Working Paper

Modelling Employment Transitions of Prime-aged Women*

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Abstract

Women comprise a growing proportion of the Australian workforce resulting in the increasing role for public policy to promote a more flexible and dynamic labour market that can further expand the choices that women face about the extent and lifecycle timing of their labour market participation. This paper investigates the factors that are associated with transitions in and out of employment for prime aged Australian women (25 to 54 years) using panel data from the first six waves of the HILDA survey. We employ two different estimation approaches, one using transition probit models and the other employing dynamic random effects models. Our analysis shows that hourly wage, childbirth, the age of youngest child and time spent not employed are the most significant factors in influencing females' labour market transitions. Our findings are broadly consistent with the international literature but we find considerably large wage effects especially for those who are moving into employment. We also find strong evidence of state dependence.

1. Introduction

Understanding employment levels, rates and changes has rightly received a great deal of research, media and policy focus. Employment is an important route out of poverty, as well as having a range of economic, social and fiscal benefits. While the employment rates of prime-aged Australian women have increased sharply over the past 30 years, the Productivity Commission (2006) finds an employment 'gap' of 7.1 percentage points when participation by Australian females aged 25-54 years is compared with that of Canada, with smaller gaps evident in comparisons with the United Kingdom and the United States.

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The literature investigating employment participation at the micro and macro level is highly evolved and has developed sophisticated techniques for modelling household decision-making, unobserved wages and selection, unobserved heterogeneity, budget constraints and utility maximisation on cross-sectional data. The analysis of cross-sectional data has been well-explored and there have been excellent studies of inter-temporal labour supply (see Hyslop 1999 and Knights *et al* 2002, amongst others). However, Hyslop (1999) notes that the inter-temporal labour supply of married women remains the least studied of labour supply research.

In addition, the comment by Kalachek *et al* (1979) that there is significant scope for development of the empirical research on labour supply *change* remains relevant today.[1] Essentially, there may be differences in employment probabilities in period t between the initially employed and the initially not employed, because the not employed bear search costs, have differences in tastes and productivity. Without therefore taking the initial state into account (in empirical labour supply modelling) the coefficients on wages, education and other variables correlated with previous labour market history are likely to be biased.

In this paper we explore the factors that influence the risk of women moving from employment to out of employment and vice versa.[2] One of the innovations that this paper makes is examining the labour supply decisions of the initially employed separately from the initially not employed. This allows us to examine how changes in our variables of interest influence the probability of employment as well as examining the (time invariant) characteristics that make individuals more susceptible to dropping out of employment or returning to employment. While unobserved heterogeneity (and unobserved shocks) cannot be entirely eliminated from our dataset we believe that controlling for these factors (with the inclusion of labour market history) through

[1] Detailed discussion of many of the issues relating to the intertemporal analysis of labour supply behaviour - such as issues of state dependence and unobserved heterogeneity - are outside of the scope of this paper. Hyslop (1999) and Knight et al (2002) examine dynamic relationships in the Australian labour market with a focus on explaining the labour market status of individuals based on previous labour market history.

[2] This can be thought of as the probability of (voluntarily or involuntarily) leaving a current employer multiplied by the probability that the individual will not enter in employment with another employer. See Farber (1999) and Booth, Francesconi and Garcia-Serrano (1999) for discussion of the risk of job exit. The framework primarily used in this paper treats the decision on labour supply in one period as separate from the decision on labour supply in another period (as we examine each group separately).

employing both transitionary probit and dynamic random effect models we can provide new insights into the study of labour supply decisions at the extensive margin (as well as their change).

The reason for focusing on the extensive margin (the employment decision) rather than the intensive margin (hours of work), is because Australian studies have shown that the extensive margin is likely to be more elastic than the intensive margin. For example a review by Birch (2005) reports that the labour force participation and hours-of-work elasticities in Australia tend to suggest that wages play a greater role in women's decision to enter the labour market than in their decisions on the number of hours worked.

Our analysis supports previous findings as to the importance of the wage rate as a key determinant of women's employment (Dex *et al*, 1998, Paull, 2006). Our results show that a rise in the wage rate increases the probability of employment, especially for women who were not employed in the initial period. Their employment probability increases by nearly 17 percentage points for a five dollar increase in the hourly wage rate. Another key finding is that child birth and the presence of young children is significantly negatively correlated with the probability of women remaining in or transitioning into employment. Lastly, we find strong evidence of state dependence as the results show that women who are initially employed are 24 per cent (according to the Orme random effect model) more likely to be employed in the subsequent period.

The paper is organised as follows. The next section examines the economic framework used for selecting our variables and interpreting our results while sections 3 and 4 discuss the data source and the empirical approach, respectively. Section 5 presents some descriptive statistics on the factors associated with female employment retention and transitions. This analysis is extended in Section 6 where probit and random effects models assist in providing a more sophisticated analysis of these factors. Section 7 concludes by summarising the main findings.

2. The Economic framework and selection of variables

In conducting our analysis, we use the standard one-sided search framework to select our variables and interpret our results. In this framework the decision to participate in employment depends on a comparison between the individual's market wage and reservation wage. The market wage is expected to be influenced by an individual's education level, workforce experience and unobserved ability and motivation. The reservation wage in turn is determined by the value of non-work time and access to non-wage income. An individual will only participate in employment if the market wage is greater than his or her reservation wage.[3]

Thus, in equation (1) employment (E_i) is a function of the market wage (w), factors that influence the reservation wage (non-market income (v) and observed characteristics (X)), and unobserved factors (ε_i) that enter the utility function.

$$E_i = f(w_i, v_i, X_i, \varepsilon_i) \qquad (1)$$

A broad range of individual and household factors potentially impact on women's costs of work and on their reservation wages. These factors include childbirth, the number and ages of children, access to childcare and alternative sources of income. These factors are expected to influence the reservation wages of women more than they affect men because women undertake more of the unpaid work associated with child-bearing and child-rearing for a variety of biological, social and economic reasons.[4]

[3] Extensions to the simple model of female labour supply typically incorporate household decision making, in particular the labour supply decisions of other individuals in the household and decisions over labour allocation among non-labour market activities such as child care and housework. Studies using a household framework (notably Apps, Killingsworth and Rees 1996 and Apps and Rees 1996) produce lower wage elasticities for female labour supply than models of individual choice; see also Birch's 2005 review).

[4] However, it is worth noting that a Productivity Commission report (2005) on male labour supply finds that around 160 000 adult men were engaged in home duties in September 2005, with about one third of the absences from the labour force of males aged 35–44 and about one quarter of the absences of those aged 45–54 years directly attributable to domestic responsibilities. These absences are quite substantial, yet the policy literature to date has little to say about the hours-of-work effects of unpaid domestic work on male participation.

The presence of children is a well-established influence on female labour supply since the arrival of children simultaneously increases the value of time in the home and the need for income (Birch 2005). Following childbirth, women tend to reduce their participation in employment. It seems that childbirth is the single most important and persistent issue for the continuity of women's labour market attachment (Jeon 2007). British research has found that for many women employment risks persist throughout the childrearing period and that a return to work following the birth of a child is often temporary (Paull, 2006).

More generally, the existing literature suggests that the presence of young children is a crucial factor influencing female employment. For example, the New Zealand Treasury reported that mothers with pre-school children (aged 0 to 4 years) have a participation rate of only 54 per cent, while mothers with school age children (aged 5 to 17 years) have a participation rate of 79 per cent (Johnston 2005). While research has found that women on lower incomes are most affected by childbirth, the literature is rather limited on the characteristics of women most affected by the presence of young children.

Another factor cited in the literature as influencing women's transitions in and out of employment is household income, with a partner's or other non-wage income decreasing women's employment probability.[5] While most studies observe household income to have a strong effect on women's participation decision this is not true for all studies. Juhn and Murphy (1997) find that the participation decisions of married women have become less sensitive to the income of partners in recent years and more sensitive to their own market opportunities.

In respect to women's own market opportunities, most labour supply studies have found a positive relationship between women's labour market involvement and their own wage rates. Higher wages increase the opportunity costs of not being in

[5] Related to household income, household debt may play a role in female employment probabilities. A study by the Reserve Bank of Australia (2007) used HILDA to estimate separate probit models of labour force participation for men and women investigating effects of owner-occupied housing debt on participation. The results show that debt along with family structure, education and health are important determinants of employment for both sexes. The difficulty with this research is that it seems plausible that employment participation and debt are jointly determined.

employment and consequently provide a stronger incentive to be employed. A review of hours-of-work elasticities shows that women in Canada, the UK, Germany and the USA have an hour of work elasticity of around 0.60. For Australian women the mean elasticity of labour force participation with respect to wages is around 0.75 (Birch 2005) [6].

In our initial modelling we know that in all cases the individual's market wage is above their reservation wage (or else women would not be working). Therefore, for the individual to not participate in the second period the reservation wage would need to rise more then the market wage (or decline by less). All else equal, we expect that individuals with higher initial wages and with characteristics associated with lower reservation wages (such as the absence of young children) will have lower exit rates from employment. In other words, it would require a larger unobserved shock to the wage rate or the reservation wage to move these individuals from employment to non-employment.

3. Data

In examining the relative importance of various factors on female labour market transitions, we use the Household, Income and Labour Dynamics in Australia (HILDA) survey. HILDA is a longitudinal household panel survey which began in 2001. The members of the initial sample of households formed the basis of the panel to be followed over an indefinite life. Its main focus is collecting information about economic and subjective well-being, labour market dynamics and family dynamics. To date, seven waves of the HILDA data have been released.

The HILDA survey is suitable for this particular research because it provides detailed information on respondent's characteristics and labour market situation. The dataset allows us to determine people's employment status at different times and the life events that respondents experience. In particular, the data permits us to determine how

[6] Birch's (2005) paper 'Studies of the Labour Supply of Australian Women: What have we learned?' notes that labour supply elasticities vary significantly according to the estimation procedure and the dataset employed.

wage rates, age of youngest child, giving birth and changing health status impact on female workforce transitions.

The analysis in this paper utilises the first 6 waves of the HILDA data. The sample is restricted to women of working age (25 to 54 years old) in a particular wave[7]. Women are classified as either employed or not employed. Being categorised as employed requires them to have worked at least one hour in the reference week. If they are either unemployed or not in the labour force they are classified as not employed. Categorising women into either employed or not employed then allows us to derive the following transition paths:

- EE (employed in t and t+1);
- EN (employed in t and not employed in t+1);
- NE (not employed in t and employed in t+1) and
- NN (not employed in t and t+1).

We treat the unemployed and not in the labour force as one group, because the percentage of unemployed working age female in our sample is small (between 2.6 per cent and 3.6 per cent over the six waves). There remains a debate as to whether unemployment and out of the labour force are behaviourally distinct states (Flinn and Heckman 1983), however, the goal of raising labour force participation is not to increase the unemployment rate, but to create a more job-rich economy. Our focus is therefore the impact of employment transitions.

4. Empirical Approach

Our empirical analysis comprises of two main approaches which are to provide a robust examination of the factors that influence women's employment retention and transitions. The first approach employs simple probit models to estimate a women's probability to transition between employment and not employment and between not employment and employment (E_{it}) (see equation (2) where $\acute{W}$ denotes the estimated wage rate, X_{it} includes observed individual characteristics and e_{it} is the error term).

[7] The reasons for studying females between 25 and 54 are that we want to exclude transitions from school to work and from work to retirement since we are interested in the particular life cycle events that influence prime aged women.

This produces employment elasticities for the cross-sectional estimators which are used to compare women who are initially employed to those who are initially not employed. In addition to looking at women's employment probability over a two-year period we also examine women's employment transitions over a three-year period[8].

$$E_{i,t} = \beta_0 + \beta_1 \hat{W} + \beta_2 X_{it} + \varepsilon_{it}$$

$$E_{i,t} = \begin{cases} 1 & if \quad E^*_{i,t} > 0 \\ 0 & otherwise \end{cases} \tag{2}$$

The purpose of this analysis is to extend earlier literature that solely uses cross-sectional data by examining elasticities within sub-groups not extensively studied before as well as examining biases stemming from the omission of labour market history variables. However, while this approach will provide valuable information on the relationships between variables and employment for the populations examined, it does suffer from some generic issues.

The weaknesses involve the estimates being inefficient, being specific to the population and not explaining the determinants of employment initially. In addressing these issues we employ a second approach which involves estimating three separate specifications two of which are pooled probit random effects models (see equation (3)). This provides a more sophisticated analysis as it accounts for state dependence and produces more generalisable results.

$$E^*_{i,t} = \alpha' E_{i,t\text{-}1} + \beta' X_{i,t} + \gamma R_{i,o} + \mu_i + \varepsilon_{it}$$

$$E_{i,t} = \begin{cases} 1 & if \quad E^*_{i,t} > 0 \\ 0 & otherwise \end{cases} \tag{3}$$

Equation (3) has the same explanatory variables (X) as equation (2) but in addition contains a number of complexities. The equation includes a lagged employment

[8] The models are based on the following 4 transition paths: Model 1 $E_{t-1},E_t,E_{t+1}/E_{t-1}, E_t,N_{t+1}$; Model 2 $E_{t-1},N_t,E_{t+1}/E_{t-1},N_t,N_{t+1}$; Model 3 $N_{t-1},E_t,E_{t+1}/N_{t-1},E_t,N_{t+1}$; and Model 4 $N_{t-1},N_t,E_{t+1}/N_{t-1},N_t,N_{t+1}$.

variable ($E_{i,t-1}$) and an initial employment condition ($R_{i,o}$) which is used as a proxy of unknown initial conditions. In addition, the error terms is decomposed into two categories: the time invariant individual specific characteristics that are not captured by the explanatory variables (μ_i) and the random disturbance term (ε_{it}).

The first specification examines the impact of employment in period t on employment in period t+1 for those women who were initially employed (t-1). For this specification we set the third and fourth terms in equation 3 equal to 0 under the assumption that we have restricted the sample to a relatively homogenous one. The second approach is the Wooldridge random effects estimator (see Oguzoglu 2007) which more efficiently estimates the coefficients and controls for unobserved heterogeneity correlated with state dependence by including the initial value of the dependent variable. The variable $R_{i,o}$ in equation (3) is simply the value of the employment variable in wave 1 (we therefore examine waves 3-6). The final estimation is the Orme random effects estimator (see Orme 2007) that while maintaining some restrictive assumptions, controls for the unobserved heterogeneity correlated with state dependence in a more defensible way by including the generalised residual from the initial (probit) regression (represented by $R_{i,o}$).

4.1 Estimating Predicted Wages

In order for these different estimation approaches to be employed, we need to estimate women's wages as the data does not provide the wage rates of those women who are initially not employed. To estimate the wages for all women we use the Heckman two step procedure which corrects for the truncated nature of the dependent variable (see equation (4)). The Heckman selection model is a two equation model.

First there is the regression model

$$\acute{W} = X\beta + u1$$

And second, there is the selection model

$$Z\square + u2 > 0$$

where the following holds and

$$u1 \sim N(0, \square)$$

$$u2 \sim N(0, 1)$$

corr(u1, u2) = rho (4)

where $\acute{W}$ is log real wages, X is a vector of personal characteristics, Z is a vector of explanatory variables and u1 and u2 are the error terms which are assumed to be jointly normally distributed and correlated by rho (p). We also derive the predicted hourly wage rate by estimating an uncorrected wage equation. The results for both regression methods are depicted in Appendix 1.

As we would expect the results of both wage regressions show that work experience and education are positively and significantly correlated with the wage rate. This corresponds with the notion of the return to education and work experience as imbedded in the human capital theory. Education and experience raise individuals' productivity, which in turn results in higher wages.

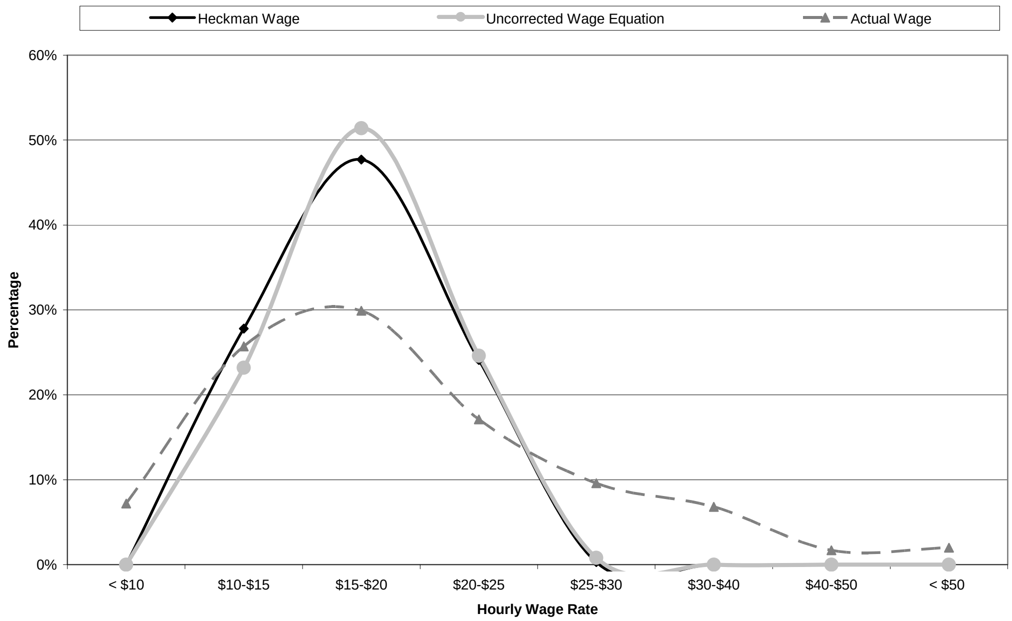
The wage equation(s) also includes a health variable, and accounts for birth place and time spent not employed (holding other variables constant). The results show that suffering from a long-term health condition and having spent time not employed are significantly negatively correlated with the wage rate. Interpreting the coefficients on these variables is beyond the scope of this paper, but they are likely to be due to some combination of the job offer arrival rate, the productivity of the jobs offered and bargaining power/ discrimination.

In Figure 1 we depict the distribution of the two predicted wage rates and the actual hourly wage rate[9]. The Figure shows that the actual wage rate is more skewed compared to both of the predicted wage rates, while the Heckman predicted wage and the uncorrected predicted wage follow a similar distribution. The Heckman and the uncorrected estimation show a highest predicted wage of between \$25 to \$30 per hour while the highest actual wage is above \$40 per hour. The latter result is likely to be due to measurement errors. We therefore use the predicted wage in our estimation models, specifically the Heckman predicted wage because it accounts for more of the endogeneity and provides a less biased estimate. We estimated the Heckman predicted wage as well as most of the other variables as of the second period (t+1). A

[9] The actual wage is derived for women employed in the second period while outlyers (above \$150) have been removed.

description of the key variables used in the regression analysis is presented in Appendix 2.

Figure 1: Actual/Predicted wages for people employed in t+1



5. Descriptive Statistics

Before going into the econometric analysis, we present some descriptive statistics in the form of a transition table (see Table 2). The Table illustrates the transition rates of women with different characteristics. It shows that nearly two thirds of prime aged women in this sample remain employed from one time period to the next while just over 12 per cent change their labour market status and 23 per cent remain not employed from one period to the other. Looking at women with different education levels, the Table shows that women with tertiary education experience the highest rate of continuous employment and the lowest rate of not being employed in consecutive periods. The reverse can be observed for women with no qualifications.

When looking at the employment transition for women that have given birth between the first and the second period, we observe that only 39 per cent of women are employed in the second period.[10] However, women return to employment as their youngest child gets older. Nearly 53 per cent are in employment in the second period when their youngest child turns 1 year old. This increases to 72 per cent for women with their youngest child turning 6 years old. These results correspond to the notion that the arrival of a child increases the demand for non-work activities while older children decrease the demand for non-work activities and increase the need for higher income (Birch 2005).

Another major influence on women's labour supply decisions is their own wage rate. Most overseas labour supply studies report a positive relationship between women's labour market involvement and their own wage rate (Birch 2005). We find evidence consistent with this in the descriptive statistics. Table 2 shows that the lower the predicated wage the lower women's employment levels. According to the results, only 30 per cent of women with a predicted wage of below $12.50 per hour are in employment in the second period, while a woman with a predicted wage of over $20 per hour has an employment probability of about 90 per cent in the second period.

[10] We derive our birth variable from the question in HILDA that asks whether a person has given birth or adopted a child in the last 12 months. For a five year period (from wave 2 to 5) we obtain a sample of 827 mothers that answer this question in the affirmative. We do not account for whether it is a first child or how many newborns a mother has in the stipulated time period. The accuracy of this measure depends on how long the interview dates are apart and the proportion of children having been adopted. Our results are determined by natural birth, rather than adoptions, as the rate of adopted children to natural birth is 1/500 (ABS 2006 and AIHW 2008). Also, deriving the birth variable differently yields similar regression results to the ones obtained with our birth variable (described above).

Table 2: Employment transitions of prime aged women

		E (t+1)	N (+1)
Prime-aged women *	**E (t)**	64.6%	5.8%
	N (t)	6.4%	23.2%
Tertiary education	**E (t)**	79.4%	5.9%
	N (t)	5.8%	9.0%
No Qualifications	**E (t)**	52.1%	5.7%
	N (t)	6.5%	35.5%
Part-time	**E(t)**	88.3%	11.7%
Full-time	**E(t)**	94.4%	5.6%
Dependent children at home	**E (t)**	60.6%	5.4%
	N (t)	7.8%	26.2%
Given Birth	**E (t)**	34.0%	29.4%
	N (t)	5.1%	31.5%
Youngest Child turns 1	**E (t)**	42.1%	7.3%
	N (t)	10.6%	40.0%
Youngest Child turns 6	**E (t)**	64.5%	5.5%
	N (t)	7.6%	22.4%
P. Wage** is below $12.5 per hour	**E (t)**	22.3%	5.5%
	N (t)	7.1%	65.1%
P. Wage** is bt $15 and $17.5 per hour	**E (t)**	78.3%	5.4%
	N (t)	5.7%	10.7%
P. Wage** is over $20 per hour	**E (t)**	84.7%	5.5%
	N (t)	4.8%	5.0%

Notes: The sample consists of women aged 25-54 years old, pooled transition data. *There are 18,110 observations. ** P. Wage stands for Predicted Wage which has been derived using the Heckman selection model. Source: HILDA Release 6.1.

6. Results

Following the descriptive statistics on women's transition rates is an econometric analysis of the factors that influence women's labour market transitions from one period to the next and over a three-year period (t-1,t,t+1). In addition, we employ three separate specifications two of which are pooled dynamic random effect models to control for unobserved heterogeneity and the influence of state dependence thus producing more efficient estimates of the coefficients (Hsiao 2005). The different estimation techniques are intended to provide a comprehensive and robust analysis of our variables of interest.

6.1. Modelling women's employment probability over a 2-year period

Table 3 illustrates the results of five probit models that examine the factors that are associated with female employment transitions.[11] Models 2 and 4 are the standard models where the wage variable enters as a continuous variable. The results show that wages are positively and significantly correlated with the probability of females remaining employed from one period to the next. An even stronger wage effect can be observed for women not employed in the initial period.

In providing an alternative picture of how wages influence female transitions, we substituted the continuous wage variable with wage dummies (that are a flexible, more easily interpreted, non-linear functional form). The wage dummies are included in models 3 and 5, which show that the female employment retention probability and the probability of women moving into employment increases as the wage range rises. As is the case with the continuous wage variable, the results using the wage dummies show that wages have a larger effect on the employment probability of women initially not employed. An additional finding is that the effect of increasing wages at low levels is larger than increasing wages at higher levels.

In addition and consistent with the descriptive analysis, giving birth and having young children are significantly negatively correlated with female employment transitions (holding other factors constant). We find that giving birth and/or having a youngest child between 0 and 5 years old significantly increases the probability of being not employed in the second period. At the same time we find that the youngest child turning 1 year old increases the chance of a woman returning to employment when initially not employed (compared to the reference category which is women without children turning 1 year old).

Some caution is required when interpreting the coefficients on the child related variables. In the case of women giving birth to their first child, the coefficients on youngest child between 0 and 5 and giving birth have to be considered together. This is because a first child affects both the youngest child and the given birth coefficients.

[11] Appendix 4 depicts further probit models which serve as sensitivity checks.

A person's health status is also shown to influence employment retention and transition. According to Table 3 prime aged females who either experience a persistent health condition (over two periods) or develop a health condition (in the second period t+1) are less likely to remain or become employed in the second (t+1) period. The opposite effect however is not observed for women whose health improves from one period to the next.

In addition, we find that weekly household income (excluding female wages and salaries) has some impact on female's employment transitions. According to our results an increase in the weekly household income decreases a woman's probability of remaining in employment. However, weekly household income has no significant effect on the probability of women initially not employed moving into employment.

Finally, we find that there is a strong negative relationship between time spent not employed and female employment transitions. Each year of not having been employed decreases a woman's probability of remaining employed and returning to employment. Not surprisingly, the negative effect seems to be stronger for women returning to employment. The degree to which this is the result of a scarring effect of non-employment, or the result of omitted variables correlated with both past and present employment status is discussed later in the paper.

Table 3: Estimated coefficients for the factors influencing female employment probability (t+1) given their initial employment status (t)

Status in initial period (t)	All (Employed (t) & Not employed (t)) (1)	Employed (t) (2)	Employed (t) (wage dummies) (3)	Not employed (t) (4)	Not employed (t) (wage dummies) (5)
Constant	-0.137	0.228	0.204	-1.560**	-0.816*
	(0.58)	(0.91)	(0.71)	(4.75)	(2.73)
Predicted wage	0.086**	0.031**	-	0.088**	-
	(12.39)	(4.85)		(8.91)	
Predicted Wage $12.5 to $15	-	-	0.413*	-	0.375**
			(2.41)		(3.78)
Predicted Wage $15 to $17.5	-	-	0.535**	-	0.702**
			(3.05)		(6.17)
Predicted Wage $17.5 to $20	-	-	0.732**	-	0.790**
			(3.85)		(5.84)
Predicted Wage is over $20	-	-	0.687**	-	1.104**
			(3.85)		(8.65)
Hours of work	-	0.013**	0.013**	-	-
		(8.78)	(8.66)		
Youngest Child between 0 and 5	-0.849**	-0.272**	-0.263**	-0.456**	-0.454**
	(17.99)	(4.68)	(4.50)	(7.00)	(6.92)
Youngest Child turned 1	-0.229**	-0.087	-0.093	0.207**	0.215**
	(4.47)	(0.94)	(0.97)	(2.93)	(3.04)
Youngest Child turned 6	-0.442**	0.003	0.008	-0.175	-0.172
	(7.27)	(0.03)	(0.07)	(1.72)	(1.68)
Given Birth	-0.812**	-1.403**	-1.405**	-0.588**	-0.584**
	(14.37)	(18.55)	(18.55)	(5.67)	(5.61)
Health Condition persists over two periods	-0.783**	-0.542**	-0.521**	-0.453**	-0.425**
	(14.58)	(8.92)	(8.44)	(6.33)	(5.83)
Health Condition improved over two periods.	-0.239**	-0.137	-0.136	-0.133	-0.134
	(5.07)	(1.93)	(1.92)	(1.65)	(1.68)
Health Condition worsens over two periods	-0.254**	-0.277**	-0.262**	-0.191	-0.146
	(5.85)	(4.47)	(4.17)	(2.40)	(1.79)
Weekly household income minus female wages	-0.050**	-0.046*	-0.045*	0.002	0.003
	(2.82)	(2.49)	(2.42)	(0.05)	(0.10)
Time spend not Employed	-0.070**	-0.018**	-0.017**	-0.026**	-0.033**
	(23.13)	(5.10)	(4.57)	(8.61)	(7.61)
Time Dummies	yes	yes	yes	yes	yes
Location Dummies	yes	yes	yes	yes	yes
Individual Dummies	yes	yes	yes	yes	yes
Log Pseudo-Likelihood	-7892.06	-3063.43	-3058.75	-2437.68	-2429.92
Pseudo R2	0.28	0.16	0.16	0.13	0.13
Percentage correctly predicted	79.7%	91.8%	91.8%	79.5%	79.5%
Mean of dependent variable	71.0%	91.8%	91.8%	21.8%	21.8%
Number of obs.	18097	12748	12748	5349	5349

Notes: The sample constitutes of women aged 25-54 years old and pooled transition data (standard errors have been clustered by xwaveid). The figures in brackets constitute t-statistics. * significant at the 5% level. ** significant at the 1% level. Source: HILDA Release 6.1.

6.1.1 Marginal effects

In order to determine the magnitude of the different factors on women's transition probabilities, we calculate the marginal effects for all the explanatory variables.[12] Looking at the marginal effects enables us to examine the relative sizes of the factors that influence women's employment transition probabilities. Table 4 presents the marginal effects for some of the key variables including predicted wage, giving birth, having a young child, changing health conditions, and time spent not employed.

Table 4: The marginal effects of key variables on women's employment probability (t+1) based on their initial employment status (t)

Status in initial period	Employed (t)	Part-time (t) (<30)	Full-time (t) (>30)	Not employed (t)
Predicted wage (t+1)	0.4%**	0.5%*	0.4%*	3.1%**
Pre. wage $12.5 to $15 (t+1)	4.4%**	6.5%*	2.1%	13.5%**
Pre. wage $15 to $17.5 (t+1)	6.9%**	9.4%*	3.9%	25.9%**
Pre. wage $17.5 to $20 (t+1)	6.1%**	7.8%**	4.8%	30.5%**
Pre. wage over $20 (t+1)	7.6%**	9.2%**	5.8%	41.9%**
Youngest Child 0-5 years	-4.4%**	-3.0%*	-5.0%	-14.2%**
Youngest Child turned 1 (t+1)	-1.2%	-1.2%	0.1%	7.6%**
Youngest Child turned 6 (t+1)	0.0%	-0.8%	3.0%	-6.0%
Given Birth (t+1)	-39.9%**	-34.2%**	-45.2%**	-17.4**
Health Condition persists	-10.4%**	-12.9%**	-7.7%*	-14.1%**
Health Condition improved	-2.0%	-2.7%	-0.5%	-4.6%
Health Condition worsens	-4.5**	-5.1%*	-4.1%	-6.4%*
Hours of work	0.2%**	0.4%**	0.0%	N/A
Time spend not Employed	-0.2%**	-0.3%*	-0.2%	-1.3%**
Predicted probability at base	0.931	0.902	0.945	0.318

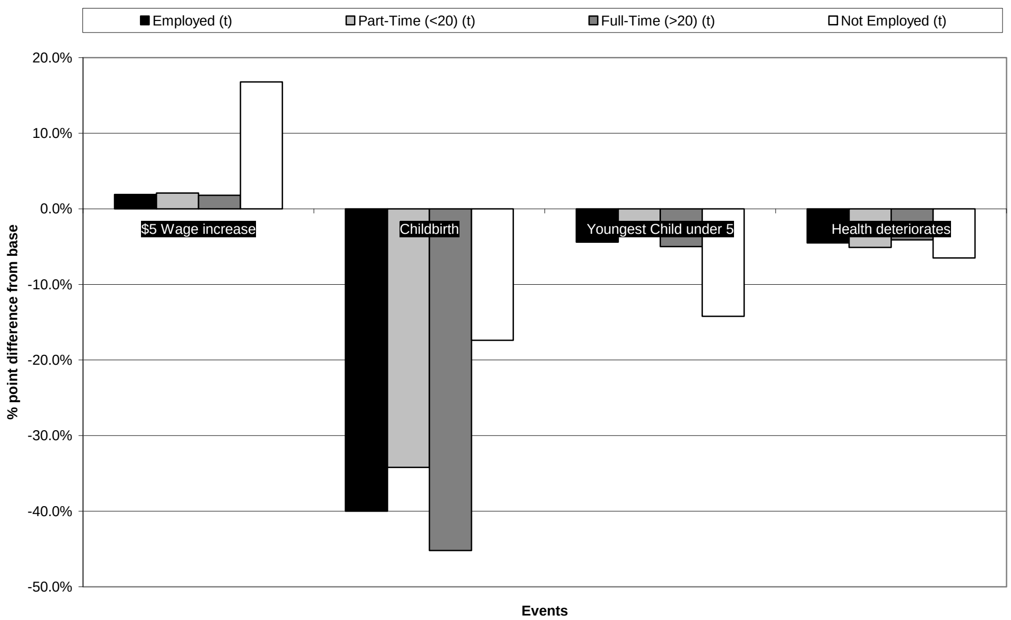
Notes: Women aged 25-54 years, pooled transition data (standard errors have been clustered by xwaveid). * significant at the 5% level. ** significant at the 1% level. Source: HILDA Release 6.1.

The probit model shows that wages have a positive effect on employment transitions. However, the magnitude differs quite substantially depending on whether women were employed or not employed in the initial period (see Table 4). According to the results a one dollar increase in the wage rate raises the employment probability of a woman initially employed by less than half a per cent. The employment probability for this particular group increases by 2 percentage points when the hourly wage rate increases by $5 dollars (see Figure 2). While this may appear small, it is still significant when considering that the base employment rate is already at a high level for the initially employed.

[12] The marginal effects where computed at the means for all continuous variables. Most of the dummy variables where set at 0 (i.e origin of birth, youngest child between 0 and 5, childbirth, dynamic health variables, lone parents, owning a house and living in regional Australia). Other dummy variables were either set at 1 (aged between 34 to 44, couple family and living in a major city in Australia) or were not set.

It might therefore not be surprising that we observe a much larger wage effect for women who are initially not employed. According to the results their employment probability increases by just over 3 percentage points for a one dollar increase and by nearly 17 percentage points for a $5 dollar increase (see Figure 2). This generally supports the finding of other Australian studies showing that wages play a greater role in women's decision to participate in the labour market than in their decision on the number of hours worked (Birch 2005).

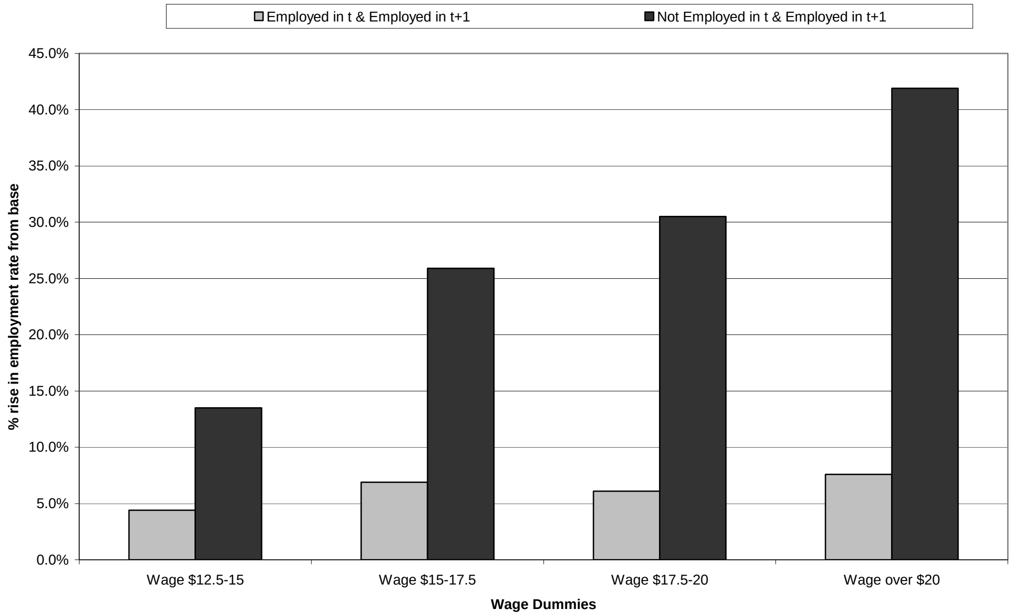
Figure 2: The marginal effects of key variables on women's employment probability (t+1) based on their initial employment status (t)



Source: HILDA Release 6.1

To further illustrate the implication of the wage rate on female's labour market transitions we present Figure 3 which depicts this relationship in terms of wage ranges. This Figure shows particularly well how moving from one wage range to another influences the employment of women that were initially not employed. Thus women with potential wages between $12.5 and $15 are 13.5 percentage points more likely to be employed than women with potential wages below $12.5, while women who are expected to have an hourly wage of over $20 increase their employment by 42 percentage points. Looking at the wage distribution we can see that increasing wages at the bottom of the distribution has a larger effect than at the top.

Figure 3: The marginal effects of different wage ranges on women's employment probability (t+1)



Source: HILDA Release 6.1

In addition to wages being important in increasing women's employment probabilities, other factors are also shown to be of significance. One of these factors is childbirth. Figure 2 shows that it reduces the employment probability of women initially employed part-time and full-time by about 34 per cent and 45 per cent respectively (in the year of childbirth). This corresponds with findings by others showing that childbirth is strongly associated with women's employment withdrawal (Jeon 2007). The probability of moving into employment by women initially not employed is also significantly reduced in the event of giving birth. Figure 2 shows that the probability of entering employment for the initially not employed is reduced by more than 17 per cent.

Another factor influencing female employment probabilities is the presence of a youngest child aged between 0 and 5 years. It reduces the employment probability of initially employed women by over 4 percentage points. The drop is slightly larger for women working full-time compared to those working part-time (Figure 2). However, the fall in predicted employment in the second period is largest for the initially not employed. The presence of a youngest child between 0 and 5 years old decreases the employment probability for these women by just over 14 percentage points.[13]

Returning to Table 4, reporting a health condition for two (consecutive) periods decreases the employment probability for initially employed women by 10.4 per cent and for those initially not employed by 14.1 per cent. The marginal effects also suggest that time spent not employed influences women's employment probabilities significantly but varies in its magnitude for different women. According to the results, one year (above the mean) spent not employed reduces the employment probability of those initially employed by only 0.2 per cent while it reduces the likelihood of women transitioning into employment by 1.2 per cent.

We also examine the marginal effects of key variables on women's employment probability over a three year period. The results of this analysis correspond with those from the 2-year period analysis in that the wage rate and child related factors (i.e giving birth and having a young child) significantly influences women's employment probability. For instance, the results reveal that a one dollar increase in the wage rate raises the employment probability for women having not been employed for two consecutive periods by 3 per cent. More detailed results and a brief description of them is presented in Appendix 3.

6.2. Random effects

So far, we have looked at the impact of various personal and economic characteristics on the probability of being employed in the second and the third period by the initially employed and initially not employed. The advantage of this approach over the cross-sectional analysis is that the groups are likely to be more homogenous and there is less risk of bias brought about through omitted variables. In addition, the methodology is transparent and relatively flexible (the variables in our initial analysis have been allowed to be related to the dependent variable in different ways depending on whether the individual was initially employed or initially not employed).

[13] The marginal effects associated with the child-related variables have to be interpreted with some caution. This applies especially to first time mothers as the marginal effect of giving birth and having a child between 0 and 5 years old would have to be combined to account for the impact that a first child has on mothers' employment retention and transitions (as our measures, in effect, measure the impact of child-birth for a subsequent child).

Nevertheless, this approach has weaknesses. One being that beyond the sample restriction on the dependent variable (and the correlations with the variables present) there are no controls for unobserved heterogeneity. The other weakness is that we do not model the determinants of the initial state (that could also be associated with the variables in the specifications) and therefore not accounting for state dependence in our analysis.

In correcting for these shortcomings we run three separate specifications. The first one is a probit model that examines the impact of employment in period t on the employment status in period t+1 for those initially employed in t-1. The other two specifications are pooled dynamic random effects models. These estimations enable us to examine the important issues of state dependence and extend our previous analysis by provide a valuable sensitivity check. Table 6 presents the probit results for the three specifications.

For the most part the results are consistent with those obtained from our earlier estimation specifications. All three models show that predicted wages significantly increase the employment probability of women while having young children (between 0 and 5 years) and having given birth significantly decreases a women's likelihood of being employed. In addition, the results show a positive correlation between the initial employment status and women's subsequent employment probability. In other words, women who are employed in time period t-1 are more likely to be employed in time period t having controlled for a women's initial employment condition.

Table 6: Estimated Coefficients from the Probit and Random Effects (RE) Models: The effects on women's probability of employment (t+1)

	Pooled (Et-2 population)	Wooldridge RE model	Orme RE model
Predicted Wage	0.104**	0.214**	0.195**
	(5.20)	(12.32)	(10.74)
Lagged dependent variable	0.049**	0.964**	1.113**
Employed t-1	(21.38)	(20.74)	(25.58)
In Relationship	-0.116	-0.082	-0.211
	(0.98)	(0.77)	(1.80)
Born – English speaking Country	-0.144*	-0.150	-0.169*
	(2.05)	(1.95)	(2.33)
Born – Non-English speaking Country	-0.150*	-0.445**	-0.366**
	(2.50)	(6.71)	(5.91)
Youngest Child between 0 and 5	-0.445**	-0.776**	-0.769**
	(3.70)	(7.75)	(7.34)
Youngest Child between 6 and 12	-0.171**	-0.298**	-0.303**
	(2.77)	(4.69)	(4.97)
Youngest Child turned 1	0.057	-0.006	0.051
	(0.57)	(0.07)	(0.60)
Youngest Child turned 6	0.011	-0.079	-0.143
	(0.08)	(0.74)	(1.34)
Given Birth	-1.225**	-1.284**	-1.242**
	(12.43)	(14.75)	(13.99)
Lone Parent	-0.040	0.006	-0.091
	(0.28)	(0.53)	(0.78)
Couple Family	0.079	0.159	0.232*
	(0.67)	(1.50)	(1.98)
Health Condition	-0.146*	-0.119	-0.135*
	(2.00)	(1.94)	(2.16)
Household Income minus Female wages	-0.066**	-0.015	-0.003
	(3.49)	(0.47)	(0.11)
Owning House	0.168**	0.260*	0.226
	(3.37)	(2.12)	(1.91)
Renting	-0.209	0.128	0.067
	(1.68)	(1.02)	(0.55)
Mortgage/ Rent Payments	0.042	0.137**	0.094*
	(1.02)	(3.75)	(2.52)
Time spend not Employed (in t)	0.006	-0.044*	-0.034
	(0.20)	(2.52)	(1.91)
Major City	-0.128	-0.740**	-0.644**
	(1.03)	(5.11)	(4.80)
Regional	-0.004	-0.567**	-0.438**
	(0.03)	(4.04)	(3.40)
Time	yes	yes	yes
Location	yes	yes	yes
Individual	yes	yes	yes
Mean of dependent variable	0.918	0.883	0.944

Notes: * significant at the 5% level. ** significant at the 1% level. The figures in brackets constitute t-statistics. Source: HILDA Release 6.1.

In order to compare the results of the random effects models to those obtained for the two period probit models (Table 4) we derived their average partial effects and present them in Table 7[14]. Looking at the Wooldridge and Orme models, the results show that a one dollar (above the mean) increase, raises the employment probability of women by between 3.7 and 4.1 per cent. This coincides with the finding of the two period probit model but shows the wage effect to be of a greater magnitude. Similarly, we find that the effect of giving birth on women's employment probability is significant. According to the random effects results, giving birth reduces the employment probability by around 23 per cent when controlling for the initial employment status. Compared to the earlier probit models the magnitude is slightly smaller but it remains a substantial factor influencing women's employment probabilities.

Table 7: State Dependence and Random Effects analysis, Estimated Average Partial Effects (APEs) for Key Variables of Interest

	Pooled (E_{t-2} population)	Wooldridge RE model	Orme RE model
Predicted wage (\$18) + \$1	1.5%	4.1%	3.7%
Predicted wage (\$18) + \$5	6.2%	17.7%	16.4%
Lagged dependent variable Employed (t-1)	22.6%	18.3%	23.9%
Given Birth	-29.2%	-23.6%	-23.0%
Child turns 1 year	0.9%	-0.4%	-0.9%
Health condition	-2.2%	-1.8%	-2.1%

Notes: The Average Partial Effects have been derived based on the preceding probit and random effects models. Source: HILDA Release 6.1

Turning to look at the impact of state dependence, we see that the effect is large. The size of the impact is similar to having given birth in the previous year. For instance, the Orme RE model shows that the impact of being employed in the previous period raises the probability of being employed in the subsequent period by about 24 percentage points. Estimates from the selected sample of those who were employed in one period prior to the initial period and of the Wooldridge RE estimates are of a similar magnitude. The results indicate that observed and unobserved heterogeneity explain more than half of the gap between the employed and the not employed. The raw gap in employment rates between the initially employed and the initially not

[14] For our average partial effects (APEs), for each individual in the sample we predict their employment probability at the base category, and then predict the employment probability in the reference category. The average of the difference is then called the average partial effect.

employed is 70.1 per cent (based on Table 2), compared to the state dependence effect of 18.3 per cent.

7. Conclusions

Explaining employment participation has received considerable policy and research focus over the past thirty years both in Australia and elsewhere (for extensive reviews see Birch 2005; and Blundell and MacCurdy 2005). This has led to an ever expanding understanding of what drives female employment at both the micro and the macro level. This paper has sought to extend current understanding on the female labour supply decision by particularly focusing on the extensive as opposed to the intensive margin, and employing transition and dynamic rather than cross-sectional models. This has allowed us to control for state dependency and unobserved heterogeneity to a greater extent than many earlier studies.

Our analysis has largely supported previous international and Australian research (Birch 2005; Jeon 2007; Paull 2006; and Gutierrez-Domenech 2004). In general, the results fit very well with the one-sided search model as we find wages and factors influencing women's reservations wages such as childbirth, the age of youngest child and time spent not employed playing a significant role in women's decision to participate in the labour market.

In particular, we find the predicted wage to be especially important for women moving from being initially not employed to employment in the second period. According to the results an increase of one dollar in the hourly wage rate increases not employed women's predicted employment in the next period by just over 3 per cent. In terms of childbirth, we find the largest effect to be experienced by women initially employed as their employment probability decreases by 40 per cent. The age of the youngest child on the other hand is more significant for women initially not employed. For them, a youngest child between 0 and 5 years detracts just over 14 per cent from base employment in the second period.

Lastly, the results from the random effects models largely coincide with those obtained from the transition probit models. However, as an important addition, the random effect models show that state dependence is substantial as women who are initially employed are 24 per cent more likely to be employed in the subsequent period (according to the Orme random effects model).

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Appendix 1: Heckman selection model

Table 1A: Heckman's two-step estimates vs the Uncorrected Wage Equation

Variables	**Heckman selection model**		**Uncorrected Wage Equation**
	Logwage (t+1)	**selection**	
Constant	2.527**	-0.018	2.555**
	(78.29)	(0.37)	(117.95)
Work Experience	0.019**	0.104**	0.018**
	(8.42)	(26.20)	(9.15)
Work Experience squared	-0.000**	-0.002**	-0.000**
	(6.77)	(18.66)	(6.88)
Tertiary Education	0.421**		0.418**
	(35.88)		(36.12)
Vocational Education	0.095**		0.095**
	(7.88)		(7.83)
Year 12	0.110**		0.109**
	(7.53)		(7.53)
Health Condition	-0.064**	-0.678**	-0.054**
	(4.24)	(25.90)	(4.23)
Born – English speaking country	0.038*	-0.046	0.039**
	(2.62)	(1.30)	(2.72)
Born- Non-English speaking country	-0.021	-0.298**	-0.018
	(1.55)	(9.80)	(1.32)
Children		-0.180**	
		(23.27)	
Youngest Child is between 0 and 5 years old		-0.351**	
		(12.73)	
Given Birth		-0.658**	
		(12.44)	
Birth variable missing		-0.005	
		(0.63)	
Household Income (minus female salary)		-0.066**	
		(6.18)	
Mortgage/Rent Repayments		0.224**	
		(14.47)	
Mortgage/Rent Repayments missing		-0.102**	
		(4.26)	
Lambda (Inverse Mills Ratio)	0.029		
	1.22		
Time Variables	yes	yes	yes
Number of Observations	11648		11724

Note: Women aged 25-54 years, pooled transition data. The figures in brackets comprise of t-statistics. * significant at the 5% level. ** significant at the 1% level. Source: HILDA Release 6.1

Appendix 2: Description of Key Variables

Table 2A: The name, description, mean and standard deviation of key variables

Variable name	Variable Description	Mean	Standard Deviation
Age 25 to 34	=1 if respondent is aged between 25 and 34 years in period t+1	0.2552	0.4360
Age 35 to 44	=1 if respondent is aged between 35 and 44 years in period t+1	0.3588	0.4796
Age 45 to 54	=1 if respondent is aged between 45 and 54 years in period t+1	0.3056	0.4607
Born- Australia	=1 if respondent was born in Australia in period t	0.7695	0.4212
Born- English speaking country	=1 if respondent was born in a English speaking country in period t	0.0973	0.2964
Born – Non English speaking country	=1 if respondent was born in a Non English speaking country in period t	0.1331	0.3397
Predicted wage	Predicted wage obtained through Heckman two-step selection model (see Appendix 1) as of period t+1	17.1823	3.4524
Predicted wage below $12.5	=1 if predicted wage is more than $0 and less or equal to $12.5 in period t+1	0.0372	0.1893
Predicted wage $12.5 to $15	=1 if the predicted wage is more than $12.5 and less or equal to $15 in period t+1	0.2410	0.4277
Predicted wage $15 to $17.5	=1 if predicted wage is between more than $15 and less or equal to $17.5 in period t+1	0.4093	0.4917
Predicted wage $17.5 to $20	=1 if predicted wage is more than $17.5 and less or equal to $20 in period t+1	0.0678	0.2515
Predicted wage over $20	=1 if predicted wage is more or equal than $20 in period t+1	0.2446	0.4299
Hours of work	Hours per week usually worked in all jobs in period t	23.0292	19.2437
Part-time work	= 1 if hours per week usually worked in all jobs is between 1 and 30 hours in period t	0.3067	0.4612
Full-time work	= 1 if hours per week usually worked in all jobs is equal or greater than 31 in period t	0.4024	0.4904
Given Birth	= 1 if respondent in period t+1 reported to have given birth or adopted a child in the last 12 months	0.0457	0.2088
Youngest Child between 0 and 5	=1 if respondent has a youngest child between the ages of 0 and 5 in period t+1	0.2263	0.4185
Youngest Child turned 1	=1 if respondent has a youngest child of 1 year old in period t+1	0.0495	0.2169
Youngest Child turned 6	=1 if respondent has a youngest child of 6 years old in period t+1	0.0322	0.1765
Remains Healthy	=1 if respondent reports to be healthy in period t and t+1	0.7465	0.4350
Health Condition persists	=1 if respondent reports a long-term health condition in period t and t+1	0.1113	0.3145
Health Condition improves	=1 if respondent reports a long-term health condition in period t and reports to be healthy in period t+1	0.0662	0.2486
Health Condition worsens	=1 if respondent reports to be healthy in period t and reports a long-term health condition in period t+1	0.0760	0.2650
Weekly household income	Female wage and salary is subtracted from the household income in period t+1	0.9287	0.9644
Time spend not employed	Self-reported time unemployed and not in the labour force in period t	7.1410	7.6172
EE1fEN0f	=1 if employed in periods t and t+1; and =0 if employed in period t and not employed in period t+1	0.9175	0.2751
NE1fNN0f	=1 if not employed in period t and employed in period t+1; and =0 if not employed in periods t and t+1	0.2175	0.4126

Notes: These descriptive statistics are based on the unweighted pooled HILDA dataset. The age dummies do not add up to a 100 because the sample is unbalanced and women that are not between 25 and 54 during the whole period have age observations recorded as missing. Source: HILDA Release 6.1

Appendix 3: Modelling Women's Employment Probability for a 3-year period

Table 3A: Marginal Effects

	EEE/EEN	ENE/ENN	NEE/NEN	NNE/NNN
Predicted wage	0.3%*	2.0%**	1.1%	3.0%**
Pre. wage $12.5 to $15	2.7%	37.0%**	8.5%	10.8%*
Pre. wage $15 to $17.5	3.9%	43.4%**	5.6%	23.8%**
Pre. wage $17.5 to $20	4.7%*	36.8%**	11.8%	30.8%**
Pre. wage over $20	5.5%*	44.5%**	12.6%	35.5%**
Youngest Child 0-5 years	-4.1%**	-2.1%	-0.2%	-13.5%**
Youngest Child turned 1	-3.0%	-2.4%	-5.5%	-3.0%
Youngest Child turned 6	1.0%	-6.6%	-5.1%	-2.0%
Given Birth	-34.9%**	-30.2%**	-39.5%**	-20.1**
Health Condition persists	-5.1%**	-12.6%*	-17.6%**	-15.6%**
Health Condition improved	-1.3%	-1.1%	-38.3%**	-5.1%
Health Condition worsens	-1.6%	-4.9%	-13.2%	-9.3%
Time spend not Employed	-0.2%*	-0.7%	-1.0%*	-0.7%**
Predicted probability at base	0.954	0.666	0.735	0.408

Notes: Women aged 25-54 years, pooled transition data (standard errors have been clustered by xwaveid). * significant at the 5% level. ** significant at the 1% level. Source: HILDA Release 6.1.

Table 3A shows that the probability of being employed in the third period is highest for women that have been employed in the two previous periods (95.4 per cent). The second highest employment probability (73.5 per cent) is experienced by women that have been employed in the second period, while women that have not been employed in either of the two previous periods have the lowest probability (40.8 per cent) of being employed in the subsequent period (t+1).

Corresponding with results from the 2-year period analysis, we find that the predicted wage rate is an important determinant of women's employment probability. However, the magnitude of the predicted wage rate on the employment probability in the third period depends on women's prior labour market transitions. According to the results a one dollar increase in the wage rate raises the employment probability for women having been employed for two preceding periods by only 0.3 per cent while it raises the employment probability for women having not been employed for two consecutive periods by 3 per cent. This strengthens the argument that the predicted wage rate has a greater influence on those not employed to transition into employment then employment retention per se.

Child related factors such as giving birth and having a youngest child between 0 and 5 are also very significant factors for women's employment probability in the third period. Child birth reduces the employment probability by between 30 and 40 per cent for women that have been employed in either of the previous or both periods. Giving birth also reduces the probability of women previously not being employed for two consecutive periods to transition into employment. However, the magnitude of child birth for this particular group is slightly lower while on the other hand having a youngest child between 0 and 5 has a much larger effect (13.5 per cent) on them compared to the impact of young children on women in the other three transition groups.

Appendix 4: Sensitivity checks

Table A4: Estimated coefficients for the factors influencing female employment probability (t+1) given their initial employment status (t)

Status in initial period (t)	Simple Employed (t)	Full-time (t)	Part-time (t)	Uncorrected predicted wage Employed (t)	Actual wage Employed (t)	Wage Premium Employed (t)[1]
Constant	0.664**	0.654	-0.090	0.234	0.533*	0.238
	(6.02)	(1.60)	(0.27)	(0.93)	(2.15)	(0.86)
Predicted wage	0.055**	0.039**	0.026**	0.031**	-	0.029**
	(7.66)	(4.19)	(2.97)	(4.79)		(4.05)
Actual wage	-	-	-	-	0.012**	-
					(5.03)	
Premium wage[1]	-	-	-	-	-	0.011**
						(4.39)
Age 25 to 34	-0.259**	0.068	0.045	0.065	0.080	0.100
	(6.20)	(0.79)	(0.52)	(1.08)	(1.26)	(1.57)
Age 35 to 44	-0.002	0.161*	0.162*	0.163**	0.170**	0.175**
	(0.06)	(2.11)	(2.51)	(3.33)	(3.26)	(3.36)
Born - English speaking country	-	-0.145	0.000	-0.033	-0.064	-0.082
		(1.74)	(0.00)	(0.57)	(1.06)	(1.34)
Born - Non English speaking country	-	-0.126	-0.066	-0.117*	-0.139*	-0.138*
		(1.51)	(0.85)	(2.06)	(2.33)	(2.32)
Youngest Child between 0 and 5	-	-0.348**	-0.159*	-0.272**	-0.267**	-0.270**
		(3.57)	(2.16)	(4.67)	(4.28)	(4.33)
Youngest Child turned 1	-	-0.081	-0.069	-0.087	-0.100	-0.111
		(0.50)	(0.57)	(0.91)	(0.93)	(1.03)
Youngest Child turned 6	-	0.362	-0.042	0.003	-0.017	-0.020
		(1.20)	(0.34)	(0.03)	(0.15)	(0.17)
Given Birth	-	-1.618**	-1.143**	-1.403**	-1.507**	-1.514**
		(13.52)	(11.00)	(18.54)	(18.54)	(18.62)
Health Condition persists over two periods	-	-0.482**	-0.546**	-0.547**	-0.548**	-0.534**
		(5.26)	(6.65)	(9.01)	(8.28)	(8.05)
Health Condition improved over two periods.	-	-0.046	-0.144	-0.137	-0.113	-0.114
		(0.40)	(1.51)	(1.93)	(1.43)	(1.45)
Health Condition worsens over two periods	-	-0.295**	-0.252**	-0.282**	-0.323**	-0.301**
		(3.30)	(2.93)	(4.55)	(5.02)	(4.66)
Time spend not Employed	-	-0.014*	-0.015**	-0.018**	-0.016**	-0.014**
		(2.55)	(3.37)	(5.15)	(4.23)	(3.71)
Time	yes	yes	yes	yes	yes	yes
Location	no	yes	yes	yes	yes	yes
Individual	no	yes	yes	yes	yes	yes
Mean of dependent variable	0.918	0.944	0.217	0.918	0.710	0.920

Notes: Women aged 25-54 years, pooled transition data (standard errors have been clustered by xwaveid). The figures in brackets are t-statistics. *significant at the 5% level. ** significant at the 1% level. [1]the premium wage has been derived subtracting the actual wage in t. Source: HILDA Release 6.1.