believe lies in the way the UK results have been interpreted. As we noted earlier, Cappellari and Jenkins (2008b), who only analysed data for men, did not actually find significant differences between low-paid employment and high-paid employment in terms of their effects on future unemployment. Their results are thus entirely consistent with what is reported here. Stewart (2007), on the other hand, does obtain quite different results, but even he still reports relative probabilities of unemployment conditional on low-paid employment compared with high-paid employment that are close to identical to that reported here.

Another possibility may lie in the different time periods covered by the data. The UK studies of Stewart (2007) and Cappellari and Jenkins (2008b) both use data from the 1990s when UK unemployment rates were very high; indeed the data period includes the recession of the early 1990s. In contrast, the HILDA Survey data used here come from a period of strong economic growth and record low levels of unemployment. It may be that in a period of economic contraction and higher levels of unemployment we might obtain very different results.

We also report on some intriguing differences between men and women, something that has not been studied in the UK literature. Why women in low-paid jobs would appear to be at relatively greater risk of experiencing unemployment than women in high-paid jobs is not immediately obvious, but would be consistent with discrimination in hiring and firing practices, at least at the bottom of the wages distribution. Alternatively, it might reflect differences in preferences for employment emanating from the secondary income earner status of women in many households. That said, such differences in preferences should, in theory, have been captured, at least in part, by our model.

Finally, an important qualification to our analysis needs to be noted. We have restricted our attention to labour force participants and thus excluded persons not actively seeking work. As a result, we exclude all transitions from employment into non-participation in the labour force. This can be defended if we believe that all such transitions are voluntary and driven by worker preferences. However, we know that discouraged worker effects exist and that some people do not seek work because they believe a suitable job cannot be found. It is thus possible that exclusion of these non-participants may generate a form of selection bias in our results.

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