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 workers who have entered low pay from higher pay also have a higher hazard rate of transitioning to higher pay; and those who have 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 tend to 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 on low pay, the less likely he or she is to transition to higher pay. http://dx.doi.org/10.1108/IJM-01-2014-0008

Key words: Earnings; low pay; data analysis; modelling

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1. Introduction

Research on low pay has increased appreciably in recent years. There are at least two reasons for this. 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 paid jobs could act as a stepping stone to higher paid jobs, since low paid jobs may help improve job skills and build up individual confidence. Second, in countries that have a national minimum wage, research on low pay, particularly the dynamics of low pay, may be used to provide evidence for setting minimum wages. Although not all low paid workers live in low income households (Healy and Richardson 2006), income of low paid 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. For example, both Healy and Richardson (2006) and McGuinness et al. (2007) find that low paid employees are more likely to be single, young, low educated, on casual employment, and migrants from non-English speaking countries (NESC). This strand of research, either using cross-sectional data or taking panel data as cross-sectional, is largely descriptive and thus provides little information on how low paid 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, 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 a low pai job with a particular interest in state dependence of low pay employment in the sense to what extent past low pay raises the likelihood of low pay employment in the future. Significant state-dependence of 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 2013; Knabe and Plum 2013). 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 and unemployment are inter-related. This question arises due to concerns that low paid workers may cycle between low pay and unemployment with little hope to move up the labour market ladder. For example, descriptive analyses by Dunlop (2001) and Perkins and Scutella (2008) show that low paid workers are more likely than higher paid 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 has almost as large an adverse impact as unemployment on future employment prospects and that low wage jobs act as a 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. 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 a worker stays 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; or a low paid job itself may provide little opportunity for workers to obtain skills that help them move up the earnings ladder. In this case, the longer a worker stays 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. [1]

It appears that there are no other Australian studies that have examined the determination of duration and duration dependence of low pay.[2] Internationally, the only published study that

[1] Another interesting and related literature, although not on low pay, examines job mobility to investigate how job changes contribute to job match quality (e.g. Gielen 2013).
[2] There is a sizable literature on duration dependence of unemployment. For a recent study on duration dependence of unemployment, see Kroft, et al. (2013), which shows negative duration dependence of unemployment as a result of employers using unemployment spell length as a signal of unobserved productivity.

takes a similar approach to the current study appears to be Phimister and Theodossiou (2009).[3] This study examines gender differences in the determinants of low pay duration in the UK and how the determinants have changed following the introduction of the national minimum wage 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 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 in Australia, focusing on the determination of duration and exit destinations of low pay. As detailed later, low pay in this study is defined as hourly earnings below two thirds of the median earnings.

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.[4]

The multivariate analysis shows that workers who have entered low pay from higher pay also have a higher hazard rate of transitioning to higher pay; and those who have 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 tend to increase the hazard rate of transitioning to higher pay, while immigrants from NESC and workers with health problems tend to have a lower hazard rate of moving into higher pay. The results also show that older workers and casual workers have a higher hazard rate of transitioning to non-employment. There is some

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[3] Phimister and Theodossiou (2009) use the British Household Penal Survey (PHPS), which is very similar to the HILDA Survey in both survey content and structure. While the longitudinal nature of the HILDA Survey allows conducting such analysis, it has drawbacks. In particular, the information used to derive the dependent variable and most of the covariates are measured at a one-year interval and therefore the exact time when changes occurred to the variables cannot be identified. But there are currently not alternative data that overcome these drawbacks and at the same time allow for a duration analysis on low pay.

[4] There are studies showing that unemployment and out of the labour force are different labour market states (e.g. Flinn and Heckman 1983). However, in this study the two states have been combined due to small cases in unemployment in the sample, which means that separating the two states as exit destinations of low pay would make the estimation of the model difficult. It is not unusual to combine unemployment with out of the labour force in studying labour market behaviour (e.g. Prowse 2012; Uhlendorff 2006; Fok et al. 2009).

evidence of negative duration dependence in the transition from low pay to higher pay, but no such evidence for other low pay exit destinations examined.

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. Watson and Wooden (2012) document details of this survey. In the first wave, 7,682 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.

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 panel surveys, the HILDA Survey collects information on earnings and working hours. In this study hourly earnings are derived by dividing weekly gross earnings from the main job 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 fewer 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 have 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). The same low pay threshold applies to both male and female employees. 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.

In Australia employees on casual employment are paid casual loading to compensate for forgone leave and other entitlements. As such, some researchers suggest that casual employees' earnings should be discounted when determining their low pay status. On the other hand, Buddelmeyer et al. (2010) argue that casual loading is just like any other pay loading for compensating for undesirable job characteristics and therefore should not be singled out for discount. This study follows Buddelmeyer et al. (2010) approach not to discount earnings of casual employees.

The first row in Table 1 shows the low pay threshold used in this study. This threshold identifies about 11 per cent of Australian 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 percentile of hourly earnings, which is also estimated for the HILDA Survey. For each wave of the HILDA Survey, the 10th percentile 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 interview 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.

Table 1: Low pay threshold defined as two thirds median hourly earnings (AU$)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
2/3 median ($)	11.67	12.08	12.50	13.08	13.56	14.39	15.15	15.97	16.67	17.33
10th percentile ($)	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.

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

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 unknown and therefore are not considered in this study.

The analysis is restricted to low paid employees 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 a low pay threshold defined by adult wages. Since we cannot tell whether a young worker is paid junior, apprentice or trainee wages from the HILDA Survey, 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, representing 6,182 observations and 3,570 individuals. The next subsection provides descriptive analysis of these spells. As explained below, the sample used for econometric modelling is a subsample of these spells and the summary statistics of the modelling sample are presented in appendix Table a1.

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 at or above the low pay threshold (denoted as 'higher pay' thereafter for ease of exposition) in the year prior to entering low pay.[5] This is somewhat surprising since one would expect those who started low pay should be those who just entered the workforce, as earlier studies show that young workers are more likely to be low paid than older ones (e.g. Healy and Richardson, 2006). However, this does not appear to be the case. Further analysis shows that the majority of these former higher paid employees did not have a pay much higher than the low pay threshold. For this purpose, we can further classify higher pay into three pay level categories: moderate pay – hours wages at or above the low pay threshold but below the median; middle pay – hourly wages at or above the median but below four thirds of the median; and high pay – hourly wages at or above four thirds of the median. The results in Table 2 show that about 36 per cent of the low paid (or near 80 per cent of those from higher pay) were on moderate pay prior to entering low pay; only about 3 per cent of the low paid (or 6.2 per cent of those from higher pay) were on high pay before entering low pay.

Table 2: Origin of low pay spells

Low pay origin	**No. of spells**	**Per cent**
Higher Pay	1,993	44.72
Moderate pay	*1,597*	*35.83*
Middle pay	*273*	*6.13*
High pay	*123*	*2.76*
Left-censored	1,125	25.24
Non-employment	584[(a)]	13.10
Wage unknown	392	8.80
Students	238	5.34

[5] 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. Nearly 80 per cent of the employees who moved from higher pay to low pay either experienced a weekly earnings decrease (73.4 per cent) or had their earnings unchanged (5.1 per cent). Of the 21.5 per cent employees whose weekly earnings increased, the vast majority (94.9 per cent) had their working hours increased so much that they became low paid.

Self-employment	125	2.80
All	4,457	100

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

Note: (a) 36.8 per cent of the non-employed were unemployed prior to entering low pay.

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 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 analysis later on.[6] 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 subsequent analysis as well.

Table 3 shows where people went when their low pay spell ended (i.e. exit destination). Encouragingly, over half of the people in the low pay spells moved up the earnings ladder to become higher paid workers.[7] Further analysis shows that the majority (near 80 per cent) of these people moved from low pay to moderate pay.[8]

Table 3: Exit destination of low pay spells

Low pay destination	**No. of spells[(a)]**	**Per cent**
Higher pay	1,543	52.48
Moderate pay	1,205	40.99
Middle pay	237	8.06
High pay	101	3.44
Right-censored	766	26.05
Non-employment	368[(b)]	12.52
Wage unknown	111	3.78

[6] 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.
[7] As shown later, this proportion is even larger when the left-censored spells and spells with unknown wages are excluded.
[8] Not surprisingly, the vast majority (90.8 per cent) of those who transitioned to higher pay experienced a weekly earnings increase and these weekly earnings increases were not always due to increased working hours: of those moving to higher pay, 41.5 per cent had a working hours decrease; 27.0 per cent had working hours unchanged; and 31.5 per cent had a working hours increase. Those who transitioned to higher pay but had weekly earnings decreased (7.9 per cent) or unchanged (1.3 per cent) had working hours decreased proportionally more, leading them to higher pay.

Self-employed	108	3.67
Students	44	1.50
All	2,940	100

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

Note: (a) This excludes left-censored spells and spells with a 'wage unknown' origin.

(b) 29.90 per cent of those moving to non-employment became unemployed.

Twenty six per cent of the low paid were still on low pay when they were last observed in the data (denoted as 'right-censored' in the table). About 13 per cent of the low paid 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 (denoted as 'wage unknown' in the table). Again, these spells will be excluded from the duration analysis later on.

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

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.

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 – Over 60 per cent of those entering low pay from higher pay exited to higher pay. The group with the second highest probability (47 per cent) of exit to higher pay is the former students. Forty per cent of those who entered low pay from non-employment moved to hither pay. Those who entered low pay from self-employment had the lowest probability (around a third) to move to higher pay.

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

	Low pay destination [a]					
Low pay origin	Higher pay	Right-censored	Non-employ	Self-employ	Student	No. Obs.
Higher Pay	60.82	26.59	9.78	1.98	0.83	1,922
Self-employ	36.21	22.41	12.93	27.59	0.86	116
Students	46.58	31.20	10.26	2.56	9.40	234
Non-employ	40.04	28.01	25.31	5.75	0.90	557
All	54.54	27.08	13.01	3.82	1.56	2,829

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

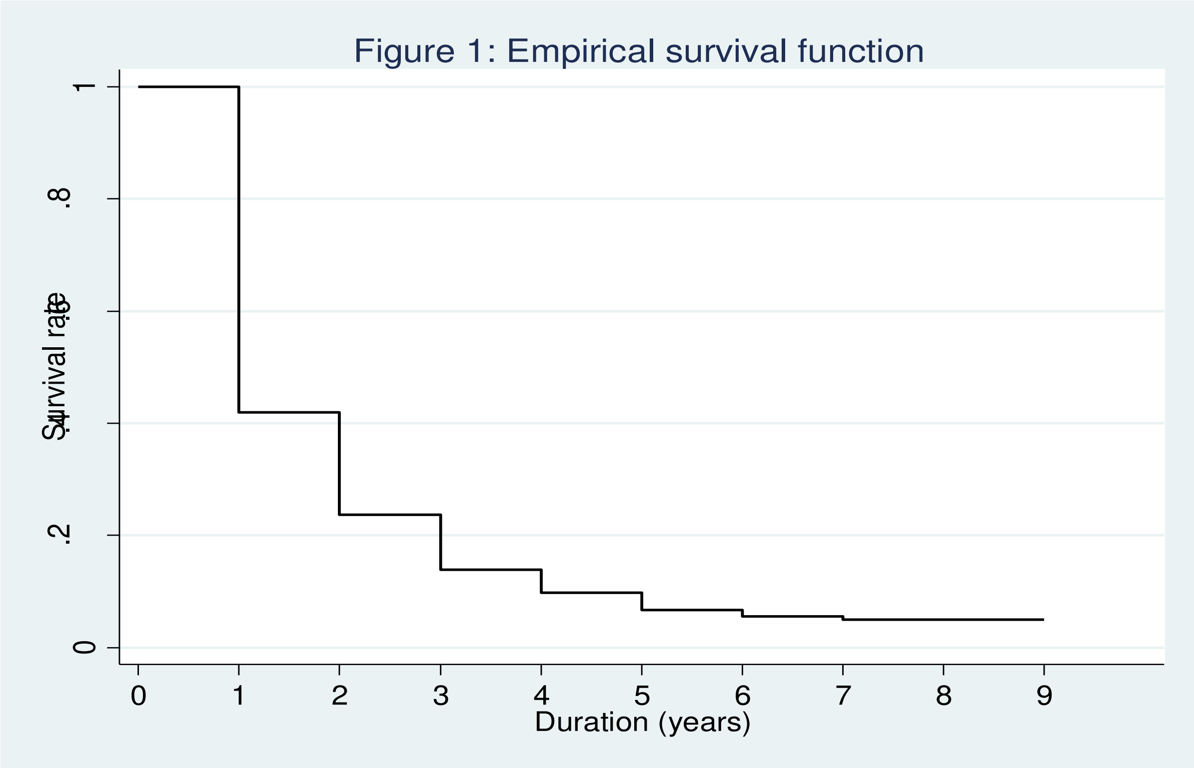
Note: (a) Right-censored spells and spells with a 'wage unknown' origin or destination are excluded from this table.

Not surprisingly, those who entered low pay from self-employment are more likely than others to move back to 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 still 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 have 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 longer than *t* years. Figure 1 shows that just over 42 per cent of the low pay spells lasted for longer than one year. Just under a quarter (24 per cent) lasted for longer than two years; about seven per cent lasted for longer than five years; and about five per cent lasted for longer than nine years.

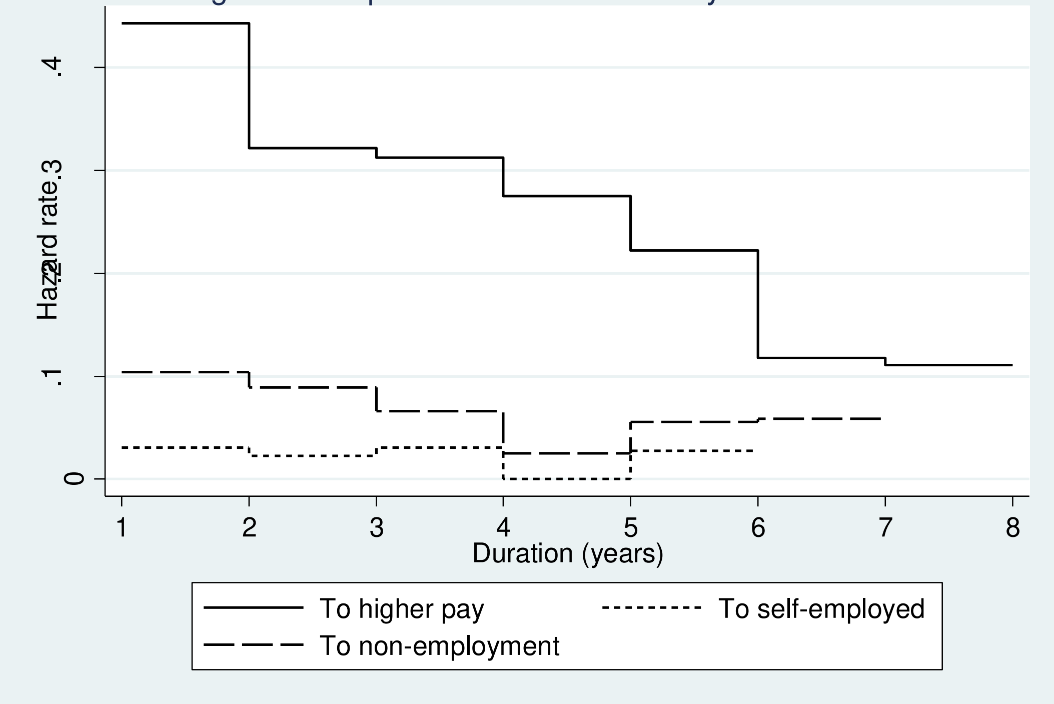


The empirical survival rates suggest that the expected duration of the low pay spells is longer than 2.2 years. However, since nearly 60 per cent of the low pay spells ended within one year, the median duration of the low pay spells is less than one year. The duration distribution of the low pay spells 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 leave for higher pay. Duration dependence is not obvious for destinations of self-employment and non-employment.



The duration dependence shown in Figure 2 may be spurious since this may be a 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 lower education behind. Similarly, those with high 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, $T_1, \ldots, T_K$, which are independent random variables.[9] 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,

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

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

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,

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

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

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 $L_k = [S_k(t) - S_k(t+1)]\prod_{\substack{l=1 \\ l\neq k}}^{K} S_l(t+1)$.

[10] 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).

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,

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

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 unobserved heterogeneity takes a Gamma distribution: a) common unobserved heterogeneity for all the exit destinations; and b) independent and destination specific unobserved heterogeneity.[11] 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 unobserved heterogeneity, so that 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.[12]

3.2. Model specification

Due to different behaviours between males and females in the labour market, it is desirable to estimate the model separately for each gender. However, as a compromise between this desirability and the feasibility of the data to address the duration dependence issue – the focus of this paper, we estimate the model for both the pooled sample of males and females (denoted as the pooled model) and each gender sample separately. To infer duration dependence of low pay, we want to estimate the baseline hazards for as detailed duration intervals as possible.

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

[12] 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.

Experiment indicates that even using the pooled sample, we can only separately estimate baseline hazards for durations of one, two and three years; durations longer than four years need to be grouped with the four year duration – that is, the hazard rates for durations of longer than four years have to be assumed to be the same as that of the four year duration. In the separate models for males and females we have to make a further restriction to the baseline hazard function to assume that the baseline hazard rates for durations of longer than three years to be the same as that of the three year duration. Otherwise, we will not be able to estimate the separate model. As shown in the result section, this further restriction in the separate model has implications for the inference of duration dependence of exiting low pay to higher pay. The results also show that only a few estimates are statistically significantly different between males and females from the separate models.

As mentioned 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: age (six age dummies with aged 25-34 as the reference), education (five dummies with those below year 12 schooling as the reference), health condition (a dummy variable with having no health condition as the reference), marital status (a dummy variable with non-partnered as the reference), country of birth (with Australian born as the reference and immigrants being divided into those from a non-English speaking country-NESC and those from a English speaking country-ESC), and capital city (a dummy variable with living outside a capital city as the reference). In addition, a set of job characteristics - casual employment, working hours (five dummies representing five broad groups of hours), union membership status, public sector jobs and firm size (four dummies with firms having less than 20 employees as the reference) – are included in the model.[13,14] These variables are often used to estimate wage equations and can therefore be reasonably extended to the determination of wage transitions. In the pooled model, sex is included as a control variable.

Summary statistics of the modelling samples 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; spells with missing values of the covariates outlined above are also excluded.

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[13] In the Australian context, for public-private wage gap see Cai and Liu (2011); for the effects of unions on wages see Cai and Waddoups (2011) and Cai and Liu (2008); for the effects of firm size on wages see Cai and Waddoups (2012).

[14] It was also experimented to include a variable indicating whether a worker experienced a job change in the previous 12 month. Workers who change labour market status (e.g. between employment and unemployment) are also likely to change jobs. Therefore, this variable is also expected to capture those workers who have changed labour market status between two survey interviews. However, this variable was insignificant in any specifications and was consequently dropped in the final specification.

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 the impact direction of the variable on 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 reference category. Table 5 presents the hazard ratio estimates and the stars in the table indicate statistical significance of the corresponding coefficient estimates.[15] The coefficient estimates and their standard errors can be found in appendix Table a2.

4.1.Baseline hazard estimates

For ease of comparison, Figures 3a to 3c plot the estimated baseline hazard rates for the pooled sample and males and females separately.

For the pooled sample (Figure 3a), the baseline hazards for all the three destinations show a downward trend, implying negative duration dependence. However, 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 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 lower than that in the first year, although it is still not statistically different from that of year two or year three.

As discussed earlier, to estimate the model separately for males and females, we need to combine the duration of three years with the longer ones. Figures 3b and 3c show that the overall downward trend baseline hazard rates remain when males and females are separately modelled, particularly for the destinations of higher pay and non-employment, although the differences

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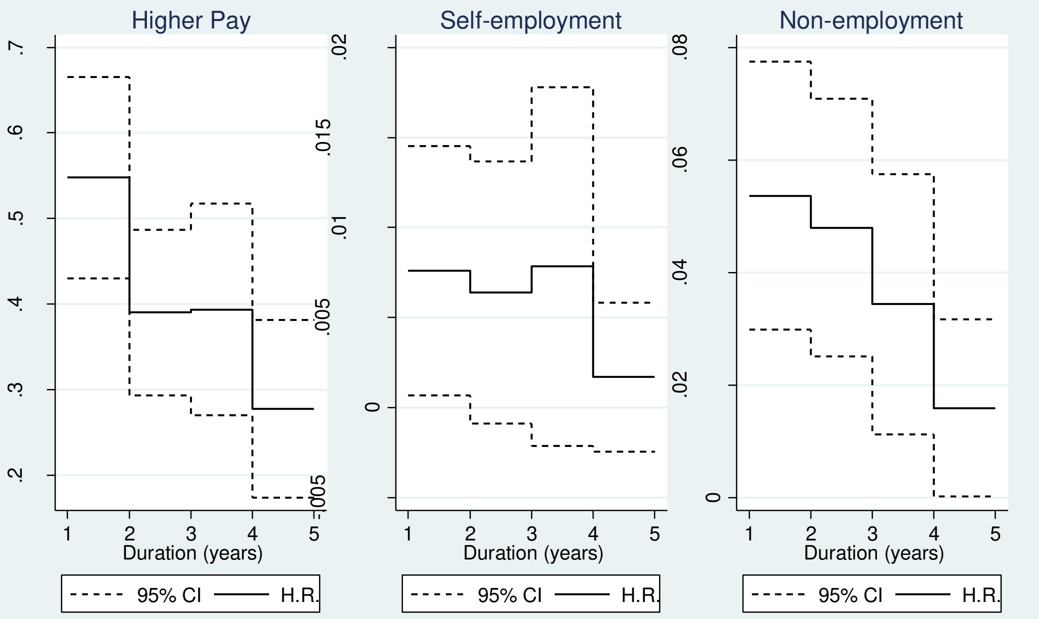
[15] The standard errors of the hazard ratio estimates can be computed using the delta method (Greene 2000). In our case the standard error of a hazard ratio estimate equals the hazard ratio estimate multiplied by the standard error of the corresponding coefficient estimate. In general, a statistically significant coefficient estimate means that the corresponding hazard ratio estimate is statistically different from one.

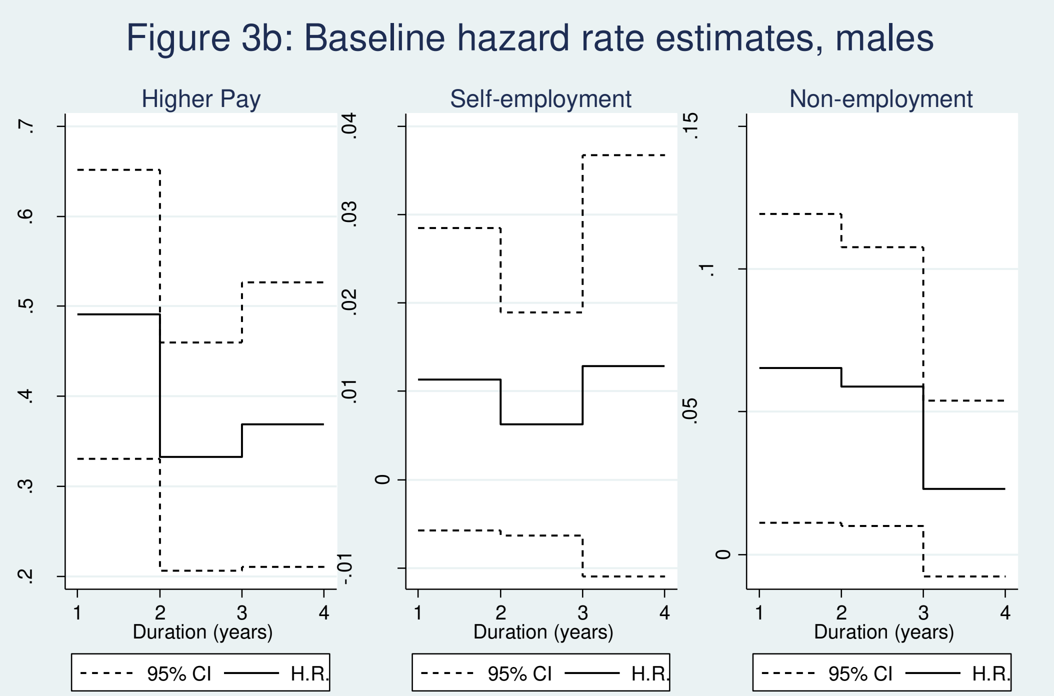
between different durations for the same destination are statistically insignificant. Furthermore, the differences of the baseline hazard estimates for the same duration and the same destination are statistically insignificant between males and females.

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.

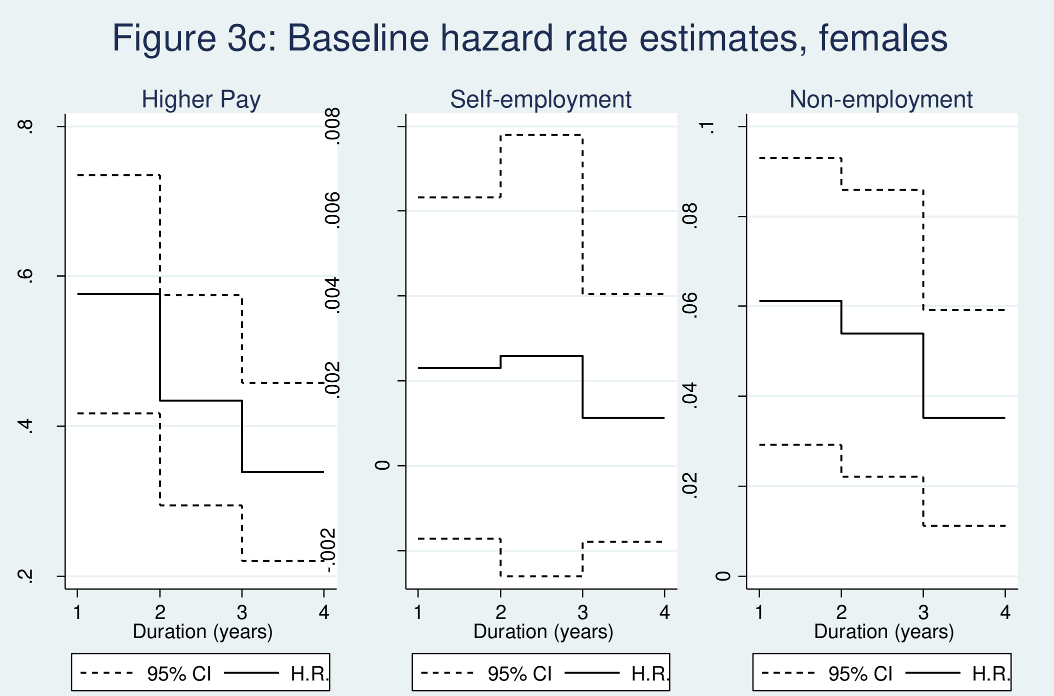
Figure 3a: Baseline hazard rate estimates, males and females



Note: Year 4 means year 4 and over.



Note: Year 3 means year 3 and over.



Note: Year 3 means year 3 and over.

4.2.Low pay origin variables

For the low pay origin variables, the reference category is those from moderate pay. The results show that relative to those who entered low pay from moderate pay, almost all other low pay origins of non-higher pay reduce the hazard rate of transitioning to higher pay. For example, from the pooled model, other things being equal, those having entered low pay from non-employment have a 32 per cent lower hazard rate of transitioning to higher pay than those from moderate pay. This effect is larger for females than for males and the gender difference is statistically significant.

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. This is still the case when males and females are separated estimated, although the estimate for females is not statistically significant.

Former students do not appear to have a different hazard rate of transitioning to higher pay compared to those entering low pay from moderate pay from the pooled model. But the separate model results show that former male students have a lower hazard rate of transitioning to higher pay than those from moderate higher pay, while the opposite seems to hold for former female students. However, the estimate on this variable for females is not statistically significant; so we cannot draw firm conclusion on the gender difference of the effects of this variable.

The estimates on the other higher pay variables suggest that overall, the higher the pay level prior to entering low pay, the higher is the hazard rate of transitioning to higher pay, but only the estimate on the high pay variable is statistically significant in the pooled model. The difference of the estimates on the high pay variable in the hazard function of transitioning to higher pay is not statistically significant between males and females.

Table 5: Model estimation results – hazard ratio estimates

	Pooled sample of males and females			Males only			Females only		
	Higher pay	Self-emp.	Non-emp.	Higher pay	Self-emp.	Non-emp.	Higher pay	Self-emp.	Non-emp.
Baseline hazard rates are shown in Figures 3a to 3c.									
Spell origin									
Higher pay									
Moderate pay	- reference category								
Middle pay	1.0667	2.1099	1.3769	0.9690	3.5888*	0.8022	1.1350	1.4277	1.5686
High pay	1.3594**	0.9380	1.1058	1.1281	2.2629	1.9106	1.4735*	0.0336	0.9298
Self-employment	0.5636***	9.7080***	0.9778	0.4668***	12.0467***	1.2473	0.6457	8.4365***	0.8490
Student	0.8414	1.3943	1.2021	0.6323**	2.5687	2.2494*	1.0608#	0.6476	0.9372
Non-employment	0.6846***	2.0408**	1.9891***	0.5238***	2.1391	2.3213***	0.7720**#	1.7999	1.8690***
Human capital									
Degree	1.1417	1.5608	0.9480	1.0755	0.8922	0.4991	1.2262*	2.2879	1.1959
Diploma	0.9748	1.0298	0.9589	0.9409	0.8958	0.7076	1.0146	1.1469	1.0454
Certificate	0.9940	1.2263	0.7882	1.1009	0.9046	0.4268**	0.9268	1.7701	1.0438#
Year 12	0.9837	1.0751	1.2382	0.8506	0.8295	1.0231	1.0795	1.3150	1.3991
Year 11 below	- reference category								
Health condition	0.7779***	1.5340	1.2659*	0.8661	1.5508	1.1410	0.7061***	1.4243	1.3241*
Demographics									
Female	0.9379	0.6046*	1.4005**						
Age 15-24	1.0111	1.0836	0.8119	1.3865**	0.7142	0.8143	0.7322**#	2.0149	0.8241
Age 25-34	- reference category								
Age 35-44	1.0376	1.7593*	0.8079	0.9936	1.6533	0.8154	1.0388	1.8201	0.8326
Age 45-54	0.9887	1.1872	0.7859	0.9519	1.2274	0.7503	0.9939	1.0799	0.8265
Age 55 plus	0.9434	0.8952	1.6433***	0.8552	0.7165	1.9593*	0.9838	1.0852	1.7692***
Married	1.0534	1.5841*	0.9706	1.1977*	1.8002	0.9532	0.9668	1.5623	0.9989
Australian born	- reference category								
Immigrant: ESC	0.9918	2.0072**	1.2795	1.0088	2.2094*	1.6205	1.0037	2.0909	1.0508

Immigrant: NESC	0.8318**	1.2208	0.9658	0.7887	1.1883	1.5569	0.8554	1.2248	0.8592
Capital city	1.1106*	0.8087	1.1361	1.1923*	0.7975	1.0555	1.0411	0.8536	1.1519
Job characteristics									
Casual job	0.9082	2.4847***	1.8654***	1.0072	1.3475	1.7423**	0.8323**	5.3297***	1.9046***
Hours <15	0.9516	1.4674	1.1757	1.1432	2.2194	0.8415	0.9414	1.1705	1.2707
Hours >=15 & <25	0.8929	0.8825	1.1777	0.8357	1.6586	0.9504	0.9190	0.6663	1.2500
Hours >=25 & <35	0.9676	0.8331	1.0263	0.9377	0.9016	1.7361*	0.9801	0.8206	0.8410
Hours >=35 & <45	- reference category								
Hours 45 & over	1.0807	1.3659	0.7234	1.0069	1.1756	0.8036	1.1675	1.8577	0.6726
Union member	1.6080***	0.7000	1.0824	1.9362***	0.6969	0.8745	1.4790***	0.7664	1.1734
Public sector	1.2253**	1.0985	0.8545	1.3126*	0.7266	0.8610	1.1517	1.3639	0.8462
Firm size <20	- reference category								
Firm size 20-99	1.1920**	0.6755	0.9929	1.1644	0.5754	1.2211	1.2034*	0.6583	0.9732
Firm size 100-499	1.2767**	0.3091	0.6724*	1.2968*	0.1582	0.5242	1.2212	0.4862	0.7668
Firm size 500 plus	1.1645**	0.5973	0.7843	1.1668	0.5365	0.4576*	1.1592*	0.5924	0.9231
Log-likelihood		-3981.19			-1429.90			-2445.39	
No. of observations		3792			1459			2333	
No. of spells		2790			1071			1719	

*** indicates significant coefficient estimates (i.e., not hazard ratio estimates) at 1%; ** at 5%; * at 10%;

# indicates the difference of coefficient estimates between males and females is statistically significant at 5%.

Turning to the hazard function of transitioning to self-employment, compared to those from moderate pay, both of those from self-employment and non-employment have a higher hazard rate of transitioning to self-employment; and those who came from self-employed have the highest hazard rate. From the pooled model the hazard rate of returning to self-employment of those who were self-employed prior to entering low pay is about ten times of those who entered low pay from moderate pay. From the separate model results, males who came from self-employment appear to have a relatively higher hazard rate of going back to self-employment than females, but the gender difference is not statistically significant.

Those who entered low pay from non-employment have a hazard rate of transitioning to self-employment that is about twice of those who entered low pay from moderate pay from both the pooled and separate models. The hazard rate of transitioning to self-employment of those from middle pay and high pay is estimated to be relatively much higher for males than for females, but again, they are generally imprecisely estimated and the differences between males and females are not statistically significant.

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

The estimation results on low pay origins therefore show a substantial degree of state dependence in the labour market transitions of low pay, in the sense that low pay employees tend to return to the labour market state from which they entered low pay.

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 none of the variables is statistically significant in the pooled model. Only the certificate variable is significant in the hazard function of transitioning to non-employment for males. The estimate on the certificate variable indicates that low paid males with a certificate have a hazard rate of transitioning to non-employment that is about 57 per cent lower than low paid males who did not complete year 12. The estimate on the certificate variable in the hazard function of transitioning to non-employment is statistically different between males and females, but the estimate for females is statistically insignificant.

The overall insignificance of the education variables seems surprising. This could be because (a) the education variables are likely correlated with other explanatory variables, particularly the variables on low pay origin, health and firm size;[16] and (b) the fact that these people are on low pay, irrespective of their education qualification, suggests that the differences in education qualification among these workers may not represent much difference in individual productivity.

Phimister and Theodossiou (2009) find that for the UK low paid workers, more education tends to increase the probability of moving into higher pay and reduce the probability of transitioning out of employment, but the effects are generally imprecisely estimated despite that they have not controlled for low pay origin in their study.

Health has increasingly been regarded as a form of human capital (Cai and Kalb 2006) and a number of studies have found that health affects labour market outcomes (e.g. Cai 2010; Cai 2009). Health appears to matter in the transition out of low pay, particularly for females. The result shows that compared with low paid females without any health conditions, the hazard rate of transitioning to higher pay of low paid females with a health condition is about 30 per cent lower. Low paid males with a health condition also appear to have a lower hazard rate of transitioning to higher pay, but the estimate is not statistically significant. On the other hand, low paid females with a health condition have a 32 per cent higher hazard rate of moving to non-employment than low paid females without a health condition. Low paid males with a health condition also seem to have a lower hazard rate of transitioning to higher pay and a higher hazard rate of transitioning to non-employment, than low paid males without health conditions, but these effects are not precisely estimated.

4.4. *Demographic variables*

For the variables on age, the reference category is those aged 25-34 years. Unsurprisingly, for the hazard function of transitioning to non-employment, those older than 55 years have a higher hazard rate than those aged 25-35 years, and this is the case from both the pooled and separate models. Interestingly, low paid young males aged 15-24 have a higher hazard rate of transitioning to higher pay, while low paid females in this age group have a lower hazard rate of transitioning to higher pay, than their respective counterparts aged 25-34 years. Could this difference reflect different life stage objectives between males and females of this age group? That is, females are perhaps more family oriented at this stage in terms of getting married and/or having children, while males are probably more career oriented. Further research on the difference is required.

[16] For example, in a model that only included the education variables, it was found that relative to those who did not complete year 12 schooling, those with a post-school certificate had a lower hazard rate of moving into non-employment, and those with a degree had a higher hazard rate of transitioning to higher pay.

From the pooled model, there is only weak evidence that those who are partnered have a higher hazard rate of moving to self-employment from low pay than those singles, but the estimates from the separate models are statistically insignificant, although the magnitude is sizable for both males and females. There is also weak evidence that partnered males have a higher hazard rate of transitioning to higher pay than single males, but not such an effect is found for females.

For the country of birth variables, Australian born is the reference category. The estimates indicate that compared to Australian born, immigrants from NESC have a lower hazard rate of transitioning to higher pay, but this estimate is only significant from the pooled model. Immigrants from ESC appear to have a higher hazard rate of moving to self-employment, particularly for males.

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

4.5.Job characteristic variables

Casual employment appears to be important in affecting workers transitioning off low pay, particularly for females. Low paid female casual workers have a hazard rate of transitioning to higher pay that is about 17 per cent lower than low paid female non-casual workers, but no difference is found between low paid casual and non-casual males in the transition to higher pay. The hazard rates of transitioning to non-employment are higher for low paid casual workers than for low paid non-casual workers for both genders. Low paid casual workers also have a much higher hazard of transitioning to self-employment than their non-casual counterparts, but such an effect is not precisely estimated for males.

The estimates on the working hour variables are generally insignificant except for males in the transition to non-employment, where there is weak evidence that males who work between 25 to 35 hours a week have a higher hazard rate of transitioning to non-employment than male workers who work between 35 and 44 hours, perhaps because males in this working hour category are in the transitional phase into retirement. Similarly, Phimister and Theodossiou (2009) find that low paid part-time workers in the UK are more likely to move out of the labour force than low paid full-time workers.

Low paid union members have a higher hazard rate of transitioning to higher pay than non-union members for both males and females, and the effect seems to be larger for males than for females although the difference is not statistically significant. Union status does not appear to have a significant impact on the hazard functions of transitioning to self-employment and non-employment. For the UK Phimister and Theodossiou (2009) find that union coverage reduces the probability of female workers' transition into higher pay, while its effects on males and on other exit destinations of low paid females are generally statistically insignificant.

Low paid workers in the public sector appear to have a higher hazard rate of transitioning to higher pay relative to low paid workers in the private sector. This estimate is only statistically significant in the pooled model and weakly significant in the model for males. For the hazard functions of the other two destinations the public sector variable has no a significant effect. Public sector jobs are generally not found to have an impact on the transition out of low pay for the UK workers, except for females where public sector jobs are found to reduce the probability of females' transition into unemployment (Phimister and Theodossiou 2009).

For the firm size variable, the reference category is firms with less than 20 employees. The results from the pooled model show that relative to low paid workers in a firm with less than 20 employees, low paid workers in a larger firm have a higher hazard rate of transitioning to higher pay. The firm size effects are less precisely estimated when males and females are separately modelled than in the pooled model. Also the firm size effects do not appear to be linear. For example, while the effect increases when firm size rises from 20-99 to 100-499 employees, it falls when firm size increases further. In general firm size does not appear to have a significant impact on the transitions to the other two destinations.

Smaller firms are found to reduce the probability of transitioning to higher pay for the UK low paid workers, particularly for the period 1999-2005, but the effects are generally not precisely estimated (Phimister and Theodossiou 2009).

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,

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

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.[17]

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.[18] 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 effect estimates are also presented. The standard errors are estimated by simulation – that is, repeated draws from the estimated distribution of the coefficient estimates. To put these estimates in context, the marginal effect as percentage of expected duration, as predicted by the models, is also presented in parenthesis in the table.

Consistent with the coefficient estimates that not many variables are statistically significant, particularly for the hazard functions of transitioning to self-employment and non-employment, not many variables are significant for the estimated effects on expected duration in both the pooled and separate models. In the model for females, only one variable is weakly statistically significant. However, the effects of those significant variables appear to accord to expectations in general.

The higher the pay was prior to entering low pay, the shorter is expected duration on low pay, but only the effect of high pay from the pooled model is statistically significant – the estimate shows that those from high pay are expected to have a low pay duration that is about half year less, which is 21 per cent of the expected low pay duration.

Those with a health condition are expected to stay on low pay for a longer period than those without a health condition, but the estimate is only weakly significant in the pooled model.

[17] 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.
[18] The values of the other variables are kept at the sample means.

Table 6: Estimated marginal effects on expected duration

	Pooled males and females			Males			Females		
	M.E.	(% of E(d))	S.E. of M.E.	M.E.	(% of E(d))	S.E. of M.E.	M.E.	(% of E(d))	S.E. of M.E.
Middle pay	-0.2354	(9.08)	0.2194	-0.0134	(0.55)	0.3091	-0.3690	(14.64)	0.3894
High pay	-0.5482**	(21.15)	0.2398	-0.2679	(11.06)	0.3253	-0.5973	(23.70)	0.8413
Self-employment	0.8740	(33.73)	0.8255	0.6502	(26.83)	0.8880	0.6432	(25.53)	0.9750
Student	0.3116	(12.02)	0.3364	0.5823	(24.03)	0.5837	-0.0821	(3.26)	0.5076
Non-employment	0.4987	(19.24)	0.3282	0.9816*	(40.51)	0.5248	0.1493	(5.93)	0.7812
Degree	-0.2816	(10.87)	0.2124	-0.0158	(0.65)	0.3245	-0.4494	(17.83)	0.8375
Diploma	0.0695	(2.68)	0.2434	0.1825	(7.53)	0.3483	-0.0496	(1.97)	0.2643
Certificate	0.0740	(2.86)	0.1769	-0.0433	(1.79)	0.2298	0.1137	(4.51)	0.3724
Year 12	-0.0465	(1.79)	0.1851	0.3025	(12.48)	0.3010	-0.2785	(11.05)	0.4809
Health condition	0.4514*	(17.42)	0.2511	0.2034	(8.39)	0.2817	0.5312	(21.08)	1.5987
Female	0.0693	(2.67)	0.1954						
Age 21-24	0.0354	(1.37)	0.2160	-0.4911**	(20.27)	0.2485	0.7148	(28.37)	0.4627
Age 35-44	-0.0524	(2.02)	0.2122	-0.0043	(0.18)	0.2861	-0.0302	(1.20)	0.7812
Age 45-54	0.0903	(3.48)	0.1782	0.1200	(4.95)	0.2610	0.0766	(3.04)	0.9615
Age 55 plus	-0.0853	(3.29)	0.2156	0.1400	(5.78)	0.3689	-0.2303	(9.14)	0.4526
Married	-0.1309	(5.05)	0.1620	-0.3626*	(14.96)	0.1992	0.0487	(1.93)	0.1807
Immigrant: ESC	-0.1137	(4.39)	0.2387	-0.1610	(6.64)	0.2825	-0.0607	(2.41)	1.1269
Immigrant: NESC	0.4339	(16.74)	0.2642	0.3487	(14.39)	0.3337	0.3701	(14.69)	0.3253
Capital city	-0.2567*	(9.91)	0.1448	-0.309	(12.75)	0.1949	-0.1239	(4.92)	0.2496
Casual job	-0.0673	(2.60)	0.2650	-0.1262	(5.21)	0.3458	0.0017	(0.07)	0.3527
Hours <15	0.0246	(0.95)	0.2107	-0.2606	(10.75)	0.3885	0.0037	(0.15)	0.4965
Hours >=15 & <25	0.1982	(7.65)	0.1884	0.3018	(12.46)	0.3718	0.0750	(2.98)	0.8968
Hours >=25 & <35	0.0727	(2.81)	0.1755	0.0036	(0.15)	0.2955	0.1079	(4.28)	0.4805
Hours 45 & over	-0.1009	(3.89)	0.1497	0.0074	(0.31)	0.1768	-0.2033	(8.07)	0.1994
Union member	-0.8625***	(33.28)	0.2268	-0.9233***	(38.10)	0.2928	-0.6859*	(27.22)	0.3823
Public sector	-0.3796**	(14.65)	0.1740	-0.4155	(17.15)	0.2622	-0.2168	(8.60)	1.0357
Firm size 20-99	-0.3437*	(13.26)	0.1915	-0.2539	(10.48)	0.2443	-0.3164	(12.56)	0.2714

Firm size 100-499	-0.3633	(14.02)	0.2480	-0.2862	(11.81)	0.3260	-0.2643	(10.49)	0.4274
Firm size 500 plus	-0.2257	(8.71)	0.1451	-0.1246	(5.14)	0.2179	-0.2290	(9.09)	0.9849

*** indicates estimate is significant at 1%; ** 5%; * 10% respectively.

(a) Standard errors are simulated using 1000 draws from the estimated distribution of the coefficient estimates in Appendix Table a2.

Young males aged 15-24 years are expected to have shorter low pay duration than males aged 25-44, but young females seem to have longer low pay duration although the effect is imprecisely estimated.

Married males are also expected to have shorter low pay duration than single males. No such an effect is found for females.

Those living in a capital city are expected to stay on low pay for shorter duration than those living elsewhere, particularly for males.

Union members are expected to be on low pay for shorter duration than non-union members for both males and females. Public sector workers are expected to be on low pay for shorter duration than private sector workers, but this estimate is only significant from the pooled model.

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, but overall the estimates are not statistically significant.

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 paid workers came from, where they went when they exited low pay, and the factors that affect the hazard rates and duration of different exit destinations. While there is a sizable literature on state-dependence of low pay employment, research on low pay duration is scarce; and this study has attempted to address this information gap.

Contrary to initial expectation, the highest proportion of low paid 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 less than 20 per cent of the low pay spells identified from the data.

While the majority of the low paid 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.

Earlier studies on state-dependence of low pay address the issue whether currently low pay causes future low pay. This study has examined state-dependence of low pay in a broader sense – that is, whether low pay origins affect the exit destinations of low pay. Both the descriptive and multivariate analyses have shown 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 return to self-employment and those who came from non-employment are more likely to move to non-employment. This suggests that one-size-fits-all policy to facilitate transitions from low pay to higher pay would not work.

There is some evidence that the longer a worker is on low pay, the less likely they are to exit to higher pay (i.e. negative duration dependence). This does not mean that low pay employment should not be encouraged. On the contrary, since there is evidence that low pay can act as a stepping stone to higher pay (e.g., Knabe and Plum 2013; Mosthaf et al. 2009; Uhlendorff 2006), unemployed workers should be encouraged to take up a low paid job when better options are not available immediately. However, the negative duration dependence of low pay in transitioning to higher pay does suggest that policy interventions aimed at improving earnings of the low paid 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 has also showed that union members, public sector jobs and working in larger firms tend to 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. Older workers and casual workers have been found to 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 expected duration on low pay.

While it is out of the scope of this paper to prescribe specific policies, the findings here would help identify workers who are at high risk of staying on low pay or transitioning into non-employment and therefore are informative for developing targeted policy to help the low paid maintain employment and/or move up the earnings ladder. For example, the results suggest that low paid older workers, casual workers and workers with past experience of non-employment need additional assistance (such as targeted on-the-job-training to address individual skill deficiency and/or workplace needs) to prevent them from leaving employment.

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Appendix: Summary statistics and coefficient estimates

Table a1: Summary statistics of the modelling samples

	Males & females	Males	Females
Spell origin[(a)]			
Moderate pay	56.77	56.40	57.01
Middle pay	7.99	7.75	8.14
High pay	3.66	4.48	3.14
Non-employment[(b)]	19.86	17.09	21.58
Students	7.63	8.78	6.92
Self-employment	4.09	5.51	3.20
Spell destination			
High pay	55.30	57.42	53.98
Right-censored	27.71	27.92	27.57
Non-employment[(c)]	13.15	9.71	15.30
self-employment	3.84	4.95	3.14
Spell duration (Right-censored treated as completed)			
1 year	77.53	77.50	77.55
2 years	14.34	14.19	14.43
3 years	5.27	5.14	5.35
4 years and over	2.87	3.17	2.68
Human capital			
Year 11 or below	33.39	30.71	35.06
Year 12	16.88	18.71	15.73
Certificate	27.19	29.68	25.63
Diploma	8.86	7.61	9.64
Degree	13.69	13.30	13.93
Health condition	21.20	22.55	20.36
Demographics			
Female	61.52		
Age 21-24	14.24	18.71	11.44
Age 25-34	24.89	28.58	22.59
Age 35-44	25.05	20.84	27.69
Age 45-54	22.84	19.40	24.99
Age 55+	12.97	12.47	13.29
Married or de-facto	62.84	56.41	66.87
Australian born	81.59	81.36	81.74
Immigrants-ESC	7.20	8.02	6.69
Immigrants-NESC	11.21	10.62	11.57
Capital city	50.61	51.61	49.98
Job characteristics			
Casual	37.79	30.57	42.31
Hours <15	11.89	5.00	16.20
Hours >=15 &<25	17.72	7.81	23.92
Hours >=25 &<35	15.40	9.66	18.99

Hours >= 35 & <45	31.88	39.00	27.43
Hours 45 & over	23.10	38.52	13.46
Union	11.45	10.42	12.09
Public	13.98	9.94	16.50
Firm size less 20	46.36	49.01	44.71
Firm size 20-99	15.37	17.07	14.32
Firm size 100-499	9.41	10.21	8.92
Firm size 500 and plus	28.85	23.71	32.06
Total no of spells	***2,790***	***1,071***	***1,719***
Total no of observations	***3,792***	***1,459***	***2,333***

Note: (a) For spell origin, destination and duration, the summary statistics are based on the spells, while the other summary statistics are based on the observations. (b) 37.00 per cent of those from non-employment were unemployed in the pooled sample; it was 54.10 and 28.57 per cent for males and females respectively. (c) 29.97 per cent of those transitioning to non-employment became unemployed in the pooled sample; it was 43.27 and 24.71 per cent for males and females respectively.

Table a2: Coefficient estimates

	To higher pay		To self-employment		To non-employment	
	Coef.	S.E. of Coef.	Coef.	S.E. of Coef.	Coef.	S.E. of Coef.
	a). Pooled male and female sample					
Year 1	-0.6015***	0.1095	-4.8795***	0.4643	-2.9254***	0.2263
Year 2	-0.9413***	0.1263	-5.0512***	0.5802	-3.0371***	0.2431
Year 3	-0.9322***	0.1601	-4.8485***	0.6483	-3.3692***	0.3424
Year 4 and plus	-1.2812***	0.1913	-6.3769***	1.2403	-4.1389***	0.5033
Middle pay	0.0646	0.1059	0.7466	0.4796	0.3198	0.2489
High pay	0.3071**	0.1548	-0.0640	0.8277	0.1006	0.3758
Self-employment	-0.5734***	0.1902	2.2729***	0.3168	-0.0225	0.3082
Student	-0.1727	0.1180	0.3324	0.5738	0.1841	0.2657
Non-employment	-0.3790***	0.0868	0.7134**	0.3283	0.6877***	0.1355
Degree	0.1326	0.0938	0.4452	0.3684	-0.0534	0.1934
Diploma	-0.0255	0.1016	0.0294	0.4615	-0.0419	0.2166
Certificate	-0.0060	0.0740	0.204	0.2862	-0.2380	0.1527
Year 12	-0.0164	0.0867	0.0724	0.3926	0.2136	0.1681
Health condition	-0.2512***	0.0739	0.4279	0.2616	0.2358*	0.1333
Female	-0.0641	0.0626	-0.5031*	0.2604	0.3368**	0.1335
Age 21-24	0.0111	0.0964	0.0803	0.4318	-0.2083	0.2054
Age 35-44	0.0369	0.0807	0.5649*	0.3015	-0.2133	0.1623
Age 45-54	-0.0114	0.0829	0.1716	0.3218	-0.2410	0.178
Age 55 plus	-0.0583	0.1022	-0.1107	0.4312	0.4967***	0.1775
Married	0.0520	0.0606	0.4600*	0.2589	-0.0298	0.1203
Immigrant: ESC	-0.0083	0.1091	0.6967**	0.2978	0.2465	0.2091
Immigrant: NESC	-0.1842**	0.0923	0.1995	0.3373	-0.0348	0.1958
Capital city	0.1049*	0.0578	-0.2123	0.2448	0.1276	0.1167
Casual job	-0.0962	0.0720	0.9102***	0.3045	0.6235***	0.1367
Hours <15	-0.0496	0.1149	0.3835	0.4041	0.1618	0.1892
Hours >=15 & <25	-0.1132	0.0927	-0.1250	0.3949	0.1635	0.1702
Hours >=25 & <35	-0.0330	0.0870	-0.1826	0.4062	0.0260	0.1812
Hours 45 & over	0.0776	0.0730	0.3118	0.3228	-0.3238	0.2021
Union member	0.4750***	0.0871	-0.3567	0.5257	0.0792	0.2143
Public sector	0.2031**	0.0803	0.0939	0.4061	-0.1573	0.1921
Firm size 20-99	0.1756**	0.0833	-0.3923	0.3893	-0.0071	0.1627
Firm size 100-499	0.2442**	0.0955	-1.1739	0.7496	-0.3969*	0.2351
Firm size 500 plus	0.1523**	0.0692	-0.5154	0.3252	-0.2430	0.1570

(to be continued)

Table a2: Continued

	To higher pay		To self-employment		To non-employment	
	Coef.	S.E. of Coef.	Coef.	S.E. of Coef.	Coef.	S.E. of Coef.
	b). Male sample					
Year 1	-0.7113***	0.1667	-4.4792***	0.7689	-2.7303***	0.4236
Year 2	-1.0990***	0.1943	-5.0667***	1.0211	-2.8320***	0.4227
Year 3 and plus	-0.9973***	0.2184	-4.3518***	0.9448	-3.7724***	0.6827
Middle pay	-0.0314	0.1780	1.2778*	0.7134	-0.2204	0.6055
High pay	0.1205	0.2434	0.8167	0.9601	0.6474	0.7160
Self-employment	-0.7618***	0.2933	2.4888***	0.5164	0.2210	0.5563
Student	-0.4583**	0.1948	0.9434	1.0492	0.8107*	0.4862
Non-employment	-0.6467***	0.1478	0.7604	0.6259	0.8421***	0.2602
Degree	0.0728	0.1617	-0.1141	0.8244	-0.6949	0.4500
Diploma	-0.0609	0.1800	-0.1101	0.7876	-0.3459	0.4591
Certificate	0.0961	0.1158	-0.1003	0.4235	-0.8514**	0.3437
Year 12	-0.1618	0.1406	-0.1869	0.6873	0.0228	0.3042
Health condition	-0.1437	0.1159	0.4388	0.4081	0.1319	0.2718
Age 21-24	0.3268**	0.1370	-0.3366	0.7775	-0.2054	0.3606
Age 35-44	-0.0064	0.1295	0.5028	0.5213	-0.2041	0.3341
Age 45-54	-0.0493	0.1340	0.2049	0.5043	-0.2872	0.3553
Age 55 plus	-0.1564	0.1719	-0.3334	0.6819	0.6726*	0.3533
Married	0.1804*	0.0979	0.5879	0.4298	-0.048	0.2437
Immigrant: ESC	0.0087	0.1713	0.7927*	0.4505	0.4828	0.3396
Immigrant: NESC	-0.2374	0.1471	0.1725	0.7035	0.4427	0.3660
Capital city	0.1759*	0.0943	-0.2263	0.3966	0.0540	0.2340
Casual job	0.0072	0.1216	0.2982	0.4409	0.5552**	0.2726
Hours <15	0.1338	0.2843	0.7972	0.8004	-0.1725	0.4853
Hours >=15 & <25	-0.1795	0.2050	0.5060	0.6863	-0.0509	0.3919
Hours >=25 & <35	-0.0643	0.1698	-0.1036	0.7513	0.5517*	0.3300
Hours 45 & over	0.0069	0.1020	0.1618	0.4693	-0.2187	0.3091
Union member	0.6607***	0.1431	-0.3611	0.8583	-0.1341	0.5249
Public sector	0.2720*	0.1546	-0.3194	1.0654	-0.1496	0.5034
Firm size 20-99	0.1522	0.1307	-0.5527	0.6273	0.1997	0.3114
Firm size 100-499	0.2599*	0.1451	-1.8437	1.6266	-0.6459	0.4935
Firm size 500 plus	0.1543	0.1117	-0.6227	0.5406	-0.7818*	0.4055

(to be continued)

Table a2: Continued

	To higher pay		To self-employment		To non-employment	
	Coef.	S.E. of Coef.	Coef.	S.E. of Coef.	Coef.	S.E. of Coef.
	C). Female sample					
Year 1	-0.5511***	0.1405	-6.0714***	0.8879	-2.7946***	0.2662
Year 2	-0.8329***	0.1641	-5.9541***	1.0223	-2.9181***	0.3009
Year 3 and plus	-1.0809***	0.1787	-6.7792***	1.3102	-3.3450***	0.3474
Middle pay	0.1267	0.1378	0.3561	0.8555	0.4502	0.2894
High pay	0.3876*	0.2064	-3.3931	145.4341	-0.0728	0.4698
Self-employment	-0.4375	0.2720	2.1326***	0.5831	-0.1637	0.4090
Student	0.0590	0.1503	-0.4345	0.9146	-0.0648	0.3370
Non-employment	-0.2587**	0.1095	0.5877	0.5522	0.6254***	0.1626
Degree	0.2039*	0.1200	0.8276	0.5311	0.1789	0.2281
Diploma	0.0145	0.1253	0.1371	0.7427	0.0444	0.2541
Certificate	-0.0760	0.0981	0.5710	0.6061	0.0428	0.1802
Year 12	0.0765	0.1142	0.2739	0.6816	0.3358	0.2154
Health condition	-0.3480***	0.0981	0.3537	0.4674	0.2808*	0.1593
Age 21-24	-0.3116**	0.1420	0.7006	0.6730	-0.1935	0.2677
Age 35-44	0.0381	0.1059	0.5989	0.4582	-0.1833	0.1922
Age 45-54	-0.0061	0.1099	0.0769	0.5443	-0.1905	0.2176
Age 55 plus	-0.0163	0.1348	0.0818	0.8487	0.5705***	0.2181
Married	-0.0338	0.0806	0.4461	0.4256	-0.0011	0.1468
Immigrant: ESC	0.0037	0.1471	0.7376	0.5747	0.0496	0.2798
Immigrant: NESC	-0.1562	0.1209	0.2027	0.4536	-0.1517	0.2455
Capital city	0.0402	0.0750	-0.1583	0.4096	0.1414	0.1384
Casual job	-0.1836**	0.0913	1.6733***	0.5382	0.6443***	0.1658
Hours <15	-0.0604	0.1324	0.1574	0.6206	0.2396	0.2238
Hours >=15 & <25	-0.0845	0.1085	-0.4060	0.6573	0.2231	0.2005
Hours >=25 & <35	-0.0201	0.1060	-0.1977	0.5757	-0.1731	0.2314
Hours 45 & over	0.1549	0.1096	0.6193	0.6222	-0.3966	0.2931
Union member	0.3914***	0.1120	-0.2660	0.9061	0.1599	0.2450
Public sector	0.1412	0.0977	0.3104	0.5272	-0.1670	0.2232
Firm size 20-99	0.1851*	0.1101	-0.4180	0.6412	-0.0272	0.2038
Firm size 100-499	0.1999	0.1315	-0.7211	1.2624	-0.2655	0.2750
Firm size 500 plus	0.1477*	0.0893	-0.5235	0.4953	-0.0801	0.1787

*** indicates estimates are significant at 1%; ** 5%; * 10%.