Analysing Nominal Data from a Panel Survey: Employment Transitions of Australian Women

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Abstract

Many processes of interest in social science research are recorded as nominal variables with two or more categories such as employment status, occupation, political preference and self-reported health status. With panel data it is possible to analyse the transitions of individuals between different states of the outcome variable. The generalized linear mixed model (GLMM) often used to analyse nominal variables with repeated observations is the dynamic multinomial logit random effects model. For this model, the marginal distribution of the response does not have a closed form solution and hence numerical integration must be used to obtain maximum likelihood estimates for the model parameters. Techniques for implementing the numerical integration are computationally intensive requiring a large amount of computer processing time that increases with the number of clusters (or individuals) in the data. In this paper we utilise and compare a classical and Bayesian approach to estimate the GLMM, with specific application to analysing employment transitions of women over four waves of an Australian panel survey. We find that Markov chain Monte Carlo simulation allows more flexible model estimation and is less computationally intensive than the classical approach using adaptive Gaussian quadrature.

1. Introduction

Longitudinal social surveys typically consist of repeated observations on the same individual at different points in time. The repeated measurements are positively correlated and so require special methods of analysis beyond those traditionally used for cross-sectional studies. Many variables that are of interest in social science research are nominal variables with two or more categories, such as employment status, occupation, political preference, or self-reported health status. With panel data it is possible to analyse the transitions of individuals between different employment states or occupations, for example. For a nominal or discrete dependent variable with repeated observations an appropriate model is the generalised linear mixed model (GLMM) where the response distribution is defined conditionally on the random effects. The GLMM for a nominal variable with three or more categories is the multinomial logit random effects model. Methods for estimating this type of model have appeared in the economics literature as discrete choice models with random effects (Hsaio, 2003; Wooldridge, 2002) as well as the statistics literature (see Hartzel et al. 2001 for a review).

In a multivariate GLMM the random effects are assumed to arise from a multivariate distribution. To obtain the marginal distribution of the response it is necessary to integrate out the random effects, however, the integration does not have a closed-form solution when the random effects are multivariate normal. Proposed methods for performing numerical integration to approximate the marginal distribution include adaptive Gaussian quadrature, AGQ (Liu and Pierce 1994, Hartzel 2001), Monte Carlo simulation techniques and approximation methods such as Laplace approximation and Taylor series expansion. The latter methods include marginal quasi-likelihood (MQL) and penalised quasi-likelihood (PQL). For details of these various methods see McCulloch and Searle (2001) and Goldstein (2003). The incorporation of random effects in discrete choice models has been addressed by Revelt and Train (1998) and Train (1999, 2003) using a simulation technique for model estimation, where the draw for each iteration is based on a Halton sequence. A simulated maximum likelihood approach has also been considered (Gong et al. 2000, Haan and Uhlendorff 2006). All of these estimation techniques are computationally intensive requiring a large amount of computer processing time that increases with the number of clusters (or individuals) in the data. For the social science researcher it is therefore important to have access to information on the efficiency of the statistical estimation techniques available.

Rabe-Hesketh, Skrondal and Pickles (2002) used the `gllamm` procedure in STATA (StataCorp, 2005) to compare the method of AGQ for estimating multilevel GLMMs with other methods utilising MQL/PQL, GQ and Markov chain Monte Carlo (MCMC) simulation. They concluded that MQL/PQL are most efficient and work well when the conditional distribution of the responses is close to normal and so do not work well for dichotomous data when the cluster size is small. Gaussian quadrature does work well for dichotomous data when the cluster size is small but this procedure requires a large number of quadrature points. This is improved by the use of AGQ. More recently, Skrondal and Rabe-Hesketh (2003) used AGQ and `gllamm` software to model political party choice, from the 1987-1992 panel of the British Election Study, specifying a multinomial logit model with correlated random intercepts.

An alternative approach utilises MCMC simulation to estimate parameters of the model and has been shown to perform better for modelling dichotomous data (Brown and Draper, 2002; Rodriguez and Goldman, 2001). MCMC simulation in a Bayesian approach also has the advantage that it allows properties of arbitrary functions of parameters to be examined and missing data to be readily imputed. A study by Pettitt et al. (2006) investigates a Bayesian hierarchical model with two correlated random intercepts for categorical employment data from a longitudinal survey of immigrants to Australia, using WinBUGS software (Spiegelhalter et al., 1998). We use a similar approach to estimate our models and compare our results and computational time with that obtained using `gllamm` (for the non-dynamic models). We investigate two forms of the model:

1. a multinomial logit model with correlated random intercepts to capture unobserved heterogeneity among individuals i.e. spurious dependence;
2. a dynamic multinomial logit random effects model with lagged dependent variable to account for state dependence.

We estimate these models in an application concerning transitions in the employment status of women, using data from four waves of the HILDA survey. Variables from the HILDA survey that are included in the model are described in Section 2. In Section 3 we present the formulation of the model and describe the Bayesian approach to estimating the parameters of the model. The results of the analyses, including a comparison of the computing efficiency of each software routine investigated, are outlined in Section 4.

2. Application to Women's Employment Transitions

2.1 Women and employment in Australia

In the 21 years prior to 2005 the overall labour force participation rate increased from 60.5 percent in 1983-1984 to 64.0 percent in 2004-05 (ABS 2006). But male and female patterns have differed markedly. While male participation rates declined from 77 percent in 1983 to under 72 percent in 2005, female participation rates increased from 44 percent to almost 57 percent in the corresponding period. Moreover, the growth in female participation occurred despite a six percentage point decline in the female full-time participation rate, from 57 to 51 percent (ABS 6202.0.01). The overall increase in labour force participation is thus largely attributable to growing female part-time employment, particularly among married women. Australia is not unusual in this regard. Britain, Europe and North America have all seen rising labour force participation rates among married women (Smits, Ultee and Lammers 1996; Pencavel 1998; Ginn and Arber 1995). The trend has led some analysts to argue that the traditional nuclear family with a sole male breadwinner, dependent non-employed spouse and dependent children, has been replaced by the new traditional family with one full-time and one part-time earner (Smits, Ulteee and Lammers, 1996; Mitchell 2005).

Given employment trends in Australia and elsewhere, understanding women's labour force participation patterns is thus a central task. But there are other reasons for focusing on women's employment, apart from wanting to explain labour market trends. Women's employment may be linked to other aspects of inequality such as the gender gap in earnings between women and men, earnings and other inequalities among different groups of women (Pencavel 1998; England, Garcia-Beaulieu and Ross 2004) or the organisation of domestic labour such as housework and childcare (Stier and Lewin-Epstein 2000). Changing patterns of female full- and part-time work may also have implications for occupational sex segregation, since part-time work may be more sex-segregated than full-time work (Blackwell 2001). Australia currently has the highest level of occupational sex-segregation of all OECD countries (EOWA 2004), and occupational sex segregation is directly linked to the gender gap in earnings, career mobility prospects, and possibilities to exercise authority and autonomy at work (Watts 2003). Finally, the emergence of the new traditional family also signals that the number of earners in a household is a critical determinant of household income and thus of levels of household income inequality.

In this paper we undertake a longitudinal analysis of women's employment using the first four waves of the HILDA data. Our primary aim is to compare two different methods for analysing longitudinal data with a nominal response. But we also provide some evidence on the factors associated with women's employment. We focus particularly on predictors reflecting women's human capital, family commitments and spouse's characteristics. Given computational complexity, our model is a simplified one, that omits several key variables, most notably occupation and the degree of sex-typing of the occupation in which a woman is employed.

2.2 Data from the HILDA Survey

A sample of the Household, Income and Labour Dynamics in Australia (HILDA) survey data was selected from women who are aged between 20 and 55 years at June 2001, excluding widows. There were 4815 women in the survey who met these criteria. Of these women, 1352 or

28% either dropped out of the survey or did not respond to the survey at wave two, three or four. Hence, the balanced sample data set consisted of 3463 women who completed questionnaires at all four waves.

The response variable, employment status, consists of three categories: employed full-time (ft); employed part-time (pt); not employed (including unemployed and not in the labour force). The explanatory variables include respondent's age, number of children ever had, age of youngest child, age left school, highest level of education achieved, current marital status, partner's job if married, partner's financial year private income and a measure of self-reported health. Variables measuring a woman's attitude towards work, her attitude towards working mothers and the partner's attitude towards working mothers were also included.

Including the respondent's age in the model captures cohort differences in employment among women and also potential experience. The age variable is centered and linear and quadratic terms are included in the model to allow for nonlinear associations between age and employment. The age left school variable is also centered. Both age left school and educational qualification index a woman's human capital. The educational qualification is measured with categories for Bachelor Degree or higher, Diploma or Certificate, and Year 12 or under which is specified as the reference category. Family commitments, which may impact on women's capacity to enter paid employment and diminish the net benefits of employment, are captured by marital status, number of children and age of the youngest child. Marital status was coded married or defacto, separated or divorced, and never married, with never married specified as the reference category. The married or defacto group is further divided into categories representing partner's job (no job, manager, professional and associate professional, white collar, and blue collar). Number of children is categorised into no children (the reference category), one or two child(ren), and three or more children. Age of the youngest child is a dummy variable indicating the presence of a child who is five years old or younger.

Partner's income is included because women's employment might be necessary to maintain household income level. On the other hand, higher partner's income would presumably increase the reservation wage and thus lower the likelihood of employment. This variable is measured in $'000 and it includes Australian pensions and benefits. For those who do not have a partner, this variable is set to zero. Some attitude variables are also included: women's attitude towards work, attitude towards working mother and partner's attitude towards working mother. The attitude towards work variable measures whether the respondent thinks having a job is important. The attitude and the partner's attitude towards working mothers have some explanatory power over mothers' choices to work. All three variables are treated as continuous in the model.

Predictors like these are standard ones in analyses of women's labour force participation (see e.g. Smits, Ultee and Lammers 1996; England et al., 2004; Ginn and Arber 1995; Alon, Donahoe and Tienda, 2001; Budig 2003; Hynes and Clarkberg 2005).

Table 1 shows the percentages of women that followed the various employment trajectories over three and four waves of data, respectively. The three most common trajectories are the ones with no change of status over all four waves with 24 percent of women in full-time employment continuously, 18 percent continually not employed and 15 percent remaining in part-time employment. These percentages are slightly lower than for women who remain in the corresponding employment states over three waves, indicating that women are more likely to change their employment situation during a longer period of time. The next most common pathways involve a change of state, between part-time and full-time employment, or between non-employment and part-time employment. The least common trajectories involve two changes of state, and/or the relatively uncommon combination of non-employment and full-time employment. These patterns are consistent with state-dependence, in which a woman's current employment status depends heavily on her previous status, and with heterogeneity, in which unmeasured factors systematically influence the probability of each outcome, at each wave.

3. Multinomial logit regression model with random effects

3.1 The model

Given the response variable an appropriate model is the multinomial logit model. Suppose that individual i has T categorical observations and let Y_{it} denote the tth observation for individual i, $t = 1,\dots,T$. If there are J possible response states then $\Pr(Y_{it} = j \mid X_{it})$, $j = 1,\dots,J$, is the probability that individual i has response j at time t given X_{it}, a column vector of explanatory variables for that observation. The multinomial model is expressed as

$$\pi_{itj} = \Pr(Y_{it} = j \mid X_{it}) = \frac{e^{X_{it}\beta_j}}{\sum_{k=1}^{J} e^{X_{it}\beta_k}}.$$

The logit model pairs each response category with an arbitrary baseline category. In our analysis the response has three states (J = 3): full-time employment (j = 1), part-time employment (j = 2) and not employed (j = 3). For identifiability, not employed is set as the reference category so that $\beta_3 = 0$. The multinomial logit model then has the form

$$\log\left(\frac{\pi_{itj}}{\pi_{it3}}\right) = X_{it}^{'}\beta_j \tag{1}$$

where j=1,2. This has a latent variable interpretation where we define the utility of choosing a particular response, for example employment state, by the random variables U_{itj} *(j = 1,…,J),* with the function $U_{itj} = X_{it}\beta_j + e_{itj}$ consisting of an observable component and random elements e_{itj} that arise from an independent extreme value distribution. The individual chooses the response state *j* if and only if the utility is greatest for this state, that is, $U_{itj} = \max_{1\le k\le J}\{U_{itk}\}, j = 1,\dots,J$. Model 1 is defined by expression (1).

If we also introduce individual-specific random effects α_{ij} to model spurious dependence and let Z_{ij} denote a vector of coefficients for the random effects, then the logit model has the form

$$\log(\frac{\pi_{itj}}{\pi_{it3}}) = \log(v_{itj}) = X'_{it}\beta_j + Z'_{ij}\alpha_{ij} \quad j = 1,2. \qquad (2)$$

The random effects $\alpha_i=\{ \alpha_{i1},\dots, \alpha_{iJ})$ capture non-observable individual effects that are specified to arise from a multivariate normal distribution with mean zero and variance-covariance matrix Σ.

The regression coefficients are assumed to be constant for all individuals *i* and different waves *t* in employment state *j*. However, each individual *i* is now considered as a cluster of observations over time (t = 1, 2, 3, 4) and a random intercept is introduced to account for any potential unobserved or spurious heterogeneity among individuals. This is denoted as Model 2 and is defined by expression (2).

Finally, from the descriptive statistics presented before, it is likely that state dependence is a strong feature of this data. That is, individuals are more likely to maintain their employment status than switching status, and one-state transition is more likely than a two-state transition. Therefore, Model 3 includes a lagged response variable that captures the impact of state dependence and is defined by expression (3). To investigate whether spurious dependence exists in addition to state dependence we also investigate a model that includes both a lagged response variable and random effects. This is denoted Model 4 as defined by expression (4).

$$\log(v_{itj}) = X'_{itj}\beta_j + L'_{itj}\gamma_j \qquad (3)$$

$$\log(v_{itj}) = X'_{itj}\beta_j + L'_{itj}\gamma_j + \alpha_{ij} \qquad (4)$$

The lag terms here mainly capture the effects of staying full time employed (i.e. from state 1 to state 1), switching between part time and full time (both from state 1 to state 2 and from state 2 to state 1) and staying part time employed.

Table 1: Percentages of women who followed the 81 possible employment transition pathways across the first four waves of the HILDA survey (N = 3463). For the first three waves there were 27 possible employment transitions. Pathways in which an employment transition occurs are grouped according to the first and final employment state.

Employment state in first and final wave	Percentage of women	
	over 3 waves 2001 – 2003	over 4 waves 2001 - 2004
Transitions from Full Time Work		
FT – FT (no transition)	26.60	23.59
FT - FT (intermediate transition)	2.14	3.60
FT – PT	5.54	6.30
FT – Not Employed	2.83	3.62
Total	**37.11**	**37.11**
Transitions from Part Time Work		
PT - PT (no transition)	18.72	15.17
PT - PT (intermediate transition)	2.57	4.97
PT – FT	6.26	7.54
PT – Not Employed	5.14	5.03
Total	**32.69**	**32.69**
Transitions from Not Employed (NE)		
NE – NE (no transition)	20.18	17.60
NE – NE (intermediate transition)	1.76	2.70
NE – PT	6.18	7.25
NE – FT	2.08	2.65
Total	**30.20**	**30.20**

3.2 Approaches to model estimation

In the classical (frequentist) framework of estimation, as outlined in Section 1, a number of methods have been proposed for approximating the integrals of the likelihood function with the preferred option being AGQ for this particular model and a small cluster size (which is four in our analysis). Few software packages have the capacity to fit GLMMs using AGQ when the response variable has more than two nominal outcomes such as in the discrete choice model (see Skrondal and Rabe-Hesketh (2004), pages 216-219, for a summary of available statistical software). To fit a multinomial logit regression model with correlated random effects to data using `gllamm` is a complex process.

In a Bayesian approach, all of the parameters in the model are assumed to be random and inferences about the parameters are made through their posterior distributions. The posterior distributions for all unknown parameters in the model are proportional to the product of the likelihood function and the specified prior distributions. A major advantage of this approach is that MCMC simulation methods (see for example Gelman et al., 2005) are available to draw samples from the posterior distributions of the unknown parameters, for models with non-standard likelihood functions. In addition: prior information about the model parameters can be incorporated; samples can easily be drawn from the posterior distributions of arbitrary functions of parameters in the model (e.g. percentiles of the parameter) and the accuracy and convergence of the solution can be improved by increasing the number of iterations of the MCMC algorithm.

The Bayesian hierarchical model for our data on the employment status of women has two levels. At the first level it is assumed that the response data Y_{it} are distributed as multinomial random variables. At the second level, the model relates the probabilities π_{itj} to the regression effects and random effects as in equation (2) above. Following Pettitt et al. (2006) who have considered similar models, non-informative normal prior distributions were specified for the regression parameters β_j, and multivariate normal prior distributions were specified for the random effects α_{ij}, with zero mean and a 2 × 2 variance-covariance matrix Σ. A non-informative Wishart prior was specified for the inverse of Σ.

In Model 4 the lagged dependent variable has been included on the right-hand side of the equation to allow us to test for state dependence in women's employment status. This is a first-order Markov model with mean ν_{itj} being conditional on past responses and so an initial condition problem arises. Following Heckman (1981b) we do not include the lagged term or random effect in the model at wave one but do so at waves two, three and four.

To fit this Bayesian hierarchical model to the HILDA employment status data, we have used the WinBUGS software (Spiegelhalter et al., 1998) which implements MCMC simulation using the Gibbs Sampler. Because we have used non-informative priors for the model parameters and random effects, the means of the posterior distributions will reflect the maximum likelihood estimates and so the results from this analysis will be comparable to the estimation approach using AGQ via the `gllamm` procedure in STATA. This is explored further in Section 4.

4. Results

4.1 Estimated model parameters

In this section we use `gllamm` via STATA and MCMC simulation via WinBUGS to estimate the multinomial logit models for women's employment status defined as Models 1 and 2. Models 3 and 4 are estimated using MCMC simulation only. For models 1 and 2, records with missing data on the covariates were excluded from the analysis reducing the dataset to 3,058 individuals and 10,547 records. In a random effects model such as Model 2, a record associated with an individual need only be removed for the year in which data is missing and the individual remains in the dataset. For models 3 and 4 which include lagged variables, all records for an individual with missing data in any year must be excluded from the data unless the missing observations are imputed. Because of the computational time required for our analyses the records were discarded reducing the dataset to 1,771 individuals and 7,084 person years. Tables 2a and 2b show the parameter estimates for modelling the response outcome of full-time employment relative to not employed, and for the response outcome of part-time employment relative to not employed, respectively, using specifications for Models 1 and 2 as described in Section 3.1. Similarly, Tables 3a and 3b show the parameter estimates for the response outcomes of full-time and part-time employment, respectively, based on Models 3 and 4.

Model 1 represents the pooled multinomial logit model. This model provides us with initial estimates for implementing the more complex Model 2 with random intercept terms. Tables 2a and 2b show that the parameter estimates for Model 1 obtained via `gllamm` and WinBUGS are almost identical for both response outcomes of full-time and part-time employment. Secondly, we analysed the data using a multinomial logit model with correlated random effects (Model 2). We used both AGQ and MCMC methods of estimation with the similar results shown in Tables 2a and 2b. But for this model with correlated random effects, the MCMC simulation procedure proved to be less computationally expensive than `gllamm` by more than 5 days, although this varied depending on the choice of initial parameter values, quadrature points and iterations. In addition, it took days to compute reasonable starting values for the AGQ method. From these results we can conclude that the MCMC simulation method is computationally faster than `gllamm` for estimating complex models such as the multinomial logit random effects model with multivariate normal random effects.

Interpreting the results for Model 2 obtained using MCMC simulation, the estimate of the variance of the random intercept for women who are employed full-time is 27.51, almost three times greater than the estimate of 10.03 for women who are employed part-time. This indicates that there is a high degree of unobserved heterogeneity among women that is unaccounted for by the explanatory variables in the model and this is greater for women in full-time compared to part-time employment. The covariance of the random effect terms for full- and part-time women is a significantly high 11.35 indicating a positive correlation between unmeasured characteristics of women and their influence on their choice of full-time or part-time employment.

Finally, we test for state dependence by incorporating the lagged dependent variable into the model. Model 3 includes the lagged dependent variable while Model 4 is an extension of Model 2 which includes both the lagged dependent variable and a term for random effects to capture unexplained heterogeneity in the data. Tables 3a and 3b show the parameter estimates for Models 3 and 4 for full-time and part-time employment, respectively. Parameter estimates for Model 2 based on the reduced dataset with 1,771 individuals are also included for comparison. The lagged terms are significant indicating the presence of state dependence. The odds of being in full-time employment are 9 times greater if a woman was previously in full-time compared to part-time employment. However, the odds of being in part-time employment are only 3 times greater if a woman was previously in part-time compared to full-time employment. The unobserved heterogeneity estimated in Model 2 is largely accounted for by state dependence estimated in Models 3 and 4.

4.2 Interpretation of Results from Dynamic Multinomial Logit Model with Random Effects

A comparison of parameter estimates for Models 2 and 4 in Tables 3a and 3b shows that the magnitudes of the standard errors are much smaller when the lagged variable is included in the model. The estimated regression coefficients for Model 4 are much more precise after accounting for state and spurious dependence, and we interpret these results here. We see that human capital and family factors are both associated with a transition in employment. Conditional on the random effects, women with a bachelor degree or higher have significantly greater odds of full-time employment than less educated women ($\exp(0.49) = 1.63$). These odds are similar for part-time employment ($\exp(0.42) = 1.52$).

In terms of family variables, the main finding is that married women with partners that are not in paid employment are less likely to be in full-time or part-time employment than women who are single. Having a young child in the home is associated with diminished odds of full-time employment ($\exp(-1.40) = 0.25$) as is the number of children a woman has had. The odds of part-time employment are also low ($\exp(-0.72) = 0.59$) when a young child is present, however, these odds are not influenced by the number of children. There is also a negative association between partner's income and women's full-time employment, with women with high income partners less likely to work full-time than women with lower income partners.

Three variables relating to attitudes to work were included in the model. A more positive attitude to work and to mothers working is associated with higher odds of full-time employment while only a positive attitude to a mother working is associated with higher odds of part-time employment. The association with partner's attitude to employment was not significant. The odds of full-time and part-time employment are diminished if self-reported health is fair to poor.

These results are broadly consistent with human capital arguments and with arguments about the impact of family and domestic responsibilities on women's involvement in paid work. Given the association between education and earnings, costs in foregone income in leaving the labour market are likely to be substantially higher for more educated, rather than less educated women. In addition, educational attainment may be tapping other variables such as labour force attachment that would be significantly associated with paid employment. Similarly, the association between age and full-time employment mirrors an age-earnings profile with the likelihood of full-time employment peaking at about the age at which earnings are at a maximum.

The results for the effects of pre-school children and number of children are consistent with an argument that women's domestic responsibilities make it more difficult for them to combine these with paid employment, particularly full-time employment. However it could also be the case that children increase the cost of paid employment to women, through the need for childcare and other services when mothers are working.

The significance of the lagged employment variable in the model indicates that if a woman is employed now then she is highly likely to be employed in the following year. The odds of remaining in full-time employment are higher than the odds of remaining in part-time employment. This indicates the presence of state dependence and the estimated regression parameters should be interpreted as additional influences on employment after this has been accounted for. That is, when a woman moves into the labour market she is likely to stay in the labour market until certain life events occur such as the birth of a child or a decline in health.

We experienced difficulty in estimating Models 3 and 4 using the `gllamm` software as it is not straightforward to estimate regression coefficients separately for wave one under the initial conditions and for later waves incorporating the lagged variable. Comparison of parameter estimates for Model 2 using AGQ and MCMC showed similar results and MCMC proved to be more computationally efficient. The Bayesian approach to estimation using MCMC simulation allowed straight forward computation of the more flexible but complex Models 3 and 4.

Table 2a: Parameter estimates for outcome of full-time employment relative to not employed. Models 1 - 2 estimated using AGQ in Stata and MCMC in WinBUGS (Model 1: 50,000 iterations with a burn-in of 10,000; Model 2: 150,000 iterations with a burn-in of 50,000)

Parameters	Model 1				Model 2			
	gllamm (AGQ)		MCMC		gllamm (AGQ)		MCMC	
	mean	se	mean	se	mean	se	mean	se
Constant	-2.166	(0.194)	-2.160	(0.184)	-5.511	(0.821)	-5.591	(0.598)
Age	0.015	(0.004)	0.015	(0.004)	0.074	(0.017)	0.076	(0.016)
Age^2	-0.001	(0.0003)	-0.001	(0.0003)	-0.004	(0.001)	-0.004	(0.001)
Age left school	0.110	(0.026)	0.109	(0.025)	0.304	(0.114)	0.305	(0.109)
Preschool child	-1.935	(0.090)	-1.937	(0.090)	-3.426	(0.276)	-3.483	(0.282)
Number of children:								
No children	-	-	-	-	-	-	-	-
1-2 children	-1.333	(0.103)	-1.348	(0.102)	-4.430	(0.414)	-4.450	(0.405)
3+ children	-1.479	(0.111)	-1.495	(0.110)	-4.755	(0.468)	-4.794	(0.456)
Education:								
Degree	1.002	(0.082)	1.004	(0.082)	2.593	(0.318)	2.642	(0.309)
Diploma	0.582	(0.070)	0.585	(0.070)	1.585	(0.287)	1.605	(0.270)
Year 12	-		-		-	-	-	-
Marital status:								
Single	-		-		-	-	-	-
Sep/Div	0.490	(0.129)	0.495	(0.128)	0.861	(0.445)	0.835	(0.432)
Married & partner's job								
No job	-0.906	(0.160)	-0.897	(0.164)	-1.851	(0.490)	-1.854	(0.508)
Manager	0.693	(0.165)	0.707	(0.171)	0.550	(0.474)	0.542	(0.505)
Professional & A/Prof	0.420	(0.147)	0.434	(0.152)	0.486	(0.435)	0.477	(0.476)
White collar	1.211	(0.168)	1.226	(0.170)	1.194	(0.475)	1.154	(0.521)
Blue collar	0.470	(0.141)	0.484	(0.145)	0.404	(0.428)	0.379	(0.469)
Partner's income	-0.069	(0.008)	-0.069	(0.009)	-0.067	(0.019)	-0.069	(0.020)
Attitude towards work	0.244	(0.020)	0.244	(0.020)	0.681	(0.091)	0.680	(0.089)
Attitude to working mothers	0.467	(0.029)	0.468	(0.028)	1.222	(0.125)	1.256	(0.105)
P'ner attitude working mother	0.130	(0.023)	0.129	(0.024)	0.306	(0.083)	0.312	(0.099)
Self reported health								
Excellent/very good	0.263	(0.063)	0.261	(0.064)	0.296	(0.147)	0.282	(0.147)
Good	-	-	-	-	-	-	-	-
Fair/poor	-0.978	(0.091)	-0.983	(0.091)	-1.190	(0.217)	-1.168	(0.218)
Between individual variance for ft state					24.499	(1.873)	27.510	(2.243)
Covariance with pt state					10.064	(0.996)	11.350	(1.157)
Individuals	3058				3058			
Person years	10,547				10,547			
Processing time					> 5 days		69 hrs	

Table 2b: Parameter estimates for outcome of part-time employment relative to not employed. Models 1 - 2 estimated using AGQ in Stata and MCMC in WinBUGS

Parameters	Model 1				Model 2			
	gllamm (AGQ)		MCMC		gllamm (AGQ)		MCMC	
	mean	se	mean	se	mean	se	mean	se
Constant	-1.276	(0.182)	-1.260	(0.176)	-2.055	(0.532)	-1.990	(0.434)
Age	0.002	(0.004)	0.002	(0.004)	0.022	(0.011)	0.023	(0.011)
Age^2	-0.002	(0.0003)	-0.002	(0.0003)	-0.004	(0.001)	-0.004	(0.001)
Age left school	0.095	(0.024)	0.095	(0.024)	0.275	(0.073)	0.282	(0.071)
Preschool child	-1.041	(0.076)	-1.042	(0.076)	-1.825	(0.186)	-1.861	(0.191)
Number of children:								
No children	-	-	-	-	-	-	-	-
1-2 children	-0.081	(0.106)	-0.093	(0.104)	-0.724	(0.281)	-0.681	(0.275)
3+ children	-0.065	(0.114)	-0.078	(0.112)	-0.760	(0.314)	-0.733	(0.312)
Education:								
Degree	0.662	(0.077)	0.664	(0.077)	1.339	(0.222)	1.344	(0.224)
Diploma	0.331	(0.066)	0.334	(0.066)	0.667	(0.192)	0.666	(0.185)
Year 12	-	-	-	-	-	-	-	-
Marital status:								
Single	-	-	-	-	-	-	-	-
Sep/Div	-0.068	(0.129)	-0.063	(0.130)	-0.132	(0.320)	-0.201	(0.310)
Married & partner's job								
No job	-1.223	(0.158)	-1.216	(0.163)	-1.977	(0.367)	-2.045	(0.381)
Manager	0.573	(0.155)	0.586	(0.161)	0.493	(0.360)	0.430	(0.377)
Professional & A/Prof	0.313	(0.141)	0.326	(0.145)	0.328	(0.332)	0.267	(0.356)
White collar	0.631	(0.162)	0.645	(0.165)	0.526	(0.369)	0.441	(0.396)
Blue collar	0.298	(0.135)	0.310	(0.140)	0.210	(0.325)	0.135	(0.347)
Partner's income	-0.026	(0.007)	-0.026	(0.007)	-0.023	(0.013)	-0.024	(0.013)
Attitude towards work	0.106	(0.018)	0.105	(0.017)	0.260	(0.058)	0.252	(0.061)
Attitude to working mothers	0.257	(0.027)	0.256	(0.027)	0.585	(0.082)	0.606	(0.069)
P'ner attitude working mother	0.078	(0.022)	0.078	(0.022)	0.176	(0.059)	0.182	(0.069)
Self reported health								
Excellent/very good	0.225	(0.059)	0.224	(0.059)	0.217	(0.115)	0.209	(0.114)
Good	-	-	-	-	-	-	-	-
Fair/poor	-0.811	(0.085)	-0.815	(0.084)	-1.109	(0.165)	-1.108	(0.165)
Between individual variance for ft state					9.263	(0.732)	10.030	(0.828)
Covariance with pt state					10.064	(0.996)	11.350	(1.157)
Individuals	3058				3058			
Person years	10,547				10,547			
Processing time					> 5 days		69 hrs	

Table 3a: Parameter estimates for outcome of full-time employment relative to not employed. Models 2, 3, 4 estimated using MCMC in WinBUGS (Model 2: 60,000 iterations with a burn-in of 4,000; Model 3 &4: 100,000 iterations with a burn-in of 4,000)

Parameters	Model 2		Model 3		Model 4	
	mean	se	mean	se	mean	se
Constant	-4.948	(1.238)	-2.824	(0.580)	-3.226	(0.660)
Age	0.092	(0.024)	0.009	(0.009)	0.009	(0.009)
Age^2	-0.006	(0.002)	-0.003	(0.001)	-0.003	(0.001)
Age left school	0.311	(0.145)	0.079	(0.051)	0.087	(0.054)
Preschool child	-3.448	(0.338)	-1.265	(0.165)	-1.397	(0.178)
Number of children:						
No children	-	-	-	-	-	-
1-2 children	-4.208	(0.538)	-0.580	(0.204)	-0.605	(0.222)
3+ children	-4.533	(0.596)	-0.629	(0.219)	-0.659	(0.240)
Education:						
Degree	2.254	(0.399)	0.440	(0.155)	0.490	(0.160)
Diploma	1.217	(0.355)	0.161	(0.136)	0.190	(0.148)
Year 12	-	-	-	-	-	-
Marital status:						
Single	-	-	-	-	-	-
Sep/Div	-0.752	(0.849)	-0.602	(0.501)	-0.485	(0.590)
Married & partner's job						
No job	-3.124	(0.767)	-1.262	(0.461)	-1.193	(0.558)
Manager	-0.576	(0.766)	-0.576	(0.460)	-0.423	(0.562)
Professional & A/Prof	-0.580	(0.733)	-0.548	(0.442)	-0.384	(0.545)
White collar	-0.011	(0.745)	-0.073	(0.469)	0.113	(0.565)
Blue collar	-0.760	(0.727)	-0.580	(0.439)	-0.429	(0.539)
Partner's income	-0.043	(0.021)	-0.026	(0.012)	-0.027	(0.013)
Attitude towards work	0.669	(0.128)	0.090	(0.039)	0.111	(0.042)
Attitude to working mothers	1.071	(0.163)	0.339	(0.059)	0.373	(0.060)
P'ner attitude working mother	0.640	(0.171)	0.028	(0.058)	0.042	(0.058)
Self reported health						
Excellent/very good	0.195	(0.180)	0.045	(0.120)	0.055	(0.126)
Good	-	-	-	-	-	-
Fair/poor	-1.321	(0.289)	-0.941	(0.188)	-1.001	(0.199)
Lags (Previously):						
Unemployed	-	-	-	-	-	-
Full time	-	-	4.925	(0.168)	4.959	(0.170)
Part time	-	-	2.705	(0.161)	2.725	(0.169)
Between individual variance for ft state	28.750	(2.713)	-	-	0.453	(0.111)
Covariance with pt state	12.270	(1.431)	-	-	0.227	(0.084)
Individuals	1771		1771		1771	
Person years	7084		7084		7084	
Processing time	20 hours		33 hours		36 hours	

Table 3b: Parameter estimates for outcome of part-time employment relative to not employed. Models 2, 3, 4 estimated using MCMC in WinBUGS

Parameters	Model 2		Model 3		Model 4	
	mean	se	mean	se	mean	se
Constant	-2.598	(1.116)	-2.343	(0.496)	-2.595	(0.573)
Age	0.041	(0.017)	0.005	(0.007)	0.005	(0.008)
Age^2	-0.007	(0.001)	-0.002	(0.001)	-0.002	(0.001)
Age left school	0.260	(0.095)	0.059	(0.042)	0.070	(0.046)
Preschool child	-1.967	(0.242)	-0.614	(0.132)	-0.715	(0.144)
Number of children:						
No children	-	-	-	-	-	-
1-2 children	-0.163	(0.414)	0.314	(0.197)	0.393	(0.211)
3+ children	-0.158	(0.453)	0.319	(0.208)	0.402	(0.224)
Education:						
Degree	1.242	(0.285)	0.383	(0.134)	0.415	(0.141)
Diploma	0.492	(0.250)	0.079	(0.116)	0.097	(0.126)
Year 12	-	-	-	-	-	-
Marital status:						
Single	-	-	-	-	-	-
Sep/Div	-0.086	(0.688)	-0.113	(0.433)	-0.047	(0.500)
Married & partner’s job						
No job	-2.002	(0.663)	-0.988	(0.408)	-1.003	(0.482)
Manager	0.782	(0.658)	0.341	(0.405)	0.458	(0.479)
Professional & A/Prof	0.691	(0.638)	0.205	(0.391)	0.329	(0.467)
White collar	0.718	(0.655)	0.573	(0.414)	0.703	(0.486)
Blue collar	0.429	(0.639)	0.186	(0.388)	0.283	(0.461)
Partner’s income	-0.018	(0.014)	-0.012	(0.010)	-0.013	(0.011)
Attitude towards work	0.237	(0.081)	0.011	(0.032)	0.020	(0.034)
Attitude to working mothers	0.538	(0.110)	0.194	(0.049)	0.219	(0.052)
P’ner attitude working mother	0.287	(0.116)	0.023	(0.048)	0.030	(0.050)
Self reported health						
Excellent/very good	0.238	(0.141)	0.131	(0.102)	0.131	(0.106)
Good	-	-	-	-	-	-
Fair/poor	-0.997	(0.211)	-0.697	(0.152)	-0.756	(0.163)
Lags (Previously):						
Unemployed	-	-	-	-	-	-
Full time	-	-	1.973	(0.145)	1.961	(0.150)
Part time	-	-	3.212	(0.102)	3.168	(0.113)
Between individual variance for ft state	10.790	(1.040)	-	-	0.401	(0.100)
Covariance with pt state	12.270	(1.431)	-	-	0.227	(0.084)
Individuals	1771		1771		1771	
Person years	7084		7084		7084	
Processing time	20 hours		33 hours		36 hours	

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