The Dynamics of Low Pay Employment in Australia

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Abstract: Using the Household, Income and Labour Dynamics in Australia (HILDA) survey, this study shows that the largest proportion of low pay spells originated from higher pay; only a small proportion were from non-employment or recent graduates. While the majority of low pay spells transitioned to higher pay, a significant proportion ended up with non-employment. The multivariate analysis shows that workers who entered low pay from higher pay also have a higher hazard rate of transitioning to higher pay; and those who entered low pay from non-employment are more likely to return to non-employment. Union members, public sector jobs and working in medium to large size firms increase the hazard rate of transitioning to higher pay, while immigrants from non-English speaking countries and workers with health problems have a lower hazard rate of moving into higher pay. There is some evidence that the longer a worker is in low paid employment, the less likely they are to transition to higher pay.

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1. Introduction

There are at least two reasons why research on low pay employment has drawn attention of academic researchers and policy makers. First, the welfare-to-work policies widely implemented across the developed countries since the mid-1990s have largely taken a “work-first” approach in the sense that any work, even if it is low paid, is better than relying on welfare. Such a policy is rationalised with the argument that low pay jobs could work as a stepping stone to higher pay jobs, since low pay jobs may help improve job skills and build up individual confidence. Second, in countries that have a national minimum wage, research on low pay employment, particularly the dynamics of low pay employment, may be used to provide evidence for setting minimum wages. Although not all low pay workers live in low income households (Healy and Richardson 2006), income of low pay workers is often used as an indicator to assess the adequacy or inadequacy of minimum wages. If low pay is just a transitory labour market state from which workers move up the earnings ladder quickly, the need to maintain an adequate minimum wage is less than in a situation where low pay is persistent. Therefore, empirical evidence on how long workers stay on low pay and the factors that affect the length of low pay is useful to inform policy decisions on minimum wages (Australian Government 2012).

There are different strands of research on low pay employment. There are studies that identify who are low paid and the characteristics of low pay workers. For example, both Healy and Richardson (2006) and McGuinness et al. (2007), although using different definitions of low pay, find that low pay employees are more likely to be single, young, low educated, on casual contacts, and migrants from non-English speaking countries. This strand of research, either using cross-sectional data or taking panel data as cross-sectional, is largely descriptive and provides little information on how low pay workers move between different earnings and labour market states.

With the availability of panel data, an increasing number of studies are devoted to the dynamics of low pay employment, particularly in terms of transitions into and out low pay (e.g. Gregory and Elias 1994; Sloane and Theodossiou 1998; Gosling et al. 1997; Stewart and Swaffield 1997, 1999; Cappellari 2002; Cappellari and Jenkins 2008). These studies examine what factors affect workers’ entry into and exit from low pay jobs with a particular interest in the persistence or state dependence of low pay employment in the sense to what extent low pay employment in the future is affected by current low pay status. Significant persistence in low pay employment has been found by a number of studies even after observed and unobserved individual heterogeneity is accounted for (e.g. Cappellari and Jenkins 2008; Uhlendorff 2006; Clark and Kanellopoulos

2009). However, these studies focus on year-on-year transitions between low pay and higher pay and do not account for the potential impact of low pay duration on the transitions.

A related theme of research examines whether low pay employment and unemployment are inter-related. This question arises due to the concern that low pay workers may cycle between low pay and unemployment with little hope of moving up the labour market ladder. For example, descriptive analyses by Dunlop (2001) and Perkins and Scutella (2008), while using different data sources, show that low pay workers are more likely than higher pay workers to move into joblessness in the future. On the other hand, using the first seven-wave Household, Income and Labour Dynamics in Australia (HILDA) survey, Buddelmeyer et al. (2010) find that previous low pay experience has only a modest effect on the probability of experiencing unemployment in the future when observed and unobserved individual heterogeneity is accounted for. This result is consistent with Cappellari and Jenkins (2008) for the UK men; but different from Stewart (2007) who finds that low wage employment has almost as large an adverse impact as unemployment on future employment prospects and that low wage jobs act as the main conduit for repeated unemployment.

Besides state dependence, another important aspect of low pay dynamics that has not drawn much research attention in the literature is duration dependence of low pay employment. Duration dependence addresses the question how duration on low pay affects the probability of exit from low pay. The work-first approach of welfare reforms could be rationalised on the promise that with work experience on low pay, workers could accumulate job skills. So the longer workers stay on low pay, the more skills they could obtain, and therefore the more likely they could move up the earnings ladder – a positive duration dependence scenario. On the other hand, the length of low pay may be used as a signal by employers to indicate that the worker is of low productivity. In this case, the longer workers stay on low pay, the less likely they will be able to move up – a negative duration dependence scenario. Since both arguments appear to be plausible in theory, whether duration dependence is positive or negative is an empirical question that needs to be tested from data. This is a focus of this study.

It appears that there are no other Australian studies that have examined the determinants of duration and duration dependence of low pay employment. Internationally, the only published study that takes a similar approach to the current study appears to be Phimister and Theodossiou (2009). This study examines gender differences in the determinants of the duration on low pay in the UK and how the determinants have changed following the introduction of the national minimum wage in the UK in 1999. They find that part-time low pay employment reduces the hazard rate of transitioning to higher pay and increases the hazard rate of leaving the labour force. For women higher education is found to increase the hazard rate of transitioning to higher pay and to reduce the hazard rate of leaving the labour force. The study also finds that the effects of many covariates on expected low pay duration are often smaller in magnitude for women than for men; and that for individuals with characteristics most associated with long low pay duration, the probability of higher pay exit is substantially lower after 1999 for women than for men.

Using the first 10 waves of the HILDA survey, this study examines the dynamics of low pay employment focusing on the determinants of duration and exit destinations of low pay. [1]

Descriptive analyses show that the largest proportion of low pay spells originated from higher pay; only a small proportion were from non-employment or recent graduates. While the majority of low pay spells are found to transition to higher pay, a significant proportion ended up with non-employment.

The multivariate analysis shows that workers who entered low pay from higher pay also have a higher hazard rate of transitioning to higher pay; and those who entered low pay from non-employment are more likely to return to non-employment. Union members, public sector jobs and working in medium to large size firms increase the hazard rate of transitioning to higher pay, while immigrants from non-English speaking countries and workers with health problems have a lower hazard rate of moving into higher pay. The results also show that female workers, workers with health problems, older workers, casual workers and part-time workers have a higher hazard rate of transitioning to non-employment. There is some evidence of negative duration dependence in the transition from low pay to higher pay.

2. Data, definition and descriptive analysis

2.1. Data source and low pay definition

This study uses data from the first 10 waves of the HILDA survey. Wooden et al. (2002) document details of this survey. So far this is the only Australian longitudinal survey that has covered 10 years. In the first wave, 7,683 households representing 66 per cent of all in-scope households were interviewed. This generated a sample of 15,127 persons who were 15 years or older and eligible for interviews, of whom 13,969 were successfully interviewed. Subsequent interviews for later waves were conducted about one year apart.

[1] Due to a small sample size, this current study does not estimate models separately for males and females, but sex is included as an explanatory variable in the multivariate analysis.

The HILDA survey contains detailed information on individual characteristics, labour market outcomes, activity and history. It also contains information on job characteristics, such as whether the job is casual, in public or private sector, the size of employers, and so on. This allows examining the impacts of both individual and job characteristics on the dynamics of low pay employment.

Like most other household surveys, the HILDA survey collects information on weekly earnings and weekly working hours. In this study hourly earnings are derived by dividing weekly earnings by weekly working hours from the main job to define low pay status. Using hourly earnings rather than weekly earnings avoids the potential issue of part-time employment – some workers may be classified as on low pay simply because they have worked few hours and the low working hours are out of their own choices (e.g. they prefer leisure to work or are balancing work with caring responsibilities). On the other hand, using hourly earnings may overestimate low pay for those who reported very long working hours as a result of unpaid overtime. To partly remedy the latter issue, weekly working hours are top-coded at 55 hours a week.

Another issue in defining low pay is where to set the low pay threshold. That is, the hourly earnings level below which workers are classified as on low pay. Different thresholds have been used in the literature. This study uses two thirds of the median hourly earnings, which appears to be the most popular definition (Buddelmeyer et al. 2010).[2] Buddelmeyer et al. (2010) show that while different low pay thresholds result in different proportions of workers classified as on low pay, they have little impact on model estimates.

The first row in Table 1 shows the low pay threshold used in this study. This low pay threshold identifies about 11 per cent of employees as on low pay for each wave. To put this low pay threshold into context, the second row in Table 1 presents the 10th quantile of hourly earnings, which is also estimated for the HILDA survey. For each wave of the HILDA survey, the 10th quantile is slightly below the two thirds median. The third row in the table shows the national minimum wage (NMW) applicable around the time when each wave of the survey was conducted. The two thirds median threshold is always higher than the NMW and the difference ranges from 2 to 4 per cent over the ten waves/years.

The focus of this study is on the duration and exit destinations of 'low pay spells'. A low pay spell is defined as a 'continuous' stay on low pay. As such, a low pay spell has a start and an

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[2] It was also experimented to use the 1st quintile of hourly earnings to define the low-pay threshold. This definition of low pay produced very similar results to those reported in the paper for both the descriptive analysis and econometric modelling. These results can be obtained from the author on request.

end. Where low pay workers come from and where they go when they leave low pay form part of the analysis of this study.

Table 1: Low pay threshold defined as two thirds median hourly earnings

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
2/3 median	11.67	12.08	12.50	13.08	13.56	14.39	15.15	15.97	16.67	17.33
10th quantile	11.36	11.80	12.24	12.71	13.33	13.75	14.78	15.28	15.83	16.75
Minimum wage	10.88	11.35	11.80	12.30	12.75	13.47	13.74	14.31	14.31	15.00

Source: Author's calculation from the HILDA waves 1 to 10.

Since low pay status is determined by using information on earnings and working hours available at the time of the survey interview each year, changes in low pay status due to changes in earnings and/or working hours between two consecutive interviews (i.e. waves) are not considered in this study.

The analysis is restricted to low pay workers aged between 21 and 64 years (inclusive) when the low pay spells started. Those aged under 21 years may be paid junior, apprentice or trainee wages and thus are more likely to be classified as on low pay based on adult wages. Since we cannot tell whether a younger worker is paid junior, apprentice or trainee wages from the data, they are excluded from the analysis. Full-time students are also excluded from the analysis for self-evident reasons. 4,457 low pay spells are identified from the 10-wave HILDA survey. The next subsection provides descriptive analysis of these spells.

2.2.Descriptive analysis

We first look at where these low pay spells came from (i.e. low pay origin). As shown in Table 2, of the 4,457 low pay spells, about 45 per cent had hourly wages that were at or above the low pay threshold (denoted as 'higher pay' thereafter for ease of exposition) in the year prior to entering low pay.[3] This is somewhat surprising since one would expect those who started low pay should be those who just entered the workforce, which is however not the case. The second largest origin of the low pay spells (about a quarter) is left-censored spells – low pay spells that started when they first entered (and in a few cases re-entered) the HILDA survey. For about nine per cent of the low pay spells (denoted as 'wage unknown'), their weekly earnings in the main

[3] Among the 1,993 low pay spells classified as from higher pay only 18.5 per cent changed employers during the previous 12 months. That is, the vast majority of those who transitioned from higher pay to low pay did not experience a job change. It is unusual for people to have a pay cut if they remain on the same job. Further analysis shows that 91.7 per cent of those from higher pay had hourly wages between the low pay threshold and the median hourly earnings prior to entering low pay. This suggests that rather than having a pay cut, these workers might have an increase of hourly earnings that is less than the increase of the low pay threshold. Since the focus of this study is on the determination of low pay duration and exit destinations, we did not pursue further the reasons that people become low pay from higher pay.

job were missing although working hours were recorded in the year prior to being found on low pay. Only 13 per cent of the low pay spells were not employed in the year prior to entering low pay; five per cent were recent graduates (denoted as 'students'); and just under three per cent were from self-employment.

For the left-censored spells, we do not know when the low pay spells started and thus have to exclude them from the duration analysis later on.[4] Similarly, for those with unknown wages prior to entering low pay, we cannot determine whether they were on low pay or not in the previous year. Therefore, these spells need to be excluded from the duration analysis as well.

Table 2: Origin of low pay spells

Low pay origin	No. of spells	Per cent
Higher Pay	1,993	44.72
Left-censored	1,125	25.24
Non-employment	584	13.10
Wage unknown	392	8.80
Students	238	5.34
Self-employment	125	2.80
All	4,457	100

Source: Author's calculation from the HILDA waves 1 to 10.

Table 3 shows where people on low pay went when their low pay spell ended (i.e. exit destination). Encouragingly, half of the people in the low pay spells moved up the earnings ladder to become higher paid workers.[5] 28 per cent of them were still on low pay when they were last observed in the data (denoted as 'right-censored' in the table). About 12 per cent of the people left employment when moving off low pay; four per cent became self-employed; and less than two per cent moved to full-time study (i.e. students).

For four per cent of the low pay spells, we cannot determine their exit destinations since their weekly earnings were missing although they had working hours recorded. Again, these spells will be excluded from the duration analysis later on.

Although we do not know their exit destinations of those right-censored spells, they can be handled easily in duration modelling. They are therefore retained for the duration analysis.

[4] Another reason for not including left-censored spells in duration analysis is that they tend to be long lasting spells and including them would therefore bias the estimates.
[5] As shown later, this proportion is even larger when the left-censored spells and spells with unknown wages are excluded.

Knowing the origins and destinations of the low pay spells, the immediate follow-up question one might ask is whether the exit destinations of the low pay spells are linked in some way to where the low pay spells come from. Table 4 sheds some light on this.

Table 3: Exit destination of low pay spells

Low pay destination	No. of spells	Per cent
Higher pay	2,242	50.30
Right-censored	1,263	28.34
Non-employment	532	11.94
Wage unknown	178	3.99
Self-employed	170	3.81
Students	72	1.62
All	4,457	100

Source: Author's calculation from the HILDA waves 1 to 10.

The table shows that those who came from higher pay are more likely than those from other low pay origins to exit to higher pay – nearly 60 per cent of those entering low pay from higher pay exited to higher pay. 47 per cent of the left-censored spells transitioned to higher pay; the group with the third highest probability (46 per cent) of exit to higher pay is those former students. Those who came to low pay from non-employment or self-employment have the lowest probability (around a third) of exiting to higher pay.

Table 4: Cross-tabulation of origin and destination (row %)

	Low pay destination						
Low pay origin	Higher pay	Right-censored	Non-employ	Wage unknown	Self-employ	Student	No. Obs.
Higher Pay	58.66	25.64	9.43	3.56	1.91	0.8	1,993
Left-censored	46.58	33.24	10.93	3.2	4.27	1.78	1,125
Non-employ	38.18	26.71	24.14	4.62	5.48	0.86	584
Wage unknown	44.64	31.38	10.46	7.91	3.57	2.04	392
Students	45.8	30.67	10.08	1.68	2.52	9.24	238
Self-employ	33.6	20.8	12	7.2	25.6	0.8	125
All	50.3	28.34	11.94	3.99	3.81	1.62	4,457

Source: Author's calculation from the HILDA waves 1 to 10.

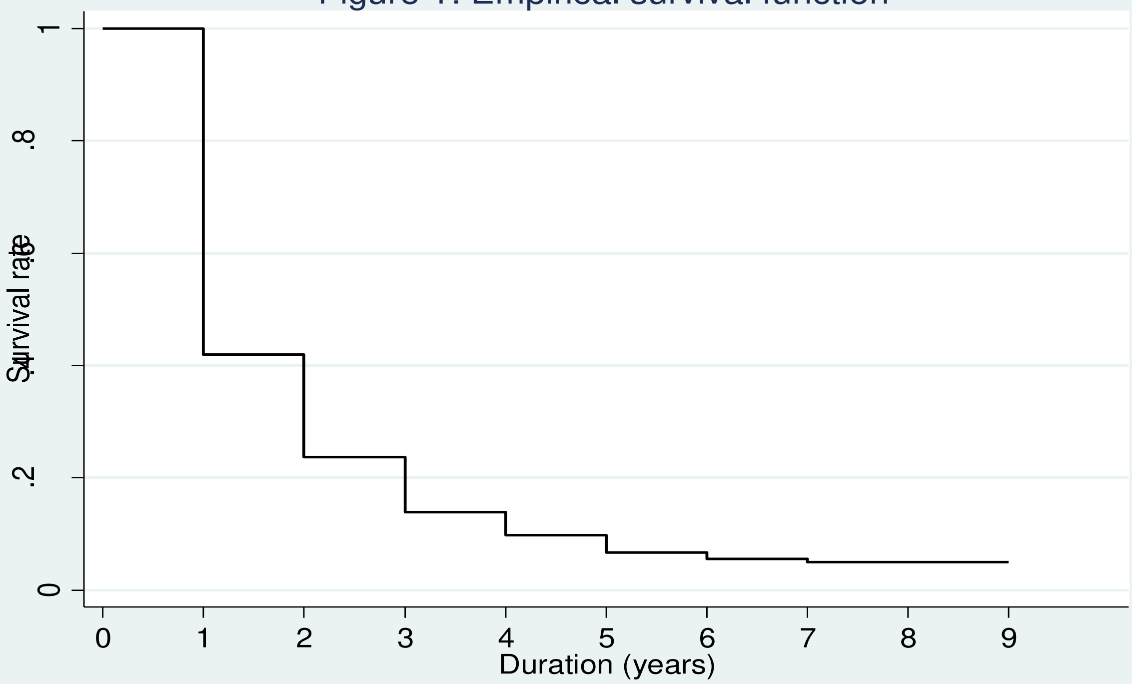
Not surprisingly, those who entered low pay from self-employment are more likely than others to move back into self-employment when leaving low pay; those who entered low pay from non-employment are more likely to end up with non-employment again; and those former students are more likely to return to full-time study. In other words, Table 4 shows substantial state-dependence in low pay transitions. The modelling analysis later will examine whether such relationship holds after individual heterogeneity is accounted for.

2.3.Empirical survival and empirical hazard functions

To shed light on how long low pay spells last and how duration on low pay affects exit from low pay, we present the empirical survival and empirical hazard functions of the low pay spells that are used for the duration analysis. That is, in this subsection those left-censored spells and spells with unknown wages prior to entry into and at the end of the low pay spells are excluded. Further, since the number of spells that left low pay for full-time studies is small, they cannot be modelled as a separate destination and are thus excluded from further analysis.

The survival function at time *t* shows the probability of remaining on low pay for at least *t* years. Figure 1 shows that just over 42 per cent of the low pay spells lasted for at least one year. Just under a quarter (24 per cent) lasted for at least two years; about seven per cent lasted for at least five years; and about five per cent lasted for at least nine years.

Figure 1: Empirical survival function



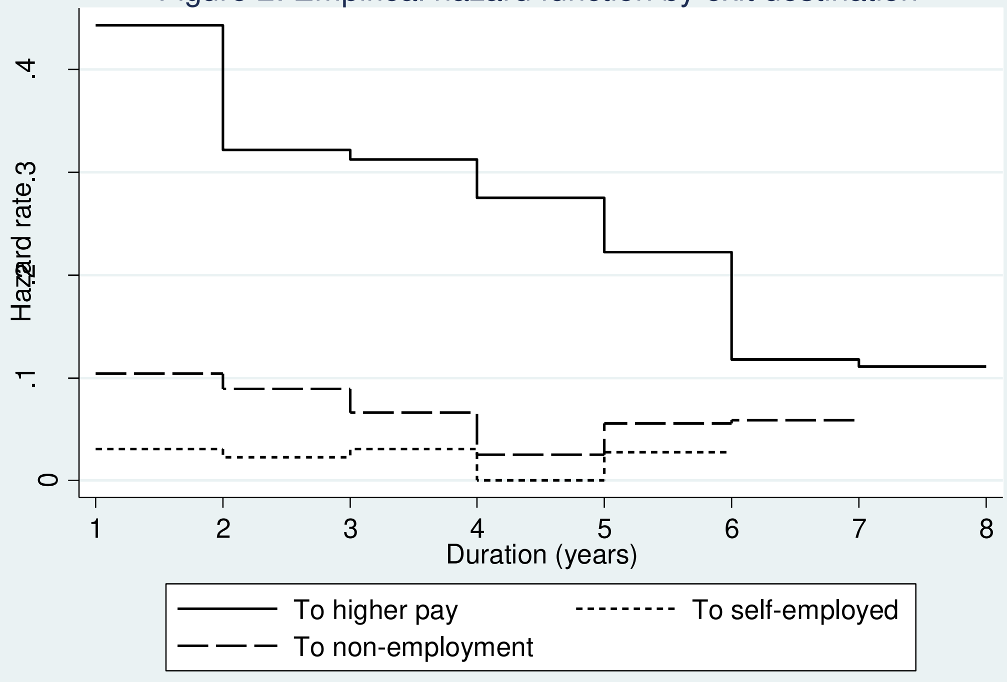
The empirical survival rates suggest that the expected duration of the low pay spells is longer than 2.2 years. However, since nearly 60 per cent of the low pay spells ended within one year, the median duration of the low pay spells is less than one year. The duration distribution of the low pay spells is very much skewed towards short duration spells.

The empirical survival function does not tell where people leave for and how duration of low pay and the rate of exit are related. Figure 2 addresses these issues by showing the empirical hazard functions by exit destination.

The hazard rate at time *t* shows the probability of leaving for a destination over the time interval [*t, t+1*), conditional on having been on low pay for time *t*. For example, the probability of leaving for higher pay when on low pay for a year is about 44 per cent; for self-employment it is just three per cent, and for non-employment it is about 10 per cent.

The empirical hazard function for higher pay exit exhibits negative duration dependence - the longer workers are on low pay, the less likely they will leave for higher pay. Duration dependence is not obvious for destinations of self-employment and non-employment.

Figure 2: Empirical hazard function by exit destination



The duration dependence shown in Figure 2 may be spurious since this may be the result of observed and unobserved individual heterogeneity. For example, it is likely that those who are highly educated exit to higher pay quicker, leaving those with low education behind. Similarly, those with higher ability may leave low pay quicker than those with lower ability. In the following sections we will take these factors into account to see whether there is genuine duration dependence.

3. Econometric modelling

3.1. The empirical model

One way of formulating a competing risk model with K exit routes is to postulate there are K latent durations for each individual, T_1, …, T_K, which are independent random variables.[6] The actual destination entered is determined by whichever of the $\{T_k\}$ is the least and that this minimum is the duration we observed. Denote the route specific hazard at time t for route k as $\lambda_k(t)$, which measures the probability of leaving for route k in the next infinitesimal period, given $T_k \geq t$. The commonly used hazard function takes the proportional hazard form,

$$\lambda_k(t \mid x(t)) = \lambda_{k0}(t)\exp(x(t)^{'}\beta_k), \tag{1}$$

where $\lambda_{k0}(t)$ is the baseline hazard at time t for exit route k, which is common to all individuals; $x(t)$ is a vector of covariates which can be time varying; and β_k is a vector of unknown parameters.

In the context of discrete time, the probability that T_k will last until time $t+1$, given that it has lasted until t, can be written as,

$$\begin{aligned} P(T_k \geq t+1 \mid T_k \geq t) &= \exp[-\int_t^{t+1} \lambda_k(u)du] \\ &= \exp[-\exp(x(t)^{'}\beta_k + \gamma_k(t))], \end{aligned} \tag{2}$$

given that $x(t)$ is constant between t and $t+1$, and where $\gamma_k(t) = \ln\{\int_t^{t+1} \lambda_{k0}(u)du\}$ (Meyer, 1990).[7] Then, the survival function of T_k is,

$$\begin{aligned} S_k(t) &= \prod_{j=0}^{t-1} \exp[-\exp(x(j)^{'}\beta_k + \gamma_k(j))] \\ &= \exp[-\sum_{j=0}^{t-1} [\exp(x(j)^{'}\beta_k + \gamma_k(j))]] \\ &= \exp[-\Lambda_k(t)], \end{aligned} \tag{3}$$

where $\Lambda_k(t) = \sum_{j=0}^{t-1} [\exp(x(j)^{'}\beta_k + \gamma_k(j))]$.

[6] Given the information in the data, models based on dependent latent durations cannot be identified (Florens, Fougére and Mouchart, 1996).

[7] This specification for the baseline hazard is known as piece-wise constant baseline hazard (Prentice and Gloeckler, 1978; Meyer, 1990; Lancaster, 1990). This specification for the baseline hazard has an important advantage for it has been shown that misspecification of the baseline hazard is a major source of error in drawing inferences concerning both the presence of duration dependence (Blank, 1989; and Manton, Stallard and Vaupel, 1986) and the impact of covariates (Dolton and van der Klaauw, 1995; and Heckman and Singer, 1985).

Given the independence assumption on the latent durations, if an individual is observed to be right-censored at t, the contribution to the likelihood function is $L_c = \prod_{l=1}^{K} S_l(t)$. If an individual is observed to leave for route k at $[t,\ t+1)$, the contribution to the likelihood function is $L_k = [S_k(t) - S_k(t+1)]\prod_{\substack{l=1 \\ l \neq k}}^{K} S_l(t+1)$.

Each individual will leave low pay through at most one exit route. Define $r_{ik} = 1$ if individual i exits through route k and $r_{ik} = 0$ otherwise. Then, $\sum_{k=1}^{K} r_{ik} = 1$ if individual i is observed to exit, and $\sum_{k=1}^{K} r_{ik} = 0$ if right-censored. The log likelihood function for a sample of n is,

$$L = \sum_{i=1}^{n}\{\sum_{k=1}^{K} r_{ik} \ln(L_{ik}) + (1 - \sum_{k=1}^{K} r_{ik})\ln(L_{ic})\}. \tag{4}$$

Model (1) assumes that there is no unobserved individual heterogeneity that affects exits from low pay. If unobserved heterogeneity did exist, the parameters would be estimated with bias. Two approaches to incorporating parametric unobserved heterogeneity have been experimented, both assuming the unobserved heterogeneity to take a Gamma distribution: a) a common unobserved heterogeneity for all the exit destinations; and b) independent and destination specific unobserved heterogeneity.[8] No evidence of unobserved heterogeneity was found in either case, since the variances of the unobserved heterogeneity terms were estimated to be not statistically different from zero.

Alternatively, Heckman and Singer (1984) suggest using a discrete distribution with a finite number of support points to approximate the distribution of the unobserved heterogeneity, so that the unobserved heterogeneity takes a non-parametric form. It has been attempted to estimate the model with two support points. The estimate for the non-normalised probability was not different from zero and the estimate for the non-normalised support point was not different from one, indicating that there was no unobserved heterogeneity.[9]

3.2. Model specification

[8] See Cai (2006) for how to implement these approaches.

[9] Meyer (1990) argues that, when the baseline hazard takes a piecewise constant form, as in this paper, the choice of the distribution of unobserved heterogeneity may not be important. Also see Lancaster (1990, p. 305) for a similar argument. Baker and Melino (2000) provide supportive Monte Carlo evidence in this regard. They find that a non-parametric specification of either the duration dependence or unobserved heterogeneity leads to well-behaved estimators, but when both are specified non-parametrically, there is a large and systemic bias in the parameters of these two components and a complementary bias in the coefficients on observed heterogeneity.

As alluded to earlier, spell origins are included in the set of the explanatory variables for the duration modelling. Also included in the model are variables on individual characteristics: sex, age, education, health condition, marital status, country of birth, and whether living in a capital city. In addition, a set of job characteristics - casual employment, part-time employment, union status, public sector jobs and firm size – are included in the model.[10] These variables are often used to estimate a wage equation and can therefore be reasonably extended to the determination of wage transitions.

Summary statistics of the modelling sample are presented in Table a1 in the appendix. Note that left-censored spells and spells with unknown origin or destination are excluded from the duration analysis.

4. Model estimation results

Due to the non-linear nature of the hazard function, the coefficient estimates cannot be interpreted as marginal effects. However, the sign of an estimate indicates whether the variable increases or decreases the hazard rate: a positive (negative) sign means the variable increases (decreases) the hazard rate.

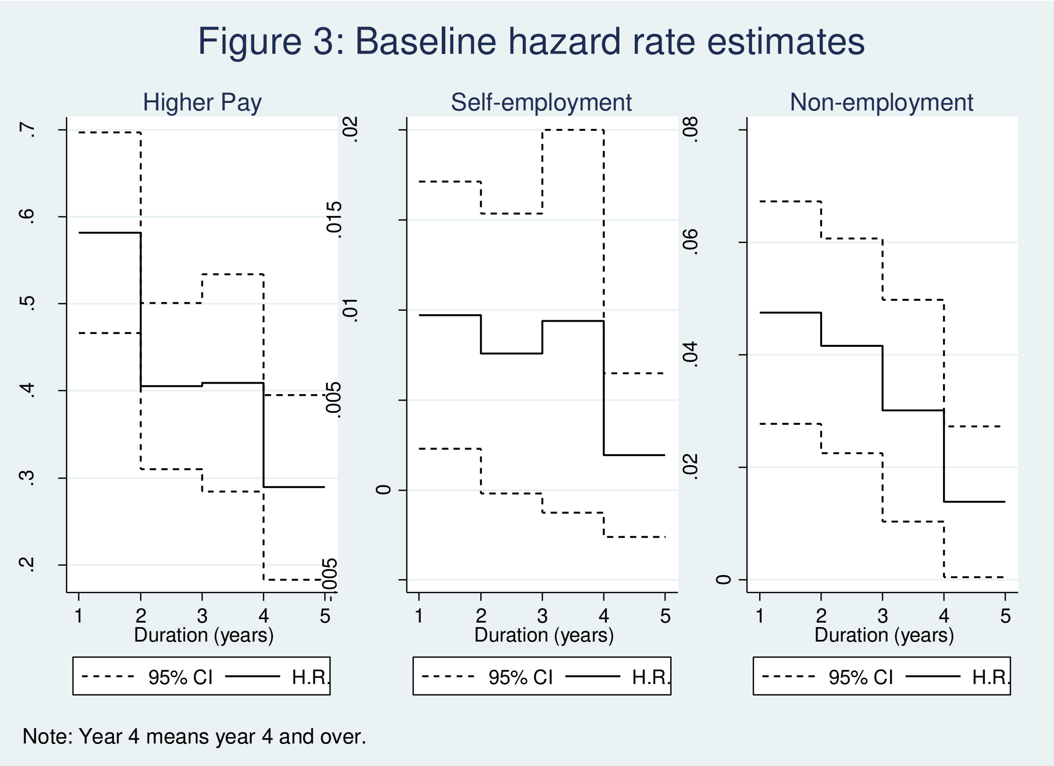
The form of the hazard function does lend to a meaningful interpretation of the exponential of the coefficient estimates. It can be shown that for a dummy variable, the exponential of the coefficient estimate represents the ratio of the hazard rates between the variable taking the value one and the variable taking the value zero, other things being equal. For example, for the variable female, the exponential of the estimate measures the hazard ratio between females and males, while keeping the other variables constant. The 'hazard ratio' interpretation applies to categorical variables as well where the ratios are all relative to the omitted category of the set of the categorical variables. Table 5 presents the coefficient estimates together with the hazard ratio estimates for ease of interpretation.

4.1.Baseline hazard estimates

We first look at the estimates for the baseline hazards. For ease of comparison, Figure 3 plots the estimated baseline hazard rates. The baseline hazards for all the three destinations show a downward trend, implying negative duration dependence. However, as shown in the figure, for the two destinations of self-employment and non-employment, the baseline hazard rates do not appear to be statistically different between different duration intervals. For the higher pay

[10] It was also experimented to include a variable indicating whether a worker experienced a job change in the previous 12 month, but this variable was insignificant in any specification and was consequently dropped in the final specification.

destination, the baseline hazard rates for the first three years are not statistically different; only for duration longer than four years is the hazard rate (statistically) significantly higher than that in the first year, although it is still not statistically different from that of year two or year three. In summary, there is some evidence of negative duration dependence for exit to higher pay, particularly after three years on low pay, but no evidence of duration dependence for exits to the other two destinations.



4.2.Low pay origin variables

For the low pay origin variables, the omitted category is those from higher pay. The estimation results show that relative to those who entered low pay from higher pay, all other low pay origins reduce the hazard rate of transitioning to higher pay. The hazard ratio estimates indicate that, other things being equal, those entering low pay from non-employment have a 33 per cent lower hazard rate of transitioning to higher pay than those from higher pay. Interestingly those from non-employment do not appear to have the lowest hazard rate of transitioning to higher pay; rather, it is those who entered low pay from self-employment that have the lowest hazard rate of transitioning to higher pay.

Table 5: Model estimation results

	To higher pay			To self-employment			To non-employment		
	Coef.	S.E. of Coef.	H.R.	Coef.	S.E. of Coef.	H.R.	Coef.	S.E. of Coef.	H.R.
Baseline hazard									
Year 1	-0.5423***	0.1010	0.5814	-4.6340***	0.3895	0.0097	-3.0463***	0.2120	0.0475
Year 2	-0.9030***	0.1197	0.4053	-4.8815***	0.5226	0.0076	-3.1808***	0.2340	0.0416
Year 3	-0.8944***	0.1556	0.4089	-4.6683***	0.5784	0.0094	-3.5034***	0.3340	0.0301
Year 4 and plus	-1.2411***	0.1877	0.2891	-6.2428***	1.1921	0.0019	-4.2749***	0.4906	0.0139
Spell origin									
Self-employment	-0.5991***	0.1896	0.5493	2.1718***	0.2805	8.7737	-0.0619	0.3035	0.9400
Student	-0.2059*	0.1159	0.8139	0.2325	0.5490	1.2617	0.1596	0.2604	1.1730
Non-employment	-0.4021***	0.0856	0.6689	0.6260**	0.2971	1.8701	0.6560***	0.1302	1.9271
Human capital									
Degree	0.1657*	0.0924	1.1803	0.4566	0.3629	1.5787	-0.0475	0.1876	0.9537
Diploma	-0.0216	0.1006	0.9786	0.0398	0.4537	1.0406	-0.0216	0.2142	0.9786
Certificate	-0.0030	0.0737	0.9970	0.2002	0.2745	1.2217	-0.2324	0.1524	0.7927
Year 12	-0.0179	0.0864	0.9823	0.0348	0.3785	1.0354	0.2273	0.1670	1.2552
Health condition	-0.2541***	0.0735	0.7756	0.4175	0.2561	1.5182	0.2402*	0.1321	1.2715
Demographics									
Female	-0.0804	0.0613	0.9227	-0.5397**	0.2484	0.5829	0.3409***	0.1305	1.4062
Age 15-24	-0.0014	0.0961	0.9986	0.0495	0.4194	1.0507	-0.2021	0.2045	0.8170
Age 35-44	0.0405	0.0804	1.0413	0.6077**	0.2960	1.8363	-0.2096	0.1618	0.8109
Age 45-54	-0.0158	0.0825	0.9843	0.153	0.3201	1.1653	-0.236	0.1776	0.7898
Age 55 plus	-0.0594	0.1013	0.9423	-0.0546	0.4039	0.9469	0.4915***	0.1757	1.6348
Married	0.0605	0.0603	1.0623	0.4584*	0.2533	1.5815	-0.0293	0.1197	0.9711
Immigrant: ESC	-0.0092	0.1079	0.9909	0.7154**	0.2947	2.0449	0.2469	0.2053	1.2801
Immigrant: NESC	-0.1931**	0.0920	0.8244	0.1983	0.3346	1.2194	-0.0213	0.1942	0.9789
Capital city	0.1059*	0.0577	1.1117	-0.2023	0.2333	0.8169	0.1254	0.1160	1.1336

Job characteristics									
Casual job	-0.0895	0.0693	0.9144	0.9239***	0.2900	2.5191	0.6333***	0.1332	1.8838
Part-time job	-0.1090	0.0675	0.8967	-0.0711	0.2897	0.9314	0.2841**	0.1350	1.3286
Union member	0.4839***	0.0859	1.6223	-0.3263	0.5171	0.7216	0.0854	0.2114	1.0891
Public sector	0.2093***	0.0788	1.2328	0.1255	0.4022	1.1337	-0.1308	0.1904	0.8774
Firm size 20-99	0.1698**	0.0828	1.1851	-0.4036	0.3669	0.6679	0.0014	0.1626	1.0014
Firm size 100-499	0.2410**	0.0947	1.2725	-1.2112	0.7377	0.2978	-0.3831	0.2340	0.6817
Firm size 500 plus	0.1572**	0.0688	1.1702	-0.5154	0.3157	0.5972	-0.2409	0.1544	0.7859
Log-likelihood		-3927.51							
No. of observations		3792							
No. of spells		2790							

*** significant at 1%; ** 5%; * 10%.

Turning to the hazard function of transitioning to self-employment, compared to those from higher pay, those from other origins have a higher hazard rate of transitioning to self-employment; and those who came from self-employed have the highest hazard rate. The hazard ratio estimates show that the hazard rate of returning to self-employment of those who were self-employed prior to entering low pay is about nine times of those who entered low pay from higher pay. Those who entered low pay from non-employment have a hazard rate of transitioning to self-employment that is about 90 per cent higher than those who entered low pay from higher pay.

For the hazard function of transitioning to non-employment, while those from self-employment and former students are not statistically different from those from higher pay, the hazard rate of transitioning to non-employment of those who entered low pay from non-employment almost doubles that of those from higher pay.

The estimation results on low pay origins therefore show a substantial degree of state dependence in the labour market transitions of low pay employment.

4.3.Human capital variables

Overall the variables on education do not appear to play a significant role in the transition off low pay, since only the degree variable is weakly significant in the hazard function of transitioning to higher pay; all other education variables are statistically insignificant. The estimate on the degree variable indicates that those with a degree have a hazard rate of transitioning to higher pay that is about 20 per cent higher than those who did not complete year 12. The overall insignificance of the education variables may not be surprising since these variables are highly correlated with the low pay origin variables.

Health has increasingly been regarded as a form of human capital (Cai and Kalb 2006). Health appears to matter in the transition to higher pay. The result shows that compared with low pay workers without any health conditions, the hazard rate of transitioning to higher pay of low pay workers with a health condition is about 20 per cent lower. On the other hand, low pay workers with a health condition have a 27 per cent higher hazard rate of moving to non-employment than those without a health condition. These results are consistent with findings in the literature that health has a significant impact on labour market outcomes (e.g. Cai 2010; Cai 2009).

4.4.Demographic variables

There does not appear to be a gender difference in the hazard rate of transitioning to higher pay, but females appear to have a lower hazard rate of moving to self-employment and a higher hazard rate of transitioning to non-employment than males.

The omitted (i.e. base) age category is those aged 25-34 years. Overall age does not seem to matter in affecting the hazard function of transitioning to higher pay. Those aged 35-44 years appear to have a higher hazard rate of transitioning to self-employment than those aged 25-34 years. For the hazard function of transitioning to non-employment, the estimates indicate that those older than 55 years have a hazard rate about 60 per cent higher than those aged 25-35 years.

There is only weak evidence that those who are married have a higher hazard rate of moving to self-employment from low pay than those singles. Marital status appears not to affect the hazard function of transitioning to higher pay or non-employment.

For the country of birth variables, Australian born is the omitted category. The estimates indicate that compared to Australian born, immigrants from non-English speaking countries have a lower hazard rate of transitioning to higher pay; while immigrants from English speaking countries have a higher hazard rate of moving to self-employment. There seems to be no difference between Australian born and immigrants in terms of transitioning to non-employment.

There is weak evidence that low pay workers living in a capital city have a slightly higher hazard rate of transitioning to higher pay than those who live elsewhere. For transitioning to self-employment and non-employment, living in a capital city does not seem to matter.

4.5.Job characteristic variables

Low pay casual workers do not appear to be different from low pay non-casual workers in terms of transitioning to higher pay. However, the hazard rates of transitioning to self-employment and non-employment are much higher for low pay casual workers than for low pay non-casual workers.

The estimate on the part-time variable is only significant for the hazard function of transitioning to non-employment, indicating that the hazard rate of transitioning to non-employment of part-time low pay workers is 33 per cent higher than that of full-time low pay workers.

Low pay union members have a higher hazard rate of transitioning to higher pay than non-union members. Union status does not have a significant impact on the hazard functions of transitioning to self-employment and non-employment.

Low pay workers in the public sector have a higher hazard rate of transitioning to higher pay relative to low pay workers in the private sector. For the hazard functions of the other two destinations the sector variable has no a significant effect.

For the firm size variable, the omitted category is firms with less than 20 employees. The results show that relative to low pay workers in a firm with less than 20 employees, low pay workers in a larger firm have a higher hazard rate of transitioning to higher pay. But the firm size effect does not appear to be linear – while the effect increases when firm size rises from 20-99 to 100-499 employees, it falls when firm size increases further. Firm size does not appear to have a significant impact on the transitions to the other two destinations.

4.6.Marginal effects on expected duration

The coefficient and hazard ratio estimates in Table 5 provide inferences as to how each explanatory variable affects the hazard function of each exit destination. However, since the same variable may affect the different hazard functions in opposite directions, it is not straightforward to infer from the coefficient and hazard ratio estimates how each of the variables affects expected duration on low pay. To estimate the effect of the explanatory variables on expected duration, we note that expected low pay duration of workers with characteristics *X*, $E[d|X]$, can be expressed as,

$$E[d|X] = 1 + \sum_{t=1}^{T} S(t|X), \qquad (5)$$

where $S(t|X) = \exp[-\sum_{\tau=1}^{t}\sum_{k=1}^{K}\lambda_k(\tau|X,\beta_k)]$ and T is the maximum duration that workers can be on low pay.[11]

We can estimate the effect of a variable on expected duration by changing the value of the variable. For example, the effect of the variable female can be estimated by the difference of the expected durations between the variable female taking the value one and taking the value zero, while the values of the other variables are kept constant.[12] The effect of categorical variables can be calculated in a similar way.

The results are presented in Table 6. The standard errors of the duration effects are also presented. The standard errors are estimated by simulation – that is, repeated draws from the estimated distribution of the coefficient estimates.

[11] Workers cannot be on low pay forever simply because there is a retirement age. We take T=50 in simulating the expected duration. Taking a larger value does not make a difference in the estimated effect.
[12] The values of the other variables are kept at the sample means.

Consistent with the coefficient estimates that not many variables are significant for the hazard functions of transitioning to self-employment and non-employment, not many variables are significant for the estimated effect on expected duration. However, those significant variables appear to accord to expectations.

Compared to those who came from higher pay, those who came from non-employment are expected to stay on low pay for about 0.56 of a year longer. Those from self-employment and former students are also estimated to stay on low pay for longer than those from higher pay, but the effects are estimated imprecisely.

Table 6: Estimated marginal effects on expected duration

	Marginal effect	S.E.[(a)]
Self-employment	0.9589	0.7069
Student	0.3949	0.3314
Non-employment	0.5584*	0.2859
Degree	-0.3525*	0.2040
Diploma	0.0542	0.2416
Certificate	0.0670	0.1683
Year 12	-0.0483	0.1836
Health condition	0.4611**	0.2293
Female	0.1070	0.1750
Age 15-24	0.0642	0.2272
Age 35-44	-0.0652	0.2006
Age 45-54	0.1014	0.1770
Age 55 plus	-0.0844	0.2072
Married	-0.1519	0.1454
Immigrant: ESC	-0.1166	0.2346
Immigrant: NESC	0.4562*	0.2641
Capital city	-0.2618*	0.1457
Casual job	-0.0899	0.1824
Part-time job	0.1510	0.1445
Union member	-0.8867***	0.1915
Public sector	-0.4030**	0.1736
Firm size 20-99	-0.3374*	0.1740
Firm size 100-499	-0.3609	0.2200
Firm size 500 plus	-0.2382*	0.1349

*** significant at 1%; ** 5%; * 10%.

(a) Standard errors are simulated using 1000 draws from the estimated distribution of the coefficient estimates in Table 5.

Relative to those who did not complete year 12, those who have a degree or higher qualification are expected to stay on low pay for 0.35 of a year less. Those with a health condition are expected to stay on low pay for about a half year longer than those without a health condition.

Gender, age and marital status do not appear to make a statistically significant difference to the expected duration on low pay.

Compared to those Australian born, those immigrants from a non-English speaking country are expected to stay on low pay for 0.46 of a year longer. Those living in a capital city are expected to stay on low pay for about 0.26 of a year shorter than those living somewhere else.

Whether working part-time or whether on a casual arrangement does not appear to matter in affecting the expected duration on low pay.

Union members are expected to be on low pay for 0.89 of a year less than non-union members. Public sector workers are expected to be on low pay for 0.40 of a year less than private sector workers. Relative to those working in a firm with less than 20 employees, those working in a larger firm are expected to stay on low pay for a shorter period.

Overall, it appears that the variables that raise the hazard rate of transitioning to higher pay have a negative impact on the expected duration on low pay, while the variables that reduce the hazard rate of transitioning to higher pay have a negative impact on the expected duration.

5. Conclusion

Using the first 10 waves of the HILDA survey, this study examined where low pay workers came from, where they went when they left low pay, and the factors that affect the hazard rates and duration of different exit destinations.

Contrary to initial expectation, the highest proportion of low pay workers were not from those who were not employed or recent graduates; instead, they were from those who were initially on higher pay. Those who were initially not employed or recent graduates made up of less than 20 per cent of the low pay spells identified from the data.

While the majority of the low pay workers did move up to higher pay over the observed time period, a significant proportion moved out of employment all together; a small proportion became self-employed.

Both the descriptive and multivariate analyses show strong evidence of state dependence in the dynamics of low pay employment. That is, those who entered low pay from higher pay are more likely to transition back to higher pay; those who came from self-employment are more likely to go back to self-employment and those who came from non-employment are more likely to return to non-employment. This suggests that one-size-fits-all policy should not work to facilitate transitions from low pay to higher pay employment.

There is some evidence that the longer someone is in low pay employment, the less likely they are to exit to higher pay (i.e. negative duration dependence), suggesting policy interventions should occur at an early stage of a low pay episode. But there is no evidence of duration dependence in the other two exit destinations, self-employment and non-employment.

The multivariate analysis helped identify workers who are at high risk of staying in low pay or transitioning into non-employment and therefore are informative for developing remedial policy.

The results showed that union members, public sector jobs and working in medium to large size firms increase the hazard rate of transitioning to higher pay, while immigrants from non-English countries and people with health problems have a lower hazard rate of moving to higher pay.

Those married, immigrants from English-speaking countries, casual workers, and those aged 35-44 years have a higher hazard rate, while females have a lower hazard rate of moving to self-employment. Workers with health problems, females, older workers, casual workers and part-time workers have a higher hazard rate of transitioning to non-employment.

The variables that raise the hazard rate of transitioning to higher pay also tend to reduce the expected duration on low pay.

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Appendix Summary statistics

Table a1 : Summary statistics of the modelling sample

	%
Spell origin	
Higher pay	68.42
Non-employment	19.86
Students	7.63
Self-employment	4.09
Spell destination	
Higher pay	55.30
Right-censored	27.71
Non-employment	13.15
self-employment	3.84
Spell duration (Right-censored treated as completed)	
1 year	77.53
2 years	14.34
3 years	5.27
4 years and over	2.87
Total no. of spells	***2,790***
Human capital	
Year 11 or below	33.39
Year 12	16.88
Certificate	27.19
Diploma	8.86
Degree	13.69
Health condition	21.20
Demographics	
Female	61.52
Age 21-24	14.24
Age 25-34	24.89
Age 35-44	25.05
Age 45-54	22.84
Age 55+	12.97
Married or de-facto	62.84
Australian born	81.59
Immigrants-ESC	7.20
Immigrants-NESC	11.21
Capital city	50.61
Job characteristics	
Casual	37.79
Part-time	43.09
Union	11.45
Public	13.98
Firm size less 20	46.36

Firm size 20-99	15.37
Firm size 100-499	9.41
Firm size 500 and plus	28.85
Total no. of observations	***3,792***

Note: For spell origin, destination and duration, the summary statistics are based on the spells, while the other summary statistics are based on the observations.