Final Report

Project 3/07:
Factors affecting the wage progression of the low paid

Umut Oguzoglu and Mark van Zijll de Jong

Melbourne Institute of Applied Economic and Social Research

Final report prepared for the Australian Government Department of Education, Employment and Workplace Relations under the Social Policy Research Services Agreement

Acknowledgements

This research was commissioned by the Australian Government Department of Education, Employment and Workplace Relations (DEEWR) under the Social Policy Research Services Agreement (2005–09) with the Melbourne Institute of Applied Economic and Social Research. The views expressed in this report are those of the authors alone and do not represent those of DEEWR.

The paper uses the confidentialised unit record file from FaHCSIA's Household, Income and Labour Dynamics in Australia Survey, which is managed by the Melbourne Institute of Applied Economic and Social Research. The views expressed in this paper are those of the authors alone and do not represent the views of the Minister for Families, Housing, Community Services and Indigenous Affairs, FaHCSIA, or the Commonwealth Government. The authors thank John Freebairn for his discussions, ideas and comments, and Guyonne Kalb for her comments.

May 2009

Table of Contents

Executive Summary

- The aim of this report is to investigate the socio-economic factors that are associated with the wage progression of low-paid workers in Australia.

- The data used for this report is obtained from the first five waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. To reflect the working age population, the sample excludes individuals who are eligible for the Age Pension and is restricted to those individuals aged between 21 and 64 years old during the five waves of HILDA.

- In this report low pay is defined as an hourly wage rate of less than 2/3 of the median wage in the selected sample. This value ranges from $11.05 per hour in Wave 1 to $13.19 per hour in Wave 5. To circumvent the impact of measurement error, individuals who report hourly wages below 5 dollars and working hours over 60 hours a week are excluded. The descriptive analysis primarily uses annual real wage growth statistics. We calculate annual wage growth for all consecutively available observations. The Consumer Price Index (CPI) for the years 2001 - 2005 is used to compute real hourly wages that are comparable across the years. We also report the probability of low pay for each socio-economic group, measured by the percentage of low-paid workers within a demographic group.

- The descriptive analysis focuses on the role of three general categories of information: demographic characteristics, employment and income support related details, and preferences (as measured by the self-reported job satisfaction levels in HILDA).

- Education is shown to be very important for the advancement of low-paid workers. Approximately 11 percent of men with secondary schooling are in low-paid jobs, whereas only 6 percent of men with post-secondary level education and

3 percent of men with bachelor or higher level degrees are in low-paid jobs. The corresponding statistics for women are 15 percent for secondary education, 11 percent for post secondary education and only 4 percent for an undergraduate degree or higher. Wage growth is also shown to be closely related to level of education. Undergraduate degree or higher educated men exhibit a median annual wage growth of 53 percent compared to 26 percent growth for the low paid with the lowest education levels.

- The likelihood of being low paid is higher for individuals with a work-limiting disability than for individuals without a work-limiting disability. Approximately 6 percent of those classified as 'not disabled' are employed as low-paid workers, which is a substantially lower proportion than the around 11 percent of those classified as 'disabled' who are employed as low-paid workers However, the wage progression of low-paid workers with disabilities is similar to those without disabilities. The estimated median annual wage growth of both groups is approximately 30 percent as long as the disability is not work-limiting. For work-limiting disabilities, the wage growth is somewhat lower at around 25 percent.

- According to the estimates based on employers' characteristics, public sector and large firms offer more opportunities for low-paid workers, facilitating wage progression. Low pay in the public sector is associated with a wage growth of around 8 percentage points more than low pay in the private sector. The availability of on-the-job training is estimated to increase wage growth by 10 percentage points.

- Earlier findings on the persistence of low pay by Buddelmeyer *et al.* (2007) are replicated in the form of a higher estimated probability of being in low-paid work for those who were on low pay in the previous period. Being previously low paid is also associated with higher exit rates from employment.

- Multivariate analysis compares the wage penalty incurred by the previously low paid with that of the previously unemployed. The importance of unobserved factors such as ability, motivation and preferences is highlighted. The multivariate model that controls for these factors estimates a wage penalty for the previously low paid of 7 percent, which is lower than the wage penalty of 10 percent for the previously unemployed.

- Taking a longer-term view, estimates from the multiple pathway model suggest that the persistently low paid and the persistently unemployed are equally affected, with an approximate wage penalty of 25 percent.

1. Introduction

The aim of this report is to investigate the socio-economic factors that are associated with the wage progression of low-paid workers in Australia. Using five waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey, this report provides an in-depth analysis into the wage dynamics of the low paid. Recently, there have been several research projects undertaken by the Melbourne Institute that examine different aspects of low-paid employment (Buddelmeyer *et al*., 2006, 2007; McGuinness and Freebairn, 2007; Freebairn *et al.,* 2008). The aim of this report is to supplement this body of work by employing alternative methodologies. Rather than considering low-paid work as a binary state, we analyse the wage levels directly. A major advantage of this approach is that the wage progression of all low-paid workers, not only those with wages increasing to a level exceeding an arbitrary threshold, is examined. We also pay close attention to issues such as measurement error and sample selection bias.

The determinants of wage levels are closely related (and often identical) to the factors associated with other employment outcomes such as labour force participation, unemployment and income support. For example, low-paid workers are also more likely to be unemployed at some point in their working life. Therefore, throughout this report we draw parallels between our study and other Australian research undertaken by the Melbourne Institute and others.

Our report contains descriptive and multivariate analysis sections. In the descriptive section we present wage growth for the low paid from different socio-economic groups. As well as demographic factors (gender, age, education, family type, state, migration status and rural location status), job-related characteristics (industry, occupation, employment status, firm size) and long-term health conditions are considered. In addition, and new to this literature, we examine the role of preferences in the form of job satisfaction. Individual-level satisfaction data on current employment, pay level and hours of work are key variables for this analysis.

In the multivariate analysis section our aim is twofold. First, we examine the extent to which the wage variation can be explained by the observed characteristics of the low-paid workers. Second, we tackle the issue of persistency in low-paid employment. To achieve the latter, we include binary variables that capture the multiple employment pathways followed by those who are currently employed. Our estimates allow a direct comparison of the wage effect of being previously low paid and the wage effect of being previously unemployed.

This report is organised as follows. The following section briefly reviews the literature; section 3 introduces our data source and discusses the sample. The descriptive analysis is presented in section 4, and is followed by the multivariate analysis in section 5. Finally, section 6 concludes.

2. Previous Research

The majority of research on low-paid employment is based on analysis of transition rates in and out of a low-paid state. In this type of analysis, all individuals with earnings below a certain threshold are categorised as low paid, after which the socio-economic characteristics of this low-paid group are described. Recently, McGuinness and Freebairn (2007) asked the question: “Who are the low paid in the Australian labour force?” They present separate descriptive statistics for part-time and full-time workers who are in low-paid employment. Based on data drawn from the fourth wave of HILDA, their analysis shows that low-paid employees are more likely to have a casual employment status; be single; have low educational levels; be aged either between 21 and 30, or be over 60; and be employed in small firms. Low-paid employees are also associated with low occupational tenure. In another descriptive study, Watson (2007) emphasises the importance of low-paid jobs for the approximately 840,000 workers who are paid at the federal minimum wage and 90,000 who are formally unemployed. Watson (2007) shows that for most, low-paid jobs are a bridge to higher-paid employment in the future.

Richardson and Miller-Lewis (2003) provide some evidence on wage mobility, finding that younger and more educated male workers who are low paid experience higher levels of wage growth than those low-paid workers who are older, female and less educated. While useful in detailing important conceptual and policy-related issues, their analysis is largely descriptive, with the evidence limited to a literature review of studies based on data from the United Kingdom, the United States and the OECD. Dunlop (2000), using longitudinal data from the ABS Survey of Employment and Unemployment Patterns (SEUP) between 1995 to 1997, finds that factors that appear to reduce the likelihood of being low paid include, among others: having tertiary qualifications, longer job tenure, more time in employment since leaving full-time education, recent on-the-job training, larger firm size and higher skill level requirements. Dunlop (2000) also finds that, conversely, mobility out of low-paid jobs to higher-paid jobs appears lower among women, persons who have never been married, workers living in rural areas, persons with low levels of English proficiency, and casual and private sector employees.

Buddelmeyer *et al.* (2006) examine transitions to and from casual employment, non-casual employment and unemployment. They focus on the characteristics that influence transitions, aiming to identify barriers to moving out of casual employment and unemployment. Thus, they focus on transitions between different forms of employment and unemployment rather than wage levels. Buddelmeyer *et al.* (2007) use four waves of HILDA data to examine persistence of and transition from low-paid work. They focus primarily on the question of whether low-paid workers are more likely to find higher-paid jobs than unemployed people. The analysis starts from the definition of mutually exclusive employment states such as low pay, medium pay, high pay and unemployment. Individuals can move between these employment states, but the effects of various individual, human capital and job-related characteristics are not a focus of their study. Freebairn *et al.* (2008) update the findings of Buddelmeyer *et al.* (2006 and 2007) by adding information from the fifth wave of HILDA to the sample of analysis. They explore the incidence of low-paid employment, the characteristics of low-paid workers and the wage transitions of low-paid workers to higher pay.[1]

The empirical methodology undertaken in this project is closely related to the literature on wages. In this type of study, hourly wages are analysed as a function of demographic and human capital characteristics. The linear form of the wage equations (unlike studies of transition rates that employ non-linear functions) provides more flexibility to cope with econometric problems such as selection and endogeneity bias. In addition to these econometric conveniences, wage equations have another important advantage over the transition rate approach. The latter only identifies individuals whose wages pass a predetermined threshold and therefore the movement between wage levels within the low-paid group cannot be observed. The wage equation approach can reveal the factors associated with wage progression for all low-paid workers.[2] Grossberg and Sicillian (1999) use data from the Employment Opportunity Project from the USA to examine the relationship between minimum wages and wage growth. They find that minimum wage jobs in the USA exhibit less wage growth than other jobs, particularly for men. Also using data for the USA in their seminal work, Gladden and Taber (2000) conclude that less-skilled workers should be encouraged to work so that work experience is accumulated, which in turn increases the human capital and hence the chances of finding higher-paid jobs in the future. Zhang (2002) examines the wage progression of low-skilled workers in Canada. The findings suggest that there is a positive return to job tenure for less-skilled workers. This is inconsistent with the view that less-skilled workers are locked into 'dead-end' jobs.

---

[1] Buddelmeyer *et al.* (2007) give an extensive survey of the literature on the transition rates of the low paid.
[2] That is, transition studies are based on limited information (where a change in wage is only observed if the wage changes from below to above a threshold, or vice versa), whereas wage equations use full information reflected by the observed wage levels.

3. Data and Sample Selection

3.1. The HILDA Survey

The data used in the analyses are derived from the first five waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Details of this survey are provided in Watson and Wooden (2004). In the first wave, 7,683 households representing 66 percent of all in-scope households were interviewed, generating a sample of 15,127 persons who were at least 15 years old and eligible for interview, of whom 13,969 were successfully interviewed. Subsequent interviews for later waves were conducted one year apart. In addition to the data collected through personal interviews, each person completing a personal interview was given a self-completion questionnaire to be returned upon completion by mail or handed back to the interviewer at a subsequent visit to the household. The HILDA attrition rates for waves 2, 3 and 4 were 13.2 percent, 9.6 percent and 8.4 percent, respectively, which is similar to other longitudinal surveys.[3] The proportion of wave 4 respondents who were successfully interviewed in wave 5 is 94.4 percent.

The HILDA survey contains detailed information on each individual's labour market activities and history. Socio-demographic characteristics of the respondents and information indicating health status are also recorded. The data from the HILDA Survey is well-suited to this study. The survey provides a rich source of information on a range of factors including income, work, family and quality of life. Importantly for the purpose of this study, it reports labour force status (both at the time of interview and for the periods between interviews), a range of personal and job-related details including age, gender, earnings, usual weekly hours of work, occupation, industry, job tenure, work experience, availability of and participation in on-the-job training, and paid leave. Information is also provided on a number of life events such as changing jobs, losing a job, promotion and relocation.

[3] Watson and Wooden (2006) discuss attrition rates in the HILDA data.

3.2. Sample Selection and Definition of Low Pay

The sample is restricted to individuals aged between 21 and 64 years during the five waves of HILDA. This reflects the working-age population by excluding individuals who are eligible for the Age Pension, and those who are likely to be at school, studying full-time or who may receive junior wages. Both groups are much less likely to participate in the labour force than the 21-64 year age group. Given our interest in the development of the wage rates of individuals, we need to base our analysis on a population that is likely to participate in the labour force and report income from wages and salaries.

This first selection results in initial sample sizes for each wave as follows; 10,495 for wave 1, 9,711 for wave 2, 9,434 for wave 3, 9,110 for wave 4 and 9,326 for wave 5. Important variables such as gender, age, household type, education and other demographics are retained, as well as a number of labour market related variables such as employment status, contract type, occupation and industry. Weekly gross wages in the main job are divided by the weekly hours in the main job to create an earnings variable, which is measured in dollars per hour. Hourly wage growth is calculated on an annual basis by comparing the earnings variable in year t+1 to the earnings variable in year t.

We use 2/3 of the median hourly earnings as the cut-off point to identify low-paid workers.[4] The median wage is calculated based on all employees (employees of own business, unpaid family workers and the self-employed are excluded) who are between 21 and 64 years of age. Individuals who report a missing or negative wage rate, or no working hours are also excluded. In order to be consistent with Freebairn *et al.* (2008), we keep full-time students in our sample since their wage represents the market wage.[5] Finally, casual workers' wages are discounted by 20 percent in order to adjust for the compensation paid to casual workers for forgone leave entitlements.[6]

[4] This cut-off point is $11.05 per hour in Wave 1, $11.43 per hour in Wave 2, $11.87 per hour in Wave 3, $12.37 per hour in Wave 4 and $13.19 per hour in Wave 5.
[5] Students include all individuals participating in education from Certificate I to Postgraduate Studies.
[6] In applying this adjustment, we follow Dunlop (2000) and Buddelmeyer *et al.* (2007).

3.3. Measurement Error

The main difficulty in our analysis is the potential for measurement errors in the weekly earnings and the working hours variables. According to Buddelmeyer *et al*. (2007), the quality of the hourly wage data derived from the HILDA survey is comparable to hourly rates obtained from the ABS Labour Force Surveys. Although this is encouraging, we still observe a considerable number of individuals with unreasonably low (or high) hourly wage rates in our sample. This is particularly problematic for the analysis of low-pay wage growth, since the low-paid group will include all those with unreasonably low wage rates. Without explicitly dealing with measurement error in the wage data, the source of annual wage growth cannot be identified. A very large annual growth rate may indicate an improvement related to observed individual characteristics, or it may simply be a by-product of misreported wages or hours of work in the base year.[7]

We proceed by setting thresholds to lessen the impact of this type of measurement error in our data. We restrict our analysis to individuals with computed hourly wages above five dollars and reported weekly working hours under 60 hours.[8] Table 1 below summarises the demographic characteristics of the observations that are excluded from our analysis. Comparing Table 1 to the first column in Table 2, it appears that misreporting is observed more among males, couples with children, Australian-born individuals and among people with medium to high education.[9] This simple exercise suggests that the measurement error (to the extent that it can be identified by our wage and hours of work thresholds) is not randomly distributed across the analysed sample, and therefore, may affect the analysis to some extent.

For the descriptive analysis, as an additional precaution, median wage growth rates (which are less sensitive to extreme values than the mean) are reported. The multivariate analysis on the other hand, implicitly addresses the measurement error by modelling it as

[7] Previous studies (that are based on transition matrices) are not immune to this measurement error problem. However, compared to the wage growth framework of the current study, the effect of this type of measurement error is much less evident in a transition matrix.
[8] We appreciate DEEWR's assistance in setting these thresholds.
[9] In Appendix A we provide additional details, related to employment, for the trimmed sample.

an unobserved individual-specific factor that is assumed to vary across individuals but is constant over time. Here, our approach (using wage levels as the outcome variable) has a tremendous advantage over studies that use nonlinear models to analyse low-paid states.

Table 1 – Summary Characteristics of Those who are Trimmed from the Sample

	Frequency of those who are Trimmed from the Sample	Proportion within those trimmed from the sample (%)
Gender		
Male	243	73.4
Female	88	26.6
Age		
21-24	23	7.0
25-29	40	12.1
30-44	152	45.9
45-54	74	22.4
55-64	42	12.7
Household Type		
Single	39	11.8
Single with Children	9	2.7
Couple	85	25.7
Couple with Children	156	47.1
Other	42	12.7
Country of Birth		
Non-ATSI Australian	262	79.2
ATSI	2	0.6
NESB	38	11.5
ESB	29	8.8
State		
New South Wales	91	27.5
Victoria	73	22.1
Queensland	80	24.2
South Australia	27	8.2
Western Australia	35	10.6
Northern Territory	2	0.6
Tasmania	20	6.0
ACT	3	0.9
Location		
Major City	155	46.8
Regional	176	53.2
Education Level		
Bachelor Degree	61	18.4
Certificate and Diploma	129	39.0
Up to Year 12	141	42.6
Government payment recipient	41	12.39
Mean weekly hours (in hours per week)		62.99

The linear framework utilised in this report eliminates the impact of measurement error that is correlated with observed characteristics.[10]

We present the demographic characteristics of the sample that are used throughout this report in Table 2. For comparison reasons we also include information on other employment categories (these are: higher pay, self-employed and not employed).

We discuss the low-paid statistics from Table 2 by comparing these to the figures related to the higher-pay sample.[11] Compared to higher-paid workers, low-paid workers in the sample are more likely to be female and to be 21-29 or 55-64 years old. The differences that can be attributed to country of birth are negligible. The low-paid individual is slightly less likely to come from an English speaking background. Also, singles are more likely to be in low-paid employment. The statistics by State imply that Queensland, South Australia and Western Australia tend to have a larger proportion of low-paid workers than the other States. The higher-paid workers are also more likely to live in the major cities. The education level affects the distribution of pay considerably. Only 13 percent of the low paid have a bachelor degree or higher qualification compared to 31 percent of the higher paid.

[10] Here we are referring to measurement error that is time invariant but person specific. Further details are provided in Appendix B under the fixed effects section.

[11] We outline the characteristics of the sample only briefly. McGuinness and Freebairn (2007) and Freebairn *et al.* (2008) provide more details on the low-paid sample.

Table 2 – Distribution of Demographic Characteristics of the Low-Paid Sample Compared to Other Groups

	Low Paid (%)	*Higher Paid (%)*	*Self-Employed (%)*	*Not Employed (%)*
Gender				
Male	40.42	50.88	62.28	31.55
Female	59.58	49.12	37.72	68.45
Age				
21-24	21.15	8.71	1.82	6.37
25-29	13.57	12.75	5.98	8.48
30-44	35.70	44.67	42.50	32.87
45-54	19.38	24.76	29.06	19.32
55-64	10.20	9.12	20.64	32.97
Country of Birth				
Non-ATSI Australian	77.00	76.30	74.84	68.18
ATSI	2.03	1.41	0.74	3.56
NESB	13.13	11.44	11.87	18.11
ESB	7.84	10.85	12.55	10.15
Household Type				
Single	14.33	13.41	10.10	14.12
Single w. dependent	7.44	4.73	2.20	9.56
Couple	27.29	30.45	35.13	33.73
Couple w. dependent	30.55	40.33	47.81	32.95
Other household type	20.39	11.09	4.76	9.64
State				
NSW	25.58	30.57	30.52	30.10
VIC	25.33	25.68	25.02	22.99
QLD	24.27	20.06	18.61	21.18
SA	10.05	8.44	9.16	10.47
WA	10.16	9.13	12.79	10.12
TAS	2.72	2.86	1.92	3.64
NT	0.76	0.84	0.55	0.28
ACT	1.12	2.41	1.43	1.23
Location				
Major city	52.54	63.59	53.39	55.22
Study Status				
Not in Study	83.63	88.02	94.19	91.21
Full-time student	6.31	1.88	0.96	3.98
Part-time student	10.05	10.06	4.85	4.81

Table 2 – Continued

	Low Paid (%)	*Higher Paid (%)*	*Self-Employed (%)*	*Not Employed (%)*
Education				
Degree or higher	12.92	31.13	23.37	11.71
Diploma	30.37	32.98	37.82	26.96
High school or below	56.60	35.84	38.68	61.01
Government payment recipient	20.90	5.31	8.27	52.28
Mean weekly hours (in hours)	30.67	37.19	37.17	0
Sample Size	2756	23875	5819	12317

4. A Descriptive Analysis of Low-Pay Wage Growth

In this section we describe the association between the socio-economic characteristics of the low-paid workers and the subsequent wage growth that they experience. The analysis is based on annual real wage growth statistics. We calculate annual wage growth for all consecutively available observations. Cross-sectional weights provided by the HILDA Survey are used in this analysis. The Consumer Price Index (CPI) for the years 2001 to 2005 is used to compute real hourly wages.[12]

We have decided on one-year growth rates in order to obtain the largest possible sample size and, hence, to improve the accuracy of our estimates.[13] One disadvantage of not using a longer time horizon may be that the transitions from low pay to higher pay that take longer to complete are not observed. However, a substantial amount of growth is observed for low-paid workers in one year. Therefore, it is of interest to examine the factors associated with a larger amount of wage growth for this group within this period.[14] Table 3 reports the median real wage growth rates for up to four years using a pooled sample of workers from waves one to four of HILDA. After an initial sharp increase in the first year, wage growth slows down in the later periods. The low paid in the first wave of HILDA enjoyed a median annual wage growth of 30.1 percent. The

[12] The base year is 2005.
[13] Preliminary analysis showed that the precision of the estimates based on a more than two-year growth rate suffers considerably due to the small sample size.
[14] In the multivariate analysis in the next section, wages in one, two and three years time are considered.

growth rates for this group for longer time horizons are 30.9 percent for two years, 41.1 percent for three years and 51.3 percent for four years.

High growth rates immediately following the initial observation of low pay is a common finding for low-paid workers. For most, low pay is a temporary state and a substantial proportion of low-paid workers transit to higher pay within a year. For those who stay on low pay longer, it is more difficult to *escape* low pay. Longer periods of time spent in low pay are associated with lower likelihoods of exiting to higher-paid jobs in the future. Therefore, the growth rates generally slow down from the second year. In addition, calculating wage growth from period t to t+1 starts from a sample where all respondents are low-paid workers, some of whom will experience a substantial increase in period t+1. This means the sample in period t+1 is a combination of low-paid and higher-paid workers. As a result, some of the higher-paid group's wages may decrease again in period t+2, possibly counterbalancing others who were still low paid in period t+1 but who experienced an increase from period t+1 to t+2.

From Table 3, it also appears that annual growth rates are more consistent across waves than the growth rates that span over two or more years. Annual growth rates are generally around 30 percent for the low-paid workers. The median growth rates over longer time horizons, however, vary considerably depending on the choice of the base year. For example, for the low paid from wave 1, the two-year growth is around 31 percent. Whereas the wage growth for the low paid from wave 2 and wave 3 are 39.2 percent and 41.4 percent, respectively. A similar discrepancy is observed for the three-year growth rates. The low paid from the first wave of HILDA had a 41 percent median wage growth in three years. For the low paid of wave 2 this rate is above 48 percent. The source of this variation may be due to macroeconomic factors that affect different *cohorts* of the low paid differently. For the descriptive statistics presented here, there is not enough information to correctly identify this intra-wave variation. Therefore we only utilise one-year growth rates where the variation among years is relatively low.[15]

[15] In the multivariate section we include time dummies to control for the effect of the base year.

Table 3 – Real Wage Growth Rates of the Median Low Pay Workers across HILDA Waves 1 - 5

	Target Wave			
	t+1	*t+2*	*t+3*	*t+4*
Base Wave:				
t = 1	30.1	30.9	41.1	51.3
t = 2	29.9	39.2	48.2	-
t = 3	32.1	41.4	-	-
t = 4	31.1	-	-	-

Before proceeding with our discussion of socio-economic factors affecting wage growth, it is worthwhile putting the growth rates presented into the correct perspective. Table 4 reports annual wage growth by the types of one-year wage transition for our sample. The statistics in brackets represent the percentage of persons in the initial state *i* moving to state *j* within one year. The transition rates are slightly different from the rates reported by Freebairn *et al.* (2008) due to our data trimming; however, the general trend is very similar. From Table 4 we see that low-paid work is associated with the highest rate of percentage growth. Workers who stay low paid in the next period have a median growth rate of 2.6 percent. The low-paid workers who transit to medium (between 2/3 of the median and the median wage) and high pay (more than the median) categories are associated with median growth rates of 41.8 percent and 110.2 percent, respectively. Medium-paid workers who do not exit their initial state exhibit a growth rate of 1.4 percent. The median growth rate for those who transit from medium pay to high pay is approximately 33 percent. For higher-paid workers who stay high paid we see a growth rate of 2.1 percent. There are also downward movements. Median pay decreases by 24 percent for the 9.2 percent of those on medium pay who transit to low pay in the next period. A small percentage of high-paid workers (2.1 percent) are observed to be in low pay employment in the following year; they experience a median wage decline of 53.4 percent. A larger proportion of high-paid workers (14 percent) transits to medium pay, experiencing a median wage decrease of 21.4 percent.

The statistics in Table 4 also show that low-paid workers exhibit the highest exit rate from work: 13.1 percent of this group become unemployed within one year. The higher the pay in the initial period, the more likely is the worker to stay employed in the next period. This finding highlights an important caveat of the analysis based on low-paid work. Since we only observe the transition (or wage growth) for workers who stay employed, high rates of exit from employment imply that the statistics may be biased and the wage growth statistics do not tell the full story. For example, we may be observing highly motivated individuals or individuals with prior information about their future (more positive) job prospects. In this case the observed wage growth may be biased upwards. For some, however, low-paid employment can be a permanent state. This is either by choice (we discuss the role of preferences in later sections) or necessity. In this scenario the wage growth that we capture here may have a downward bias. In either case the observed sample may not be representative of the low-paid population.[16]

Table 4 – Median Wage Growth by Year to Year Transitions

	State at t+1					
	Low (< 2/3 median)	Medium (2/3 – median)	High (Median>)	Self-employed	Not Employed	Total
Initial State (t)						
Low Paid	2.6	41.8	110.2	63.4	-	
	(34.0)	*(38.7)*	*(10.3)*	*(3.9)*	*(13.1)*	*(100.0)*
Medium Paid	-24.1	1.4	32.9	3.2	-	
	(9.2)	*(59.6)*	*(21.1)*	*(2.4)*	*(7.8)*	*(100.0)*
High Paid	-53.4	-21.4	2.1	-2.8	-	
	(1.8)	*(14.0)*	*(77.0)*	*(2.8)*	*(4.4)*	*(100.0)*
Self-employed	-36.9	-9.4	17.7	-0.8	-	
	(2.1)	(3.8)	(6.5)	-80.1)	(7.5)	(100.0)
Not Employed	-	-	-	-	-	
	(3.4)	*(7.3)*	*(4.6)*	*(3.3)*	*(81.4)*	*(100.0)*

Note: The annual transition rates are in brackets. Remaining statistics represent the median annual real wage growth rate for a given category.

The descriptive analyses in subsections 4.1 to 4.5 consist of three sets of statistics by demographics, health, employment, income support and preferences (as measured by job satisfaction). The first key statistic that we focus on is the median real annual wage growth rate. The annual growth rate enables us to observe wage progression for all low-paid workers, not only those whose real wages move from below to above an arbitrary

[16] We aim to address the selection bias explicitly in the multivariate analysis section.

threshold (in our case, 2/3 of the median wage). It is important to note that, in order to qualify as high paid in the next period, workers who are initially at the bottom of the wage distribution need to progress considerably more than those who are only slightly below the low-pay threshold. Therefore, the transition rates underestimate the wage progression for the very low-paid workers and overestimate the progression for those who are only marginally low paid. We emphasise this discrepancy by reporting transition rates to high pay along with median growth rates in the tables in Sections 4.1 to 4.5. Finally, we present the share of low-paid workers in any given category by the percentage of low-paid workers within a socio-economic group (such as, industry, education level or family type). Our aim is to interpret the wage growth rates of low-paid workers in the context of their relative importance in a given socio-economic category.

4.1. Demographic Factors

Table 5 reports the median wage growth by demographic characteristics of the low-paid sample for men and women separately. The personal characteristics are measured in the base year (the year that individuals are identified as being low-paid workers). The median wage growth is the median percentage annual increase in the real wage of the low-paid workers group.

The highest percentage of low-paid workers is found among the sample of 21 to 24 year olds. This may be partly due to the presence of full-time students in our sample. For men, the youngest age group exhibits the highest annual wage growth. The lowest wage growth for men is observed for the 45 to 54 year olds. This group, however, has the lowest probability of being low paid. Compared to 21.6 percent of 21 to 24 year old men, only 4.4 percent of men between 45 and 54 years are in low-paid employment. For women, there are no clear differences in wage growth across the age distribution, except for the oldest female group. The median wage growth of the latter group is 22.6 percent per annum, which is the lowest among low-paid women who mostly experience a wage growth of around 30 percent.

Table 5 – Demographic Characteristics

	Proportion of Low Paid within the Full Sample (%)		Transition from Low Pay to Higher Pay (%)		Median Wage Growth of the Low Paid (%)	
	Male	Female	Male	Female	Male	Female
Age Group						
21-24	21.6	18.8	64.0	63.9	34.1	29.1
25-29	8.6	11.0	62.1	64.2	28.7	31.9
30-44	5.0	8.9	68.1	66.6	30.9	31.5
45-54	4.4	8.4	59.5	58.1	22.1	31.4
55-64	6.5	11.4	53.8	48.3	27.5	22.6
Country of Birth						
Non-ATSI Australian	7.2	10.2	64.8	62.0	29.8	30.3
ATSI*	-	-	-	-	-	-
ESB	4.2	7.9	62.5	54.9	30.4	36.0
NESB	7.9	11.3	68.6	66.1	38.3	28.2
Household Type						
Single	8.7	7.9	58.3	58.5	18.9	28.7
Single with Children*	-	12.8	-	54.6	-	18.5
Couple	5.4	9.3	65.8	62.0	30.7	29.9
Couple with Children	4.2	9.6	75.5	66.0	35.4	34.6
Education						
Degree or higher	3.1	3.8	71.4	74.8	52.8	50.3
Post Secondary	5.9	10.9	69.4	68.4	38.9	33.6
Secondary	11.1	14.5	61.2	57.6	25.6	26.7
Primary*	-	-	-	-	-	-
Full-time Student	23.60	25.90	64.10	73.30	43.30	43.70
Part-time Student	6.90	9.50	56.90	64.10	31.80	36.00
State						
New South Wales	6.0	8.2	68.7	67.4	31.7	32.1
Victoria	6.2	10.6	66.9	61.4	29.0	34.5
Queensland	8.5	12.3	60.5	57.9	30.5	26.6
South Australia	8.7	11.2	66.7	62.8	21.7	32.1
Western Australia	7.1	11.3	58.9	57.0	30.4	26.1
Northern Territory*	-	-	-	-	-	-
Tasmania*	9.7	-	71.4	-	44.1	-
ACT*	-	-	-	-	-	-
Major City	9.2	12.7	61.3	64.3	39.0	31.9
Regional or remote areas	5.6	8.5	69.0	60.4	27.2	30.1

* indicates that some statistics are removed due to inadequate sample size.

Male workers from non-English speaking backgrounds (NESB) exhibit the highest median wage growth (38.2 percent). Men from English-speaking backgrounds are the least likely to be low paid. For women, the pattern is different. The NESB women show the lowest wage growth (28.2 percent) and they are most likely to be low paid. The family type seems to be relevant to wage growth as well. For men and women, being a member of a couple with children makes it more likely to exit low pay: the transition rate into higher pay is 75.5 percent for men and 66 percent for women. The wage growth for this group of individuals is consistent with this finding. Low-paid men and women from a couple with children have a higher growth rate compared to other household types; 35.4 percent and 34.6 percent, respectively.

As expected, the proportion of low-paid workers in a group decreases with the level of education. Compared to 11.1 percent of men with secondary schooling, only 5.9 percent of men with post-secondary level education and 3.1 percent of men with a bachelor degree or higher are in low-paid jobs. The corresponding statistics for women are 14.5 percent for secondary education, 10.9 percent for post secondary education and only 3.8 percent for degree and higher. The wage growth of the more educated low-paid workers is higher than for those with lower education. The annual wage growth rate for the most educated sample is 52.8 percent for men and 50.3 percent for women. For the low paid with secondary schooling, the median growth is only 25.6 percent and 26.7 percent for men and women, respectively.

When it comes to state of residence, there appears to be no specific pattern in median wage growth rates. South Australia has the lowest wage growth for low-paid men (21.7 percent) whereas Tasmania has the highest (44.1 percent). For women, it appears that Victoria exhibits the highest low-paid wage growth (34.5 percent), while Western Australia has the lowest (26.6 percent). Comparing transition rates and median growth rates, we come to different conclusions with respect to the role of major cities. Transition rates imply that low-paid men from major cities are less likely to exit low pay than men from regional or remote areas. 61.3 percent of low-paid men from major cities exit low pay compared to 69 percent of the low paid from other areas. The median wage growth in major cities, however, is much higher than the median wage growth in regional areas. Compared to a 39 percent increase in major cities, corresponding wage growth for regional areas is only 27.2 percent for men.

4.2. Long-Term Health Conditions and Work Limitations

Health is the main determinant of a person's work capacity. Unsurprisingly, ill health is strongly associated with labour force exits in Australia (Wilkins, 2004; Cai and Kalb, 2006; Mavromaras *et al.,* 2007; Oguzoglu, 2009). By affecting an individual's productivity, long-term ill health is expected to limit the wage prospects of workers across the earnings distribution. Consistent with this hypothesis, Mavromaras *et al.* (2007) show that due to their lower productivity, disabled individuals endure a wage penalty in the Australian labour market. Given that low-paid jobs are more commonly associated with low skills and physically intensive work than higher-paid jobs, (physical) health may be most important for the low paid.

Ill health in the form of a disability is expected to affect not only the incidence of low pay now but also the probability of exiting low pay in future periods. This may occur via two channels. First, a direct effect: the disabled may stay disabled in the future and the lower productivity will translate again to lower earnings. Second, a current disability, by increasing the probability of current low-paid employment, can indirectly increase the incidence of low pay in the next periods. This occurs due to persistence in the low-paid state. Oguzoglu (2009) shows a similar result for the direct and indirect impact of a current disability on future labour force participation levels.

Table 6 – Long-Term Health Conditions

	Proportion of Low Paid within the Full Sample (%)		Transition from Low Pay to Higher Pay (%)		Median Wage Growth of the Low Paid (%)	
	Male	Female	Male	Female	Male	Female
Health Status						
Not Disabled	6.6	9.8	66.3	63.4	31.0	31.3
Disabled and Not Work Limited	5.9	10.0	60.4	55.4	29.9	31.9
Disabled and Work Limited	10.9	14.2	60.56	53.26	26.6	24.5

Table 6 includes information on long-term health conditions. From the HILDA Survey we can identify three categories. First, the ‘not disabled’ are individuals without any long-term health conditions. Second, the ‘disabled and not work limited’ group contains individuals whose long-term health conditions do not cause limitations for the type and the amount of work they can do. The third category consists of the disabled who experience work limitations due to their long-term health conditions (the ‘disabled and work limited’).

In Table 6 a higher percentage on low pay is observed for the work-limited disabled group. Around 11 percent of the work-limited disabled are low paid compared to 6.6 percent of the ‘not disabled’ and 5.9 percent of the ‘disabled without work limitations’. The growth and transition rates are fairly similar across different disability categories. The ‘not disabled’ low paid have enjoyed wage growth of around 31 percent. Median wage growth for disabled men and women without work limitations is 29.9 and 31.9 percent, respectively. The work-limited low-paid workers have experienced only slightly lower median growth rates: 26.6 percent for men and 24.5 percent for women. The transition rates are quite similar within the disabled group (with and without work limitations), and they are 6 to 8 percentage points higher for those without any disability. This finding emphasises the importance of low-paid work for the disabled. Individuals who stay employed despite the difficulties caused by health conditions advance nearly as much as individuals without these difficulties. Given that only a small percentage of the disabled group participate in the labour force, the wage growth of those who participate is encouraging.

4.3. Employment Characteristics

In this section we focus on factors related to employment such as industry, occupation, full-time and part-time work, and type of contract. We also use the limited information available on employers: firm size, access to job training, and public versus private companies. Table 7 shows that part-time work is associated with a higher probability of being low paid: 20.2 percent of male part-time workers and 14.7 percent of female part-time workers are employed in low-paid jobs. For full-time employees, the proportion on low pay is 5.6 and 6.5 percent for men and women, respectively. This contradicts recent findings of a part-time premium by Booth and Wood (2006) using HILDA. However, it should be noted that Table 7 only reports the share of low-paid workers among part-time workers without controlling for any other characteristics that determine wage levels. Therefore, our findings are not directly comparable to Booth and Wood (2006).

In terms of wage growth there is no substantial difference between full-time and part-time workers. There is also almost no gender wage growth gap across low-paid workers of the same category. Supporting the findings of McGuinness and Freebairn (2007) is our finding that casual work appears to have a greater tendency to be low paid.

Table 7 - Job Characteristics

	Proportion of Low Paid within the Full Sample (%)		Transition from Low Pay to Higher Pay (%)		Median Wage Growth of the Low Paid (%)	
	Male	Female	Male	Female	Male	Female
Employment Status						
Full-time	5.6	6.5	66.0	66.5	30.3	30.3
Part-time	20.2	14.7	63.0	60.0	31.7	30.9
Contract Type						
Fixed-term Contract	7.1	5.4	59.7	70.8	29.7	41.1
Permanent / On-Going	4.7	5.4	65.1	65.7	28.0	26.5
Casual	26.9	30.5	66.1	59.4	34.4	32.5

The growth rates by industry and occupation are considered next. Conceptually, we think of three possible ways their role in wage growth can be identified. First, macroeconomic shocks can alter the opportunities in an industry (the mining boom in Western Australia, or the decline of the manufacturing sectors are good examples). An initially low-paid worker within a booming industry can move up the pay scale since his work experience suddenly (or gradually) becomes more marketable.[17] Second, an industry can foster wage progression by providing opportunities for the low-paid worker. Again, work experience

[17] This assumes that the industry or occupation in question has certain barriers to entry, in the sense that workers from less fortunate industries (or occupations) cannot find employment quickly in the booming industry (or occupation).

as a low-paid worker helps workers to transit to higher-paid positions within the industry. A third channel through which the low-paid work can contribute to future wage growth is the transferability of skills across industries or occupations. In Webster *et al.* (2007), wages of occupations across different industries are shown to move in a similar fashion. Similarly, the wage levels of different occupations within the same industry are reported to be related. If their findings hold for some of the low-paid occupations, individuals can switch to higher-paid jobs if their occupational skills are transferable from low-paid industries to high-paid industries.

We report the statistics by industry and occupation in Table 8. 'Labourers and related workers' are associated with the lowest growth rates for men (around 20 percent a year). For women the poorest growth is observed for 'intermediate production and transport workers' and 'elementary clerical and service workers' (21.7 percent and 22.4 percent, respectively). Male and female professionals who are initially defined as low paid have a median growth of 68 percent and 68.7 percent per annum, which is the highest among all occupational categories. However, the proportion of low paid in the 'professional' occupation category is very low (2.9 percent and 2.7 percent for men and women, respectively). This indicates that observing a 'professional' as being low paid may be due to some unobservable factors (or measurement error) not due to the occupational characteristics and there are more opportunities for this group to increase their pay. Similarly, the likelihood of observing 'associate professionals' defined as low paid is low (4.9 percent for men and 6.7 percent for women). Therefore, high transition rates of this occupational category should be interpreted with some caution.

The industry classification shows that 'agriculture, forestry and fishing' is the most disadvantaged category in terms of moving to the category of higher-paid employment. Workers from this industry are also more likely to be low paid than workers in other industries (22.8 percent of men and 37.1 percent of women in this industry are low paid). Their median wage growth rates are also the lowest for men. Median growth for men is only 17.6 percent, while female wages have grown at a rate of 26.4 percent for this sector. The lowest median growth for women is in the 'transport and storage' sector (7.3

percent per annum). The low-paid workers in the 'education' sector have enjoyed the largest wage growth rates, with median growth rates reaching 68 percent for men and

Table 8 – Industry and Occupation

	Proportion of Low Paid within the Full Sample (%)		Transition from Low Pay to Higher Pay (%)		Median Wage Growth of the Low Paid (%)	
	Male	Female	Male	Female	Male	Female
Occupation						
Managers and Admin. *	-	-	-	-	-	-
Professionals	2.9	2.7	67.2	78.5	68.0	68.7
Associate Professionals	4.9	6.7	68.1	65.4	41.9	29.1
Tradespersons and Related	7.0	18.5	61.0	62.9	31.0	28.6
Advanced Clerical and Service Workers*	-	-	-	-	-	-
Intermediate Clerical, Sales and Service Workers	8.4	14.1	73.8	63.3	32.0	32.9
Intermediate Production and Transport Workers	9.5	21.8	69.8	48.7	26.8	21.7
Elementary Clerical, Sales and Service Workers	13.6	20.4	67.7	59.8	38.4	22.4
Labourers and Related Workers	19.0	29.2	56.6	54.7	20.4	30.1
Industry						
Agriculture, Forestry and Fishing	22.8	37.1	45.8	38.9	17.6	26.4
Mining*	-	-	-	-	-	-
Manufacturing	5.6	12.6	69.1	66.2	29.5	31.6
Electricity, Gas and Water Supply*	-	-	-	-	-	-
Construction	4.9	9.1	71.8	53.9	31.7	27.0
Wholesale Trade	9.4	8.2	70.0	52.4	35.1	25.4
Retail trade	13.5	18.9	59.7	60.3	21.7	23.8
Accommodation, Cafes and Restaurants	19.0	29.9	69.8	56.8	46.0	20.7
Transport and Storage	5.5	12.7	80.7	45.8	25.4	7.3
Communication Services*	-	-	-	-	-	-
Finance and Insurance*	-	-	-	-	-	-
Property and Business Services	5.3	9.2	68.4	68.1	45.5	33.6
Government and Defence*	-	-	-	-	-	-
Education	2.7	5.9	68.4	78.8	68.0	55.4
Health and Community Services	7.0	7.7	71.0	64.1	30.3	41.5
Cultural, Recreational and Personal Services	10.6	12.6	60.0	55.7	41.2	27.5

***** indicates that some statistics are removed due to inadequate sample size.

55.4 percent for women. The 'transport and storage' industry has very high exit rates from low pay for men (80.7 percent) however median wage growth rates are relatively modest (25.4 percent for men). This indicates that most of the low-paid men in this industry are only marginally below the low pay threshold.

According to Table 9, small firms have a higher tendency to employ low-paid workers and they seem to provide fewer opportunities for them to progress to higher-paid jobs. The wages of low-paid men and women from larger firms exhibit median growth rates of 40.5 and 35.4 percent, respectively. The wage growth of the small firm employees are 29.6 percent for men and 28.1 percent for women. This may imply that larger firms, by containing more higher-paid jobs, facilitate skill transfers for the initially low-paid employees. It is also possible that workers with higher abilities apply to larger firms knowing that they have a greater chance of advancing compared to workers employed in small firms. Table 9 also shows that the public sector has a higher percentage of low-paid workers and a higher chance for them to advance compared to the private sector. The wage growth for the low-paid workers from the public and private sector is 33.9 percent and 26.7 percent, respectively.

Table 9 - Employer Characteristics

	Proportion of Low Paid within the Full Sample (%)		Transition from Low Pay to Higher Pay (%)		Median Wage Growth of the Low Paid (%)	
	Male	Female	Male	Female	Male	Female
Firm Size						
Firm size less than 50	9.4	12.5	63.9	59.9	29.6	28.1
Firm size 50 or more	3.6	6.7	68.8	68.1	40.5	35.4
Public vs. Private						
Government Firm	10.0	26.0	61.5	61.5	33.9	33.9
Private Firm	8.9	14.4	66.5	59.1	26.7	26.7
Job Training						
Access to Job Training	5.8	7.9	68.0	69.0	35.8	38.1
No Access to Job Training	8.6	13.8	62.3	55.7	26.6	25.3

Table 9 compares wage growth between the low paid who have access to on-the-job training to those who have not. The effect is immediately visible. The low paid with training have a median wage growth of 35.8 percent. This is an almost 10 percentage point higher median wage growth than for the low-paid men without training. For women, the impact is even more pronounced. Compared to a wage growth of 25.3 percent for the low paid without on-the-job training, the wages of those with training grow at a rate of 38.1 percent per year.

4.4. Labour Market State and Income Support Experience

There is recent evidence emphasising the role of past labour market states on current employment outcomes.[18] Buddelmeyer *et al.* (2007) show that low pay can be a persistent state for some individuals. That is, past low-paid employment has a direct effect on the probability of being in low-paid employment in the future. There is also some international evidence on the direct influence of low-paid employment on unemployment in future periods (Stewart, 2007; Capellari and Jenkins, 2004). However, this finding is not supported by Buddelmeyer *et al.* (2007) for Australia, who find that previously low-paid workers are not more likely to enter unemployment compared to workers in high-paid employment.

There is also Australian research that examines the role of past income support receipt on future employment outcomes. Most recently, using administrative data on income support recipients, Black *et al.* (2006) show that earned income while on income support is significantly associated with lower welfare reliance in the future. For low-paid work this finding has important implications. Individuals who work while being supported by the welfare system are more likely to progress to be less reliant (or not reliant at all) on income support in the future than income support recipients who have no other income in addition to government benefits.

Table 10 presents median wage growth by current and past income support, and by past labour force status. We divide income reliance into four categories using the TPI measure (the proportion of total earnings that is drawn from income support). Individuals with a

[18] For recent examples, see Buddelmeyer *et al.* (2007), Oguzoglu (2009, 2007) and Mavromaras *et al.* (2007).

TPI lower than 50 percent (but more than zero) are classified as ‘Weakly reliant’, 50 – 90 percent reliance is defined as the ‘Moderately reliant’, and the ‘Heavily reliant’ are defined as those with a TPI greater than 90 percent.

Table 10 - Labour Market and Income Support Experience

	Proportion of Low Paid within the Full Sample (%)		Transition from Low Pay to Higher Pay (%)		Median Wage Growth of the Low Paid (%)	
	Male	Female	Male	Female	Male	Female
Income Support at t						
Not Reliant	6.0	8.1	64.7	64.7	30.3	31.0
Weakly Reliant	26.3	27.2	57.1	51.6	29.1	30.2
Moderately Reliant	32.5	39.5	38.5	46.6	28.1	30.1
Heavily Reliant	30.4	60.5	64.3	52.6	49.1	45.7
Income Support at t-1						
Not Reliant	4.9	7.5	61.1	66.1	29.8	30.9
Weakly Reliant	15.7	23.1	43.8	61.1	22.2	31.5
Moderately Reliant	18.9	26.3	42.9	41.7	22.0	17.4
Heavily Reliant	30.7	34.5	60.7	48.7	35.1	39.6
Labour Force at t-1						
Low pay	34.3	36.4	48.5	42.7	17.5	17.4
Medium pay	7.1	10.1	60.2	73.2	31.4	33.1
High pay	1.4	2.1	80.0	77.6	55.7	55.7
Self-Employed	3.0	7.3	58.8	66.7	40.7	49.4
Not Employed	19.7	19.0	63.8	70.2	30.3	34.1

Note: Job change status refers to a change of job between years t (base year) and t +1

It appears that the degree of welfare reliance is positively correlated with the proportion in low-paid employment. Only 6 percent of those who are not on income support are observed to be low paid. Of the weakly reliant income support recipients, 26.3 percent are on low pay. For the moderately and heavily reliant income support recipients this statistic is 32.5 percent and 30.4 percent, respectively. The slight drop in the probability of low pay for the heavily reliant is due to the low incidence of paid employment among this group. Naturally, the direction of the causality regarding these statistics is from low pay to income support. That is, individuals supplement their low earnings with income from income support, rather than income support directly causing the incidence of low-paid employment. In order to examine the impact of past income support on the proportion of workers on low pay, Table 10 includes welfare reliance from the previous wave of HILDA. This shows that past income reliance is closely related to the current probability of being low paid. The percentages of low-paid workers among the weakly, moderately and heavily reliant income support recipients from the past wave are 15.7, 18.9 and 30.7, respectively. This may be an indication of persistence in income support receipt. The transition rates to higher pay seem to be decreasing with the degree of current and past income support receipt, except for a sharp increase for the previously highly-reliant individuals. The median wage growth rates are consistent with this finding. Individuals who were not on income support before being low paid are associated with a median growth rate around 30 percent. The transition rate to higher pay for this group is 61.1 percent for men and 66.1 percent for women. It appears that among the (past) weakly reliant, 43.8 percent of men and 61.1 percent of women have switched to higher pay by enjoying a median wage growth of 22.2 percent and 31.5 percent, respectively. For those who relied moderately on income support, the wage growth drops slightly to 22 percent for men and more sharply for women to 17.4 percent per year. The wage growth rates for heavily-reliant individuals are the largest of all groups and the transition rates of the male group are comparable to those who were not reliant on income support. This may be due to the type of income support received by the heavily reliant.

The final issue examined in this section is the role of past employment status on the transition rate to high pay of the low paid. From Table 10, the persistence of the pay levels over time is immediately apparent. Only 1.4 percent of previously high-paid workers are currently in low-paid jobs. For the previously low paid, the probability of staying in the low-paid state is more than 34 percent. The median wage growth is closely related to the previous pay levels as well. Currently low-paid workers with higher past wage levels have a higher transition rate back to high pay. Being low paid in two consecutive periods is associated with a median wage growth of 17.4 percent. For the previously medium paid, the wage growth rates are 31.4 percent for men and 33.1 percent for women. If the low-paid worker was employed in a high-paid job in the past wave, the wage growth is approximately 56 percent. The transition rates to the higher-paid jobs support these findings; being high for the previously high paid and low for the previously low paid. It is also interesting to note that the previously not employed are less likely to be employed as low-paid workers than the previously low-paid workers. This is probably partly because the previously not-employed are more likely to be out of work in the current year as well. However, the median wage growth of this group is also higher than that of the previously low paid. With 30 percent for men and 34 percent for women, the wage growth of the not-employed in the past is almost twice as high as the workers who come from a low-paid state.

4.5. Preferences

In this section we investigate the role of individual preferences in the decision to move out of or stay in a low-paid job. The underlying assumption is that people have the capacity to move out of low-paid employment (and move into higher pay) if they choose to do so. If this assumption holds, we can explain why some individuals 'choose' to stay in low pay by observing their satisfaction related to aspects of their work. Some low-paid jobs, for example, can be transitory paths towards retirement for mature-age workers. It may also be that the low-paid worker is a secondary earner in the household who is happy with the challenges (or flexibility) provided by the low-paid work and has little incentive to move up the pay scale. In order to disentangle this issue, we present the wage growth rates associated with the worker's satisfaction with their job, pay and working hours. In the HILDA Survey, satisfaction variables are measured on a scale of zero (totally dissatisfied) to 10 (totally satisfied). In order to facilitate the interpretation of the results, we convert satisfaction variables into binary variables; satisfaction levels of five or more are re-classified as 'satisfied,' and 'not satisfied' refers to satisfaction levels of four or less. Table 11 summarises the results. If preferences play an important role, we expect to see higher exit rates and higher wage growth for those who are initially not satisfied with certain aspects of their work.

Transition rates associated with overall job satisfaction do not support the importance of preferences. Men who are satisfied and men who are not satisfied with their work are equally likely to move towards higher pay in the next period. Women are slightly less likely to exit low pay if they are not satisfied with their low-paid job, indicating that preferences are not important.

Table 11 – Preferences

	Proportion of Low Paid within the Full Sample (%)		Transition from Low Pay to Higher Pay (%)		Median Wage Growth of the Low Paid (%)	
	Male	Female	Male	Female	Male	Female
Satisfied with Job	6.7	10.0	65.2	62.5	30.3	30.3
Not satisfied with Job	9.7	12.1	65.5	58.2	39.7	36.2
Satisfied with pay	5.9	9.5	67.4	63.2	30.5	30.9
Not satisfied with pay	13.7	13.8	58.7	58.4	29.5	30.2
Satisfied with hours	6.7	9.8	63.4	63.0	29.5	30.4
Not satisfied with hours	9.0	13.0	75.8	57.8	40.3	32.6

The median growth rates associated with overall job satisfaction are in line with the preferences hypothesis. Both male and female low-paid workers exhibit considerably higher wage growth if they are not satisfied with their jobs initially. The median wage growth for satisfied workers is around 30 percent (for both men and women), the rates for ‘not satisfied’ workers, on the other hand, are around 40 percent for men and 36 percent for women.

An important aspect of work where preferences appears to play a role is with regard to working hours. Men are more likely to exit low pay (at a rate of 75.8 percent) if they are not happy with their working hours. Men who are unhappy with their working hours are also associated with about a 10 percentage point higher growth rate compared to men who are happy with their initial working-hours arrangement. For women, the difference in growth rates between happy and unhappy workers is much smaller, at about 2 percent. The satisfaction with pay has either no effect or the effect is in the opposite direction of what would be expected if preferences affected individuals’ outcomes with regard to wage growth.

5. Multivariate Analysis – Wage Growth Estimations

In this section we analyse the conditional association between socio-economic factors and wage growth using multivariate analysis.

Throughout this section our analysis is based on wage equations of the following form:

$$\begin{aligned} &\ln(w_{it+s}) = \beta_1 X_{it} + \beta_2 Z_{it} + \alpha_i + \varepsilon_{it} \\ &\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2), \quad s = 0,1,2,3 \end{aligned} \qquad (1)$$

Where $\ln(w_{\mathrm{it}})$ is the natural logarithm of the hourly wage of individual i at wave t. The explanatory variables of the wage equation consist of demographic characteristics, X_{it}, and information on individual i's employment, Z_{it}. We restrict the sample to those who are identified as being low paid in any of the waves of HILDA. All explanatory variables refer to the initial year t when individual i was in low-paid employment. The role of the term s is to alter the reference time for the wage levels. When $s = 0$, we analyse the wage variation in the current year. When $s > 0$, our focus switches to future wage levels; that is, to the wage progression of the (initially) low-paid individuals.

The estimation strategy is dictated by the assumptions governing the form of unobserved heterogeneity captured by α_i. The explicit inclusion of individual unobserved characteristics in the econometric specification is useful as it helps control for a number of unobserved factors such as preferences, motivation to work, ability (which cannot be captured by education alone), quality of the match between the worker and the job, or any other individual characteristics unknown to the researcher, that have the potential to alter wage levels. These unobserved factors are assumed to be constant over time but are allowed to vary across different individuals. We present estimates based on two different general assumptions: first, the POOLED regression results where the unobserved factors are assumed to be identical for everyone in the sample and second, the PANEL results where these factors are allowed to vary across the sample.[19]

Finally, a time-varying error term, ε_{it}, is included in the estimation and is conventionally assumed to follow the standard normal distribution with mean equal to zero and a variance equal to a constant to be estimated, σ_{ε}^{2}.

5.1. The Source of Wage Variation among the Low Paid

Our first attempt to understand the determinants of wage levels for the low paid examines the wage in the year individuals are first observed to be low paid. This exercise can be seen as a descriptive study to demonstrate how heterogeneous the low-paid workers actually are. In Table 12 we present the results using a limited amount of demographic information such as gender, age, major city residence, education, disability status, and employment characteristics such as years of total work experience (and its square) and job tenure (job-specific experience) in years.[20] Table C1 in Appendix C introduces additional employment details such as occupation, industry, union status, full-time employment, casual work and firm size.

First we note that the model fit (as measured by the *R-square* statistic) is poor. Using the POOLED model, only 5 percent of the variation in current wages can be explained by the variables in the model. By including additional employment characteristics, the model fit improves only slightly to 7 percent for the POOLED model and 10 percent for the PANEL model (see Table C 1 in appendix C). A comparable model for higher-paid workers (not reported) produced a fit of around 20 to 30 percent. The poor fit for the low-

[19] The PANEL Regressions can be either Fixed Effects or Random Effects depending on the assumption about the correlation between unobserved and observed characteristics. The latter specification requires this correlation to be zero, while the former relaxes this assumption. Appendix B provides further details about these two types of model.

[20] We have experimented with the degree of demographic detail we can include in the analysis. Inclusion of family type, country of birth, more detailed education categories and state did not change the results and these variables were generally insignificant.

Table 12 – Wage Variation among Low–Paid Workers

	Pooled Regression		*Panel Fixed Effects*	
	Coefficient	*S.E.*	*Coefficient*	*S.E.*
Male	0.01	0.02		
Age(Ref: 21-29)				
30-44	-0.09**	0.03		
45-54	-0.13**	0.05		
55-64	-0.12*	0.05		
Major city	-0.01	0.02	0.07	0.12
Education				
Degree or higher	-0.06+	0.03	0.04	0.14
Full-time Student	-0.03	0.03	-0.10	0.06
Disabled	-0.12**	0.03	-0.01	0.03
Experience				
Work Exp.	0.01+	0.00	0.05	0.04
$(\text{Work Exp}/10)^2$	-0.01	0.01	-0.03	0.03
Emp. Tenure unknown	-1.00**	0.38		
Employment Tenure	-0.01**	0.00	0.00	0.00
Constant	2.32**	0.03	1.47*	0.61
R-Square	0.05		0.02	
Sample Size	3179		3179	

Note: +,*,** indicate significance at 10%, 5% and 1%, respectively. The dependent variable is the natural logarithm of real hourly wages at time *t*. Models include time dummies.

paid sample may be due to the relatively small sample size and the limited variation in wage rates within the low-paid sample. Alternatively, standard human capital models that have been shown to be successful in explaining wage variation may not be appropriate when we look at low pay in isolation. This concern goes beyond the estimation methods, because it implies that the return to an investment in human capital for a low-paid worker is not large enough to be identified by the researcher. This is likely to be because low-paid workers do not have (time or opportunity to accumulate) enough investments to begin with. Another alternative explanation is that low-paid work is essentially a bad match, in the sense that it requires skills that are not transferable from previous work experience or from education.[21] The low-paid work may be *chosen* out of convenience or necessity.

We proceed with our discussion of individual results from Table 12. According to the POOLED results, the wage decreases with age in the low-paid sample. Low-paid workers in the age category over 55 years are expected to receive 12 percent less than the youngest group (aged 21-29 years). The negative coefficient on educational attainment is surprising. This may be due to individuals who are currently studying. Long-term health conditions appear to be significant in wage setting. A disabled low-paid worker is expected to earn 12 percent less than a non-disabled low-paid worker. Work experience is rewarded in low-paid work. Every additional year of experience brings a one percent increase to the worker's wage. Time spent in the same job has the opposite effect. Compared to a new low-paid worker, a low-paid worker with one year of additional job tenure is expected to earn one percent less in wages.

Appendix C reports estimates based on the augmented model where additional employment-related details are included in the wage equation (see Table C1). It appears that work experience is no longer significant. This may be due to industry-wide experience differences. Employment tenure in a low-paid job is still expected to decrease the wage of low-paid workers. Industry appears to be significant in explaining the variation in wage levels. After controlling for occupational and other observed differences, the low-paid workers from the Property and Business sector, and those in Health and Community services are expected to earn the least.

The PANEL results do not add much to our understanding of wage determinants for the low paid. It should be noted that due to the estimation methodology, the PANEL fixed effects estimates only capture the effect of a variable if this variable has changed during

[21] Here a bad match is defined as the worker being over-skilled for the low-paid job. For a recent study on over-skilling in Australia, see Mavromaras *et al.* (2009).

the sampling period for an individual.[22] If there are not enough individual changes within the sample, the estimates are likely to be insignificant.

5.2. Wage Progression of Initially Low-Paid Workers

This section presents results of the wage progression for the initially low paid. We estimate the model introduced in the previous section by using the wage of later years (up to 3 years) as the dependent variable. The explanatory variables are measured in the initial period t in which the individual is observed to be low paid. Table 13 presents the POOLED model estimates, and Table 14 presents the estimates from the PANEL model.

The education premium appears to be increasing with time. The initially low-paid worker with a bachelor degree or higher degree enjoys an estimated wage increase of 16 percent per year. The wage growth attributable to the education is 18 percent for two years and 27 percent for three years. A disabled worker is expected to have 20 percent lower wage growth than a comparable worker without a disability. This negative impact persists in the second and the third years (due to the disability, wages are expected to be 20 and 17 percent lower, respectively). An additional year of work experience at the base year contributes to wage levels by two percent for the first year and one percent for the second year. There is no significant effect of initial differences in work experience on the wage levels in year t+3.

The model fit is slightly better than in Table 12. This implies that as the low-paid workers progress, their wages become more and more related to observed characteristics of their productivity; such as experience and education.[23] Those who are temporarily low-paid have now had a chance to move on to a higher-paying job. In Appendix C we report the results of the augmented model where additional employment details are added.

[22] That is, the fixed effects model estimates the effects of changed characteristics on the wages of the switchers, whereas the POOLED model pools both switchers and not-switchers and estimates the effects of characteristics on all wages not allowing for individual differences in unobserved heterogeneity.

[23] *R-square* statistics from the models in Tables 13 and 14 are still relatively poor. The same models applied to higher-paid workers have a goodness of fit of around 20 percent.

According to the results in Table C 2, blue collar workers have a wage decline of 7 percent. Full-time employment is shown to have a 6 percent wage premium, but the coefficient is significant only at the 10 percent level. A surprising finding is that after controlling for industry and occupation, the casual worker at the base year is expected to have a wage increase of around 6 percent the next year. The industry of employment in the base year is shown to have no effect on the wages at *t*+1. Low-paid work in a small firm is estimated to decrease the next year's wage by 7 percent.

Table 13 – Wage Progression of the Low Paid – Pooled Regressions

	Wage at t+1		*Wage at t+2*		*Wage at t+3*	
	Coefficient	*S.E.*	*Coefficient*	*S.E.*	*Coefficient*	*S.E.*
Male	0.01	0.03	0.03	0.03	0.01	0.04
Age(Ref: 21-29)						
30-44	-0.09*	0.04	-0.10*	0.04	-0.10+	0.06
45-54	-0.18**	0.07	-0.15*	0.07	-0.15	0.09
55 - 64	-0.13	0.09	-0.20*	0.10	-0.17	0.11
Major city	0.03	0.03	0.02	0.03	0.01	0.04
Education						
Degree or higher	0.16**	0.05	0.18**	0.04	0.27**	0.05
Full-time Student	0.09*	0.04	0.16**	0.05	0.13*	0.05
Disabled	-0.20**	0.05	-0.20**	0.05	-0.17**	0.06
Experience						
Work Exp.	0.02*	0.01	0.01*	0.01	0.01	0.01
$(\text{Work Exp}/10)^2$	-0.03	0.02	-0.02	0.02	-0.02	0.02
Emp. Tenure unknown	-0.43	0.38	-		-	
Employment Tenure	-0.01*	0.00	-0.01	0.01	-0.01**	0.01
Constant	2.54**	0.05	2.62**	0.05	2.67**	0.06
R-square	0.06		0.08		0.11	
Sample Size	1739		1199		758	

Note: +,*,** indicate significance at 10%, 5% and 1%, respectively. The dependent variable is the natural logarithm of real hourly wage at *t*+1, *t*+2 and *t*+3, respectively. Models include time dummies.

The PANEL estimates from Table 14 are not very informative since after removing the time-invariant factors from the model almost none of the coefficients are significant. As was the case for the POOLED model, the goodness of fit for the model improves slightly when we focus on future years. The variables that are significant tend to have the opposite sign to what is expected. Both work experience and education, for example, are estimated to affect future wages negatively. After controlling for additional employment characteristics (reported in Table C 2 in Appendix C) the direction of the impact of education and experience is as expected, however they are not statistically significant.

Table 14 –Wage Progression of the Low Paid – Panel Fixed Effects Regressions

	Wage at t+1		*Wage at t+2*		*Wage at t+3*	
	Coefficient	*S.E.*	*Coefficient*	*S.E.*	*Coefficient*	*S.E.*
Major city	-0.24	0.25	0.06	0.24	-0.06	0.24
Education						
Degree or higher	0.21	0.23	0.01	0.23	-0.75*	0.30
Full-time Student	0.01	0.12	-0.11	0.12	-0.08	0.17
Disabled	-0.06	0.06	0.04	0.07	0.15	0.09
Experience						
Work Exp.	0.04	0.09	-0.18+	0.10	-0.67**	0.18
$(\text{Work Exp}/10)^2$	-0.06	0.07	0.20*	0.08	0.37*	0.17
Emp. Tenure unknown	-		-		-	
Employment Tenure	-0.01	0.01	0.00	0.01	0.00	0.01
Constant	2.18+	1.31	4.48**	1.49	12.65**	2.97
R-square	0.07		0.17		0.18	
Sample Size	1739		1199		758	

Note: +,*,** indicate significance at 10%, 5% and 1%, respectively. The dependent variable is the natural logarithm of real hourly wage at *t*+1, *t*+2 and *t*+3, respectively. Models include time dummies.

Controlling for Selection Bias

An important issue when examining any results from wage modelling is potential sample selection bias. The issue arises because we do not observe the wage rate and hours of work for those for whom the reservation wage exceeds the market wage. That is, the group that does not work because the wage offered is lower than the minimum rate the individuals find acceptable. As a result, the observed wages may not be representative of the complete group of interest. The problem is particularly important for low-paid employment since employment – unemployment cycles are more frequently observed among this group of workers. In addition, knowing that a current educational qualification provides an unacceptably low wage level, a potentially low-paid individual may stay out of the work force and instead invest in human capital. This possibility can bias the impact of education for the observed individuals downwards. As mentioned earlier, wage equations can be extended to deal with the sample selection bias (Heckman, 1979). We check for selection bias in Appendix C: Table C 3 provides the estimates using the Heckman selection method. The results suggest that the wage estimates are subject to selection bias. However, the similarity of the 'corrected' estimates to the results provided in this section implies that the impact of the selection bias is relatively low.

5.3. The choice between Unemployment and Low-Paid Employment

A priori, the causal effect of job and employment tenure on wage growth is ambiguous. There are two conflicting theories. Human capital theory suggests that job mobility (including churning between unemployment and low-paid jobs) is associated with lower productivity and higher instability. Through experience and on-the-job training, workers acquire specific skills that contribute to productivity and to wages. If the predictions of human capital theory are correct, we would expect to observe higher wage growth for those who work continuously with the same employer. Similar arguments can be made for workers who had continuous employment spells although they changed employers. Despite the expectation that the beneficial effect of on-the-job training is less for job changers, they are still expected to benefit from continuous work by avoiding the scarring effect of unemployment. The scarring effect works through two channels. First, prospective employers may use the unemployment spell as a signal of lack of employability. Second, unemployment spells result in depreciation of acquired human capital. As a result, a longer unemployment spell is expected to be associated with worse future labour force performance.

The theory of job matching, on the other hand, suggests a positive effect of job mobility on wage growth. According to this view, if workers leave their –presumably low-paid– jobs in pursuit of a ‘better’ match, they may have higher likelihoods of finding higher-paying jobs compared to the workers who are ‘stuck’ with bad matches (low-paid jobs). The time spent in low-paid employment restricts the time available for the search for better employment. If a specific low-paid job does not contribute to human capital at all, low-paid employment can also be seen as reducing the time available for productivity-increasing activities, for example education or training.

In order to test the predictions of these two alternative theories we modify the wage equation (and our sample) slightly to allow a comparison of the impact of being unemployed in the past periods to the impact of being on low pay in the past periods. The dependent variable in question is again the natural logarithm of hourly wages in the current year. Our model uses a similar approach to Stewart (2007) by including past low-pay states and past unemployment states as explanatory variables. The model can be written as follows:

$$\ln(w_{it}) = \beta_1 X_{it} + \beta_2 Z_{it} + \delta_1 LP_{it-1} + \delta_2 UE_{it-1} + \alpha_i + \varepsilon_{it} \qquad (2)$$

where $LP_{it\text{-}1}$ and $UE_{it\text{-}1}$ are binary variables that indicate the low-pay status and unemployment in the previous wave. The sample is restricted to individuals who are in the labour force (employed or looking for work) for as long as they are observed in HILDA. Once again we report estimation results from POOLED and PANEL regressions separately. However, this time we utilise a random effect specification for the panel data results due to potential bias associated with the fixed effect specification when a lagged dependent variable is included in the model.[24] Another advantage of random effect specification is that time-invariant characteristics such as gender and age categories can be included in the panel data model. Two specifications are estimated: the first

[24] Model (2) is essentially a dynamic panel data model where fixed effect models are shown to perform extremely badly. The technical reader is referred to Judson and Owen (1999) for a recent presentation of this problem.

specification only includes the past employment status from *t*-1, the second specification also includes the status at *t*-2. The results are reported in Table 15.

Past employment status variables are highly significant. Both status at *t*-1 and *t*-2 appear to have an independent effect on current wage levels. Based on the POOLED results, the reduction in the expected wage due to past employment states is substantial. A previously low-paid worker is expected to suffer a wage penalty of 42 percent if he or she is still employed. This impact is almost twice as much as the wage penalty endured by the previously unemployed. Some of the large impact of the past low-paid status can be explained by the low-paid status at *t*-2. The effect of past low-paid employment drops to -36 percent after we also include the low-paid status from period *t*-2. There seems to be an independent effect of the *t*-2 variable. The combined effect of being on low pay for two consecutive periods translates to a massive 64 percent decline in current wages. This finding supports earlier findings on the persistence of the low-paid state. When we compare the persistently low paid to persistently unemployed, we observe that the penalty for being unemployed in *t*-1 and *t*-2 is much less, around 30 percent (a 14 percent reduction associated with *t*-1 and a 16 percent reduction associated with *t*-2).

The conclusions drawn based on the PANEL estimates are considerably different. These suggest that a big portion of the wage-dampening effect of past low-paid employment is due to individual-specific unobserved factors. Not only is the wage penalty for the previously low paid much lower than the POOLED estimates (around 7 percent), it is also 3 percentage points lower than the wage decline for the previously unemployed estimated in the PANEL model. The estimates from the POOLED results may be an artefact of the differences in ability, motivation or preferences towards work. Some of the high-ability individuals who suffer from a temporary market disequilibrium may prefer unemployment, knowing that a better match for their unobserved ability (in the form of a higher-paid job) should be available soon. Similarly, low-ability individuals may settle in a low-paid job if they believe this is a good match for their skill endowment. In this case, the remarkable wage penalty estimated by the POOLED model reflects, at least partly, differences in unobserved abilities, rather than the direct effect of being in a low-paid job.

Table 15 – The Impact of Being Low Paid on Future Wages

	Pooled Regression				*Panel Random Effects*			
	Coef.	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*
Male	0.13**	0.01	0.13**	0.01	0.14**	0.01	0.14**	0.01
Age(Ref: 21-29)								
30-44	0.01	0.02	0.00	0.02	0.02	0.01	0.01	0.02
45-54	-0.04+	0.03	-0.04	0.03	-0.02	0.02	-0.03	0.02
55 - 64	-0.06+	0.03	-0.05	0.03	-0.06*	0.02	-0.06*	0.03
Major city	0.08**	0.01	0.06**	0.01	0.08**	0.01	0.07**	0.01
Education								
Degree or higher	0.29**	0.01	0.27**	0.01	0.31**	0.01	0.30**	0.01
Full-time Student	0.02	0.04	0.00	0.05	0.00	0.02	-0.05+	0.03
Disabled	-0.05**	0.01	-0.05**	0.01	-0.03**	0.01	-0.03**	0.01
Experience								
Work Exp.	0.02**	0.00	0.01**	0.00	0.02**	0.00	0.02**	0.00
$(\text{Work Exp}/10)^2$	-0.03**	0.01	-0.02**	0.01	-0.04**	0.00	-0.03**	0.01
Emp. Tenure unknown	-0.25+	0.15	-0.06	0.13	-0.33**	0.11	-0.08	0.14
Employment Tenure	0.01**	0.00	0.00**	0.00	0.00**	0.00	0.00**	0.00
Past Employment								
Low paid at *t-1*	-0.42**	0.02	-0.36**	0.02	-0.07**	0.01	-0.12**	0.01
Low paid at *t-2*			-0.28**	0.02			-0.11**	0.01
Unemployed at *t-1*	-0.22**	0.02	-0.14**	0.03	-0.10**	0.02	-0.10**	0.03
Unemployed at *t-2*			-0.16**	0.02			-0.10**	0.02
Constant	2.65**	0.02	2.75**	0.03	2.55**	0.02	2.63**	0.02
R-Square	0.27		0.30		0.26		0.30	
Sample Size	15792		10626		15792		10626	

Note: +,*,** indicate significance at 10%, 5% and 1%, respectively. The dependent variable is the natural logarithm of hourly wage at time *t*. All models include time dummies.

Once the unobserved ability is controlled for in the PANEL approach, unemployment is shown to have a more damaging impact on the wage levels than low-paid work does. Alternatively, individual preferences towards work and unobserved match quality can explain discrepancies between POOLED and PANEL results. Section 4.5 shows that job satisfaction can play an important role in the wage progression of low-paid workers. Low-paid workers who are relatively happy with their job are less likely to look for high wage growth in future periods. Building on this finding we can speculate that workers who are not satisfied with their current job prospects (that is, those with a low job match quality) may choose to look out for a better match. A better match may be achieved by additional investment in human capital. Ultimately, the wage growth gap estimated in the POOLED model could be attributable to differences in unobserved preferences.

Finally, it is worthwhile noting that our observations on possible sources of the wage gap between previously unemployed and previously low paid do not seem to hold entirely for the persistently low paid. We observe that the combined wage penalty of being in a low-paid job for two consecutive periods is estimated to be much lower in the PANEL model (23 percent) than in the POOLED model (64 percent). However, this effect is still slightly higher than the effect for the persistently unemployed. Those who were unemployed in periods *t*-1 and *t*-2 suffer a wage loss of around 20 percent in the current period.

5.4. The Impact of Multiple Employment Pathways on Future Wages

Given the strong results obtained in the Section 5.3, the final section of the multivariate analysis examines the impact of past employment states more closely. Namely, we investigate the effect of the following 9 possible combinations of employment states in periods $t-1$ and $t-2$:

ll:	Low Paid	at *t*-1 and *t*-2
uu:	Unemployed	at *t*-1 and *t*-2
lh:	Higher Paid	at *t*-1 and *t*-2
lu:	Low Paid	at *t*-1 and Unemployed at *t*-2
hl:	Higher Paid	at *t*-1 and Low Paid *t*-2
hu:	Higher Paid	at *t*-1 and Unemployed at *t*-2
ul:	Unemployed	at *t*-1 and Low Paid *t*-2
uh:	Unemployed	at *t*-1 and Higher Paid *t*-2

Our approach is related to the methodology used by Buddelmeyer *et al.* (2007) where the above pathways are used to explain the probability of entering unemployment in period *t*. Slightly modifying their notation to serve our purpose, model (2) can be rewritten as follows;

$$\ln(w_{it}) = \beta_1 X_{it} + \beta_2 Z_{it} + \sum_k \delta_k (s_{it-1})(s_{it-2}) + \alpha_i + \varepsilon_{it} \qquad (3)$$

where s_{it-1} is a dummy variable denoting one of the three states (low pay, higher pay and unemployment) in time $t-1$ and s_{it-2} is a dummy variable denoting one of the same three states in time $t-2$. The model can be estimated by including 8 binary variables in the wage equation. The state '*hh*' is left out of the model, therefore all pathway coefficients represent the relative (percentage) wage difference between a given pathway and being in higher pay in the two previous periods. As in the previous section, our preferred panel data specification utilises the random effects approach due to the dynamic nature of the model.

Table 16 presents the regression results. In our discussion, we focus on the variables that capture the impact of past employment states. In Buddelmeyer *et al.* (2007), it is shown that differences in past pathways do not significantly contribute to the variation in current unemployment levels. Namely, a previously high-paid worker is not less likely to be unemployed than a previously low-paid worker. However, our results suggest that there is a considerable impact of past employment status on current wage levels. The pathway variables are jointly significant in both models. The findings from the multiple pathway analysis are consistent with the estimates in the previous subsection. The 20 percentage point wage gap between the persistently low paid ('*ll*' state) and the persistently unemployed ('*uu*' state) disappears when unobserved factors are controlled for. The wage penalty of persistent low pay is estimated to be 25 percent in the PANEL model, compared to the POOLED estimate of 65 percent. The wage of those who had a spell of unemployment before being low paid ('*lu*' state) is 23 percent lower than persistently high-paid workers ('*hh'* state). Workers who become unemployed after a low-paid spell

Table 16 – The Impact of Multiple Pathways

	Pooled Regression		*Panel Random Effects*	
	Coef.	*S.E.*	*Coef.*	*S.E.*
Male	0.13**	0.01	0.14**	0.01
Age (Ref: 21-29)				
30-44	0.00	0.02	0.01	0.02
45-54	-0.04	0.03	-0.03	0.02
55-64	-0.05	0.03	-0.06*	0.03
Major city	0.06**	0.01	0.07**	0.01
Education				
Degree or higher	0.27**	0.01	0.30**	0.01
Full-time Student	0.01	0.05	-0.05	0.03
Disabled	-0.05**	0.01	-0.03**	0.01
Experience				
Work Exp.	0.01**	0.00	0.02**	0.00
$(\text{Work Exp}/10)^2$.	-0.02**	0.01	-0.03**	0.01
Emp. Tenure unknown	-0.06	0.13	-0.08	0.14
Employment Tenure	0.00**	0.00	0.00**	0.00
Past Pathways (Ref: hh):				
ll	-0.65**	0.04	-0.25**	0.02
uu	-0.42**	0.06	-0.25**	0.05
lh	-0.35**	0.02	-0.09**	0.02
lu	-0.44**	0.06	-0.23**	0.05
hl	-0.28**	0.02	-0.10**	0.01
hu	-0.14**	0.03	-0.08	0.03
ul	-0.30**	0.06	-0.17*	0.07
uh	-0.11*	0.04	-0.07+	0.04
Constant	2.74**	0.03	2.63**	0.02
R-Square	0.30		0.30	
Sample Size	10626		10626	

Note: +,*,** indicate significance at 10%, 5% and 1%, respectively. The dependent variable is the natural logarithm of the hourly wage at time *t*. All models include time dummies.

(‘*ul*’ state) are doing slightly better, with a wage penalty of 17 percent. A high-pay spell in the past is associated with higher wage growth at time *t*; in all pathways that include a high-paid period (‘*lh*’, ‘*hl*’, ‘*hu*’, and ‘*uh*’ states) there is a beneficial effect on wage growth compared to the other states not including a high-pay spell. The results from the PANEL model are conditional on demographic and employment characteristics at time *t* as well as unobserved individual factors. Therefore, estimated differences in wage growth are not due to observed and unobserved discrepancies in ability and preferences.

6. Conclusion

The main objective of this report is to analyse the factors associated with the wage progression of low-paid workers. We contribute to recent Australian research on low-paid employment by analysing the wage levels directly rather than focusing on transition rates between low-pay and high-pay states. A major advantage of our approach is that the wage progression of all low-paid workers, not only those with wages passing an arbitrary threshold, is included in the analysis. We also allow for gender differences.

The descriptive analysis of this report focuses on the role of three general categories of information. First, demographic characteristics are analysed. Educational attainment is shown to be very important for the wage advancement of the initially low-paid workers. The probability of being low paid for those with a bachelor or higher degree is estimated to be 3.1 percent compared to a probability of 11.1 percent for workers with secondary schooling. Wage growth is also reported to be considerably higher for the highly educated. Annual wage growth rates for the most educated of the low-paid sample are estimated to be 52.8 percent for men and 50.3 percent for women. These rates were only 25.6 percent for men and 26.7 percent for women with the lowest level of education. The findings of this report highlight the importance of low-paid jobs for the disabled. They show that disabled individuals who stay employed in a low-paid job are as likely to experience wage increases as low-paid workers who do not have disabilities. This indicates that low-paid work may be a stepping stone for some of the most disadvantaged sections of the labour force.

Second, employment-related factors are investigated. Our estimates suggest that wage growth is more likely in the public sector and in large firms. The employers that provide on-the-job training are also shown to have workers who enjoy higher wage growth rates. The wage growth for the low paid with on-the-job training is estimated to be 10 percentage points higher than for the low paid who do not have access to training. Labour market status in the past and past income support receipt are demonstrated to be very important as well. Supporting earlier findings by Buddelmeyer *et al*. (2007), low pay is estimated to be a persistent state. The previously low paid are more likely to be currently employed in low-paid jobs, and they also have higher tendencies to exit employment compared to the previously higher paid. Additionally, our findings using past income support reliance point to a close relationship between the degree of reliance and the wage growth of the low paid. In order to identify causal effects of income support on the wage progression, we use welfare reliance from a previous period. Compared to 4.9 percent of previously non-reliant men, 15.7 percent of the weakly reliant, 18.9 percent of the moderately reliant and 30.7 percent of the heavily reliant are employed as low-paid workers. Wage growth of low-paid workers is reported to be closely related to their previous income support experience as well. With the exception of the heavily reliant, the wage growth decreases with the degree of past reliance, especially for men. Annual wage growth of around 30 percent for the non reliant is higher than the wage growth of the weakly and the moderately reliant (both around 22 percent).

The final section of the descriptive analysis is reserved for the role of preferences. Our hypothesis is that, for some, persistence in low-paid employment can be explained by the self reported satisfaction levels about different aspects of the low-paid job in question. We speculate that individuals who are relatively happy with certain characteristics of the low-paid jobs have fewer incentives to progress to higher-paid employment. Supporting our hypothesis, both men and women are shown to have lower wage growth if they are initially satisfied with their work. Wage growth for men who are satisfied is estimated to be around 10 percentage points less than for men who are not satisfied. For women, the estimated wage growth difference between satisfied and non-satisfied low-paid workers is around 6 percentage points. Satisfaction with working hours of the low paid is also found to be important for men: male low-paid workers are more likely to exit low pay if they are not satisfied with their working hours. We do not observe the same pattern for low-paid women.

The aim of the multivariate analysis of this project is twofold. First, by employing a standard model of human capital we explore the source of variation in wages among low-paid workers. The wage differences that can be attributed to differences in observed characteristics are surprisingly low. Our basic model can only explain 5 percent of the variation in the current wages of the low paid. The same type of model is reported to explain around 30 percent of the variation in wages of higher-paid workers. We draw two rather conflicting conclusions from this finding. First, since low-paid workers generally have very low levels of human capital, observed individual factors contribute very little to the wage determination process. The low-paid job may be *chosen* out of convenience or financial necessity (both are time-variant unobserved factors for which we cannot control). Second, low-paid work can essentially be a '*bad match*', in the sense that the observed human capital characteristics of the worker (for example work experience and education) are irrelevant for the requirements of the low-paid job. This finding is supported by results from Mavromaras *et al.* (2009) who found a high degree of over-skilling among low-paid workers in Australia.

The second aim of the multivariate analysis is to provide an in-depth look into wage penalties incurred by the persistently low paid. Our approach indirectly examines the choice between low-paid work and unemployment. Our estimates suggest that a significant portion of the lower wage that is due to low-paid work in the past can be explained by unobserved characteristics such as motivation, ability, preferences and job match quality. Without controlling for these factors, past low-paid employment is associated with a 45 percent lower wage for the currently employed. Not controlling for unobserved effects, the impact of past unemployment is estimated to be a 22 percent lower wage. The conclusions drawn after unobserved factors are taken into account are remarkably different. The estimate of the past low-paid wage penalty, free of unobserved heterogeneity, is around 7 percent, which is not only much lower than the finding based on the model which does not control for unobserved factors, but it is also 3 percentage points lower than the wage penalty estimated for the previously unemployed. This may indicate that the wage gap between the previously low paid and the previously unemployed is largely due to unobserved differences in ability or preferences. Namely, high-ability individuals who are temporarily out of employment may prefer not to apply for low-paid jobs knowing that a better match for their unobserved ability should be available soon. Similarly, workers who are not satisfied with current job prospects may choose to wait for a better match. Since a better match can be achieved in the form of additional investment in human capital, the differences in preferences translate into higher wages in future periods.

Finally, we investigate the impact of two-year pathways on current wages. The role of individual-specific unobserved factors is highlighted again. After controlling for these factors, wage penalties incurred by the persistently low paid and the persistently unemployed are estimated to be the same: a 25 percent lower hourly wage than those who were in a higher-paid job in the previous two years.

7. References

Black, D., Oguzoglu, U., and Wilkins, R. (2006) “Reliance on Income Support in Australia: A Dynamic ‘Income-Based Analysis’ Using Payments Administration Data”, Report prepared for the Australian Government Department of Education, Employment and Workplace Relations.

Booth, A., and Wood, M. (2006) “Back-to-front Down-under? Estimating the Part-time/Full-time Wage Differential over the Period 2001-2003”, The Australian National University Centre for Economic Research Discussion Paper No. 525.

Buddelmeyer, H., Wooden, M. and Ghantous, S. (2006) “Transitions from Casual Employment in Australia”, Report prepared for the Australian Government Department of Education, Employment and Workplace Relations.

Buddelmeyer, H., Lee, W.-S., Wooden, M. and Vu, H. (2007) “Low Paid Dynamics: Do Low Paid Jobs Lead to Increased Earnings and Lower Welfare Dependency over Time?” Report prepared for the Australian Government Department of Education, Employment and Workplace Relations.

Cai, L. and Kalb, G. (2006) Health Status and Labour Force Participation: Evidence from Australia, *Health Economics,* 15, 241-261.

Capellari, L. and Jenkins, S.P. (2004), “Modelling Low Pay Transition Probabilities, Accounting for Panel Attrition, Non-response, and Initial Conditions”, CESifo Working Paper No. 1232, July.

Dunlop Y. (2000) Labour Market Outcomes of Low Paid Adult Workers: An Application Using the Survey of Employment and Unemployment Patterns, ABS Occasional Paper 6293.0.00.005, Australian Bureau of Statistics, Canberra.

Freebairn, J., Tseng, Y., and Fok, Y.K. (2008) “Pathways to Higher Pay”, Report prepared for the Australian Government Department of Education, Employment and Workplace Relations.

Gladden, T and Taber, C. (2000) “Wage Progression Among Less Skilled Workers” in *Finding Jobs: Work and Welfare Reform*, Card D. and Blank R. (eds), Russell Sage Foundation , New York.

Grossberg, A., and Sicillian, P. (1999) “Minimum Wages, On-the-Job Training and Wage Growth”, *Southern Economic Journal*, 65 (3), pp. 539-556.

Heckman, J. J. (1979) “Sample Selection Bias as a Specification Error” *Econometrica*, 47 (1), pp. 153-161.

Judson, R.A. and Owen, A.L. (1999). “Estimating dynamic panel data models a guide for macroeconomists” *Economics Letters*, 65, Issue 1, pp. 9-15.

Mavromaras, K., Oguzoglu, U., and Black, D. (2007) “Disability and Employment in the Australian Labour Market.” Report prepared for the Australian Government Department of Education, Employment and Workplace Relations.

Mavromaras, K., McGuinness, S., and King, Y. (2009) “Assessing the Incidence and Wage Effects of Overskilling in the Australian Labour Market” *The Economic Record*, 85(268), pp. 60-72.

McGuinness, S. and Freebairn, J. (2007) “Who Are the Low Paid?” *Australian Journal of Labour Economics*, 10 (1) pp. 17-37.

Oguzoglu, U. (2007). “Severity of Work-limitation and Work”, Melbourne Institute Working Paper Series No. 30/2007.

Oguzoglu, U. (2009). “Dynamics of Work-limitation and Work in Australia”, forthcoming in *Health Economics*.

Richardson, S. and Miller-Lewis, L. (2003) “Low Wage Jobs and Pathways to Better Outcomes”, National Institute of Labour Studies, Monograph Series Number 7.

Stewart, M.B. (2007) “The Inter-related Dynamics of Unemployment and Low Pay”, *Journal of Applied Econometrics*, 22 (3), 511-531.

Watson, I. (2007) “Low Paid Workers in Australia: Insights from HILDA”, Report prepared for IR Victoria.

Watson, N. and Wooden, M. (2004). “The HILDA Survey Four Years On”, Australian Economic Review, 37: 343-349.

Watson, N. and Wooden, M. (2006). “Modelling Longitudinal Survey Response: The Experience of the HILDA Survey”, HILDA Project Discussion Paper series No. 2/06, University of Melbourne (http://melbourneinstitute.com/hilda/hdps/HILDA DP 2.06.pdf).

Webster B., Mavromaras K., and Oguzoglu, U. (2007) “Skill Shortages and the Absence of Wage Pressures”, Report prepared for the Australian Government Department of Education, Employment and Workplace Relations.

Wilkins, R. (2004) “The Effects of Disability on Labour Force Status in Australia”, *Australian Economic Review*, 37 (4) pp. 359-382.

Zhang, X. (2002) “Wage Progression of Less Skilled Workers in Canada: Evidence from the SLID (1993-1998)”, Statistics Canada Analytical Studies Branch Working Paper No. 11F0019 / 194.

Appendix A: Additional Characteristics of Trimmed Sample

Table A 1 - Labour Force Characteristics of those who are Trimmed from the Sample

	Frequency of those who are Trimmed from the Sample	Proportion within those Trimmed from the Sample (%)
Employment Status		
Full-time	293	88.5
Part-time	38	11.5
Job Type		
Fixed-term Contract	22	6.7
Permanent / On-Going	145	43.8
Casual	55	16.6
Occupation		
Managers and Administrators	103	31.2
Associate Professionals	66	20.0
Tradespersons and Related Workers	40	12.1
Advanced Clerical and Service Workers	4	1.2
Intermediate Clerical, Sales and Service Workers	30	9.1
Intermediate Production and Transport Workers	50	15.2
Elementary Clerical, Sales and Service Workers	9	2.7
Labourers and Related Workers	28	8.5
Industry		
Agriculture, Forestry and Fishing	33	10.1
Mining	11	3.4
Manufacturing	30	9.2
Electricity, Gas and Water Supply	2	0.6
Construction	29	8.9
Wholesale Trade	15	4.6
Retail trade	39	12.0
Accommodation, Cafes and Restaurants	20	6.1
Transport and Storage	36	11.0
Communication Services	1	0.3
Finance and Insurance	5	1.5
Property and Business Services	29	8.9
Government Administration and Defence	7	2.2
Education	21	6.4
Health and Community Services	25	7.7
Cultural, Recreational and Personal Services	23	7.1

Appendix B: Estimation of the Panel Data Models

In this appendix we provide some details of the estimation methodology used in our panel data analysis.

Fixed Effects Model

A fixed effects model may be represented by an equation of the form:

$$y_{it} = \beta X_{it} + \alpha_i + \varepsilon_{it}$$

where y_{it} is an individual's hourly wage in period t, and α_i contains a constant term and a set of individual-specific dummy variables. The main advantage of fixed effects models is that the assumption that unobserved effects are uncorrelated with observed characteristics captured by X_{it} can be relaxed. For example, it could be argued that unobserved characteristics such as working preferences may be a major determinant of occupation choice, which in turn may affect wage progression. Unfortunately, the relaxation of this assumption comes at a price – namely, we cannot include any observed time-invariant characteristics (such as country of birth) in the analysis. Fixed effects estimation does not ignore the effect of time-invariant variables, since the estimate of β is conditional on time-invariant characteristics, but it does not produce explicit estimates of their effects.

In practice, with a large dataset containing many individuals, it is not computationally feasible to estimate the effect of each α_i. The usual approach, which we take as well, is to use the Least Squares Dummy Variable (LSDV) method, which eliminates all fixed effects from the model before the estimation of the parameters of interest, β. This approach essentially 'wipes out' the α_i. by transforming the model such that each variable represents the deviation from individual means, that is:

$$y_{it} - \overline{y}_i = \beta\left(X_{it} - \overline{X}_i\right) + \varepsilon_{it} - \overline{\varepsilon}_i$$

where $\overline{X}_i$ represents the average time-variant characteristics of an individual recipient:

$$\overline{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it} \tag{1}$$

Ordinary least squares (OLS) regression of the transformed model produces the fixed effects estimates.

Random Effects Model

An alternative assumption in a panel model could be that unobserved individual-specific terms are distributed randomly across individual recipients. This assumption leads to a random effects model, which can be represented as:

$$y_{it} = \beta X_{it} + \alpha_i + \varepsilon_{it}$$

In this model, the individual-specific effect α_i and the error term ε_{it} are assumed to follow Normal distributions with means of zero and variances of σ_α^2 and ${\sigma_\varepsilon}^2$, respectively.

Under the assumption of homoscedasticity, that is constant variances σ_α^2 and σ_ε^2, the model parameters β can be estimated by Generalised Least Squares (GLS). The GLS approach requires a two-step strategy, where in the first step consistent estimates of the variances are obtained by OLS estimation from pooled data. The second stage produces the estimated parameters β.

In random effects models the marginal effects of time-invariant characteristics are separately identifiable. Therefore, unlike fixed effects models, we can quantify the effect of variables such as place of birth and make inferences about them. However, if the assumption of zero correlation between observed and unobserved traits is not correct, the random effects model produces biased estimates for both time-invariant *and* time-varying variables.

Appendix C: Additional Regression Results

Table C 1 - Wage Variation among Low Paid – Including Additional Information

	Pooled Regression		*Panel Fixed Effects*	
	Coefficient	*S.E.*	*Coefficient*	*S.E.*
Male	-0.01	0.02		
Age(Ref: 21-29)				
30-44	-0.07*	0.03		
45-54	-0.10*	0.05		
55 - 64	-0.05	0.05		
Major city	-0.02	0.02	0.09	0.13
Education				
Degree or higher	-0.03	0.03	0.08	0.14
Full-time Student	-0.01	0.03	-0.13*	0.06
Disabled	-0.12**	0.03	0.00	0.03
Experience				
Work Experience	0.01	0.00	0.06+	0.04
$(\text{Work Experience}/10)^2$	-0.01	0.01	-0.02	0.03
Employment Tenure unknown	-0.99**	0.34	-	
Employment Tenure	-0.01**	0.00	0.00	0.00
Full-time employment	0.02	0.02	-0.11**	0.03
Casual employment	-0.03	0.02	-0.12**	0.03
Union member	0.07**	0.03	0.03	0.04
Blue collar occupation	0.01	0.02	0.00	0.03
Industry				
Agriculture, Forestry and Fishing	-0.15**	0.05	-0.06	0.26
Manufacturing	-0.10+	0.05	-0.10	0.25
Construction	-0.16*	0.06	-0.40	0.27
Wholesale Trade	-0.07	0.05	-0.06	0.26
Retail trade	-0.09*	0.05	-0.14	0.26
Accommodation, Cafes and Restaurants	-0.14**	0.05	-0.09	0.26
Transport and Storage	-0.04	0.05	-0.04	0.26
Communication Services	-0.07	0.08	0.08	0.30
Finance and Insurance	-0.08	0.08	1.11**	0.39
Property and Business Services	-0.23**	0.06	-0.15	0.26
Government Administration and Defence	-0.17+	0.09	-0.15	0.28
Education	-0.17**	0.06	-0.43	0.27
Health and Community Services	-0.22**	0.05	-0.13	0.26
Cultural, Recreational and Personal Services	-0.19**	0.06	-0.14	0.26
Small Firm (less than 50 employees)	0.00	0.02	-0.06+	0.03
Constant	2.46**	0.06	1.42**	0.62
R-square	0.07		0.10	

Table C 2 – Wage Progression of the Low Paid – Additional Information (The Effect of Characteristics Observed in Base Year *t* on Wage at *t+1*

	Pooled Regression		*Panel Fixed Effects*	
	Coefficient	*S.E.*	*Coefficient*	*S.E.*
Male	-0.01	0.04		
Age(Ref: 21-29)				
30-44	-0.08+	0.04		
45-54	-0.15*	0.07		
55 - 64	-0.07	0.09		
Major city	0.00	0.03	-0.21	0.28
Education				
Degree or higher	0.12*	0.05	0.28	0.22
Full-time Student	0.09*	0.04	-0.01	0.12
Disabled	-0.21**	0.05	-0.07	0.06
Experience				
Work Experience	0.01*	0.01	0.06	0.09
$(\text{Work Experience}/10)^2$	-0.02	0.02	-0.06	0.06
Employment Tenure unknown	-0.46	0.32	-	
Employment Tenure	-0.01**	0.00	-0.01	0.01
Full-time employment	0.06+	0.03	0.04	0.06
Casual employment	0.06*	0.03	-0.01	0.05
Union member	0.13**	0.04	0.00	0.08
Blue collar occupation	-0.07*	0.03	0.03	0.06
Industry				
Agriculture, Forestry and Fishing	-0.29+	0.16	0.19	0.45
Manufacturing	-0.21	0.16	0.09	0.43
Construction	-0.11	0.16	0.18	0.46
Wholesale Trade	-0.10	0.16	0.10	0.44
Retail trade	-0.20	0.15	-0.01	0.44
Accommodation, Cafes and Restaurants	-0.24	0.15	0.02	0.45
Transport and Storage	-0.10	0.16	0.09	0.47
Communication Services*	-0.03	0.17	-0.03	0.55
Finance and Insurance*	-0.14	0.26	-3.81**	0.67
Property and Business Services	-0.18	0.16	0.14	0.44
Government Administration and Defence*	0.09	0.19	0.10	0.47
Education	-0.10	0.16	0.32	0.46
Health and Community Services	-0.24	0.16	0.24	0.45
Cultural, Recreational and Personal Services	-0.27	0.16	0.16	0.45
Small Firm (less than 50 employees)	-0.07*	0.03	-0.08	0.05
Constant	2.79**	0.17	1.74	1.34
R-Square	0.17		0.19	

Note: The dependent variable is the natural logarithm of hourly wage at time t+1. All explanatory variables are measured at time *t*.

Estimates for a Wage Model Including Selection Bias Correction

We have re-estimated model (1) while explicitly addressing the selection bias problem. The methodology we use was introduced by Heckman (1979). The Heckman method specifies two equations: a wage equation (our original model (1)) and a non-linear model of the probability of observing the wage sample (that is, the selection equation). In our case this is being in a low-paid job in the base year and still be employed in the relevant future year. These two equations are estimated jointly using the full information maximum likelihood method. The results are presented in Table C 3.

Table C 3 - Wage Estimates Using the Heckman Selection Model

	Wage at t		Wage at t+1	
	Coef.	*S.E.*	*Coef.*	*S.E.*
Male	0.01	0.02	0.01	0.03
Age(Ref: 21-29)				
30-44	-0.09**	0.03	-0.09*	0.04
45-54	-0.14**	0.05	-0.18**	0.07
55 - 64	-0.13*	0.05	-0.13	0.09
Major city	-0.01	0.02	0.03	0.03
Degree or higher	-0.06+	0.03	0.16**	0.05
Full-time Student	-0.03	0.03	0.09*	0.04
Disabled	-0.13**	0.03	-0.20**	0.05
Work Experience	0.01+	0.00	0.02*	0.01
$(\text{Work Experience}/10)^2$	-0.01	0.01	-0.03	0.02
Emp. Tenure unknown	-1.00**	0.38	-0.43	0.38
Employment Tenure	-0.01**	0.00	-0.01	0.00
Constant	2.24**	0.04	2.51	0.12
Selection Equation:				
Age *(continuous in years)*	-0.01**	0.00	-0.01*	0.00
ATSI	0.06	0.08	0.00	0.10
NESB	0.06	0.04	-0.01	0.05
ESB	-0.12**	0.05	-0.16**	0.06
Job satisfaction	1.19**	0.05	1.03**	0.06
Pay Satisfaction	-0.28**	0.04	-0.11*	0.05
Constant	-1.81**	0.06	-2.26**	0.07
athrho	0.11**	0.04	0.03	0.12

Note: athrho is the parameter that controls the correlation between the wage equation and selection equation. Its significance indicates that estimates may be biased due to selection.