Methods for Categorical Longitudinal Survey Data: Understanding Employment Status of Australian Women

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Abstract

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 longitudinal survey data it is possible to analyse the transitions of individuals between different employment states or occupations (for example). In the statistical literature, models for analysing categorical dependent variables with repeated observations belong to the family of models known as generalized linear mixed models (GLMMs). The specific GLMM for a dependent variable with three or more categories is the multinomial logit random effects model. For these models, 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 available but are computationally intensive requiring a large amount of computer processing time that increases with the number of clusters (or individuals) in the data and are not always readily accessible to the practitioner in standard software. For the purposes of analysing categorical response data from a longitudinal social survey, there is clearly a need to evaluate the existing procedures for estimating multinomial logit random effects model in terms of accuracy, efficiency and computing time. The computational time will have significant implications as to the preferred approach by researchers. In this paper we evaluate statistical software procedures that utilise adaptive Gaussian quadrature and MCMC methods, with specific application to modeling employment status of women using a GLMM, over three waves of the HILDA survey.

1. Introduction

1.1 Women and employment in Australia

In the last 20 years the overall labour force participation rate increased from 60.5 percent in 1983-1984 to 63.5 percent in 2003-04 (ABS 2005). But male and female patterns have differed markedly. While male participation rates declined from 77 percent in 1983 to under 72 percent in 2004, female participation rates increased from 44 percent to almost 56 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 nonemployed 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 three waves of the HILDA data. Our primary aim is to compare two different methods for analysing longitudinal data with a categorical unordered outcome. 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 women's and their partners' attitudes to paid employment, and the degree of sex-typing of the occupation in which a woman is employed.

1.2 Methods for analysing categorical longitudinal survey data

Longitudinal social surveys typically consist of repeated observations on the same individual at different points in time. The repeated measurements are typically positively correlated and so require special methods of analysis beyond those traditionally used for cross-sectional studies. One way of dealing with correlation among repeated observations for an individual is to introduce random effects into the regression model. These models for continuous dependent variables are known as linear mixed models (LMM) (see Pinheiro and Bates 2000, Diggle et al. 2002 among others) and routine methods are available in standard statistical software to estimate the model parameters. However, it is only within the past decade or so that LMMs have been seriously considered for analysing panel survey data and their application in social science literature has been limited (Johnson, 1995 p. 1065).

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 longitudinal survey data it is possible to analyse the transitions of individuals between different employment states or occupations (for example) using appropriate statistical techniques. For a categorical or discrete dependent variable with repeated observations one such model is the generalised linear mixed model (GLMM). This is an extension of a generalised linear model to incorporate both fixed and random effects, so that the response distribution is defined conditionally on the random effects. The GLMM for a dependent variable with three or more categories is the multinomial logit random effects model. While methods for estimating this type of model have appeared in the economics literature as discrete choice models with random effects (see for example Hsaio, 2003 and Wooldridge, 2002) as well as in the statistics literature (see Hartzel et al. 2001 for a review), the procedures for estimation are both complex and computationally intensive.

In a multivariate GLMM such as the multinomial logit random effects model, the random effects are assumed to arise from a multivariate distribution, generally a multivariate normal 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 Gauss-Hermite quadrature, Monte Carlo simulation techniques and approximation methods such as Laplace approximation and Taylor series expansion (see Hartzel et al. 2001 for references). 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) where random coefficients for the explanatory variables are considered to vary with the response category. Train (2003) uses a simulation technique for model estimation, where the draw for each iteration is based on a Halton sequence. This method is used in an application by Leth-Petersen and Bjorner (2005) on transitions in the stock of household car ownership. Gong et al. (2000) used a simulated maximum likelihood approach to estimate the parameters of a dynamic multinomial logit panel model with random effects to explain the labour market of individuals in urban Mexico.

Hartzel et al. (2001) extend methods previously used for multinomial logit random effects models by utilising the adaptive Gaussian quadrature (AGQ) method (Liu and Pierce, 1994) for numerical integration. AGQ is often computationally more efficient than ordinary quadrature for performing numerical integration. Other generalisations include the use of a Monte Carlo EM algorithm and more flexible contrasts for the response categories (Hedeker, 2003). In general, AGQ is the preferred method as the number of quadrature points required to approximate the integrals effectively is much lower than for ordinary quadrature.

However, all of these techniques are very computationally intensive requiring a large amount of computer processing time that increases with the number of clusters (or individuals) in the data. Typically, the number of individuals in a longitudinal survey is very large (often in the thousands) while the number of repeated observations is small (less than ten or twenty). Therefore, a major issue with the analysis of categorical response data from a longitudinal survey is the absence of comparative information about the performance of the statistical estimation techniques and the availability of software to actually implement the techniques.

Software available that utilises ordinary Gaussian quadrature for analysing multinomial responses with mixed effects includes MIXNO (Hedeker, 1999) and LIMDEP (Greene, 1998). Software that utilises MQL and PQL for hierarchical or multilevel models are HLM (Bryk et al, 2000) and MLwiN (Goldstein et al, 1998). The `nlmixed` procedure in SAS is available for implementing adaptive Gaussian quadrature, however, the code for specifying the likelihood of a multinomial logit random effects model is not straight forward and various alternatives such as a Poisson log-linear model have been suggested (Chen and Kuo, 2001; Malchow-Moller and Svarer, 2003). These approaches do not provide a satisfactory solution for the social science researcher.

A promising recent development is the availability of a procedure called `gllamm` in the STATA (StataCorp, 2005) software that uses the adaptive Gaussian quadrature technique for estimating multilevel GLMMs. The procedure is described in detail by Rabe-Hesketh, Skrondal and Pickles (2002) and is also compared with other methods utilising MQL/PQL, AGQ and Markov chain Monte Carlo (MCMC) simulation. It appears 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. Another promising alternative to AGQ is the use of Markov chain Monte Carlo (MCMC) simulation to estimate parameters of the model. Browne and Draper (2002) show that MCMC performs better in a simulation study of dichotomous data. MCMC simulation also has the advantage that it allows properties of arbitrary functions of parameters to be examined and missing data to be readily imputed.

In a more recent study, Skrondal and Rabe-Hesketh (2003) consider a multilevel model for nominal response data with three categories, relating to political party choice, from the 1987-1992 panel of the British Election Study. The authors fit a multinomial logit model with correlated random intercepts to the data using `gllamm`. Although the code used to specify the model using `gllamm` in STATA is more straight forward than with other software, the authors do comment that speed is an issue but it is not clear how this compares to the use of MCMC simulation. Haan (2004) also utilises the `gllamm` software to estimate a multinomial logit random effects model for discrete choice labor supply using data from the German Socio-Economic Panel (GSOEP) survey, however, he specified only one random intercept term in his model. A study by Pettitt et al. (2005) investigates a Bayesian hierarchical model for categorical employment data from a longitudinal survey of immigrants to Australia. They implement the MCMC technique known as the Gibbs sampler to estimate a multinomial logit random effects model, using the freely available WinBUGS software (Spiegelhalter et al., 1998). We use a similar approach to estimate our model and compare our results from this method with results obtained using `gllamm`.

In seeking a computationally efficient method and procedure for modelling categorical response data from a longitudinal survey, and building on recent findings in the literature, we have undertaken an empirical study to compare the methods of AGQ and MCMC in fitting a multinomial logit random effects model to women's employment status over three waves of the HILDA survey. In comparing these methods we plan to investigate three models:

1. a static pooled multinomial model with no random effects;
2. a multinomial logit model with correlated random intercepts to capture unobserved heterogeneity among individuals i.e. spurious dependence;
3. a multinomial logit random effects model with lagged dependent variable to account for state dependence.

Similar models are considered by Leth-Petersen and Bjorner (2005) using the Halton sequence simulation method described in Train (2003). Here we have investigated the first two models only but will consider the third model in a subsequent paper. The computational time will have significant implications as to the preferred approach by researchers.

In this paper, we compare the computational efficiency of methods and software for estimating multinomial logit random effects models in an application concerning the employment status of women, using data from three waves of the HILDA survey. The methods are implemented using the relevant statistical software routines in SAS, Stata and WinBUGS. 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 software routines available for estimation of the model are discussed in Section 4. The results of the analyses, including a comparison of the computing efficiency of each software routine investigated, are outlined in Section 5. In future research we will simulate data from the models under investigation to assess more rigorously the method of estimation that is more feasible under particular conditions.

2. Data from the HILDA Survey

A sample of the Household, Income and Labour Dynamics in Australia (HILDA) data was selected from women who are aged between 20 and 55 at June 2001, excluding widows, and who participated in all three waves during 2001-2003. There were 3755 women in the survey who met these criteria.

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, current marital status, number of children ever had, age of youngest child, age left school, highest level of education achieved and partner's financial year private income. Marital status was coded married or defacto, separated or divorced, and never married, with married or defacto the reference category for dummy variables. Number of children ever had, was categorised into no children, one or two children and three or more children. No children is the reference. Age of youngest child is a dummy variable indicating the presence of a child 5 or under in the household. Educational qualification is measured with dummy variables for Bachelor's degree or higher, and tertiary diploma or certificate. The reference category was completed high school or less. Partner's income, which includes Australian pensions and benefits was set to zero for those women without a partner.

Age left school and educational qualification index a woman's human capital. Respondent's age is capturing cohort differences in employment among women and also potential experience. Age is modelled with linear and quadratic terms to allow for nonlinear associations between age and employment. Family commitments which may impact on women's capacity to enter paid employment, and may also diminish the net benefits of employment, are captured by the variables for marital status, number of children and age of youngest child. Partner's income is included because women's employment may be necessary to maintain household income levels; a higher partner's income presumably increases a woman's reservation wage and thus lowers her likelihood of employment. 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: Number of women who followed each of the 27 employment transitions across three waves of the HILDA survey. The pathways highlighted in bold correspond to the women who remain in the same employment state across all waves; the pathways in italics correspond to those followed by the majority of the remaining women.

Full time employed in wave 1

Wave 2	Wave 3	N
employed ft	**employed ft**	**1002**
	employed pt	87
	not employed	53
employed pt	employed ft	62
	employed pt	*98*
	not employed	15
not employed	employed ft	22
	employed pt	19
	not employed	37

Part time employed in wave 1

Wave 2	Wave 3	N
employed ft	employed ft	109
	employed pt	54
	not employed	15
employed pt	*employed ft*	*117*
	employed pt	**695**
	not employed	91
not employed	employed ft	17
	employed pt	42
	not employed	87

Not employed in wave 1

Wave 2	Wave 3	N
employed ft	employed ft	40
	employed pt	11
	not employed	9
employed pt	employed ft	15
	employed pt	*108*
	not employed	55
not employed	employed ft	28
	employed pt	*106*
	not employed	**761**

Table 1 documents the 27 possible employment trajectories over the three waves of data. The three most common trajectories are the ones with no change of status over the three waves with 27 percent of women being continuously in full-time employment, 20 percent being continually not employed and 19 percent remaining in part-time employment. The next most common pathways involve one change of state, between part-time and full-time employment, or between non-employment and part-time employment. Together with the immobile trajectories these account for 87 percent of women. 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 on her previous status, and 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. As we have three waves of observations it is appropriate to include random intercepts to account for unobserved heterogeneity or spurious dependence between individuals.

Suppose that individual i has T categorical observations and let Y_{it} denote the tth observation for individual i, $t = 1,\ldots,T$. If there are J possible response states then $\Pr(Y_{it} = j \mid X_{it})$, $j = 1,\ldots,J$, 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

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

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} $(j = 1,\ldots,J)$, with the function

$$U_{itj} = X_{it}\beta_j + e_{itj} \qquad (2)$$

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, $U_{itj} = \max_{1 \le k \le J}\{U_{itk}\}, j = 1,\ldots,J$.

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

$$\log\left(\frac{\pi_{itj}}{\pi_{it3}}\right) = \log(v_{itj}) = X_{it}^{'}\beta_j + Z_{ij}^{'}\alpha_{ij} \quad j = 1,2. \qquad (3)$$

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

In this study it is appropriate to estimate the following three models:
<u>Model 1</u>:

$$\log(v_{itj}) = X'_{itj}\beta_j$$

Assuming that the error terms are *iid* with homogenous variance, the regression coefficient remains the same for all individuals i in employment state j.
<u>Model 2</u>:

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

Each individual i is now considered as a cluster of observations over time $(t = 1,2,3)$. The regression coefficient remains the same for all individuals i in employment state j, however, a random subject-specific intercept term has been introduced to account for unobserved heterogeneity among individuals.
<u>Model 3</u>:

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

In addition to the random intercept term, α_{ij}, the lagged response variable, L_{it}, has been included in the model to investigate the presence of state dependence.

We have not investigated Model 3 in this paper but will do so for a complete version of the paper.

3.2 Approaches to model estimation
In a multinomial logit model with dependent random effects, the marginal likelihood of the data is obtained by integrating out the random effects. However, in this model the integration over the random effect terms does not have a closed-form solution and hence numerical integration techniques are required. In the classical (frequentist) framework of estimation, as outlined in Section 1.2, a number of methods have been proposed for approximating the integrals of the likelihood function with the preferred option being adaptive Gaussian quadrature for this particular model and a small cluster size (which is three in our analysis). In this approach some of the variables and parameters in the model are considered to be random while others are fixed. This method is available for application using `gllamm` in STATA and using `nlmixed` in SAS.

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 (3) above. Following Pettitt et al. (2005) 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.

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. This is explored further in Section 5.

4. Software implementation

Longitudinal or panel data consisting of repeated observations on individuals can be considered as hierarchical or multilevel. The first level in the hierarchy consists of the observations over time and the second level is the individual. If the individuals are also clustered within groups then the group is an additional level within the hierarchy. Procedures for fitting models to this form of data come under several headings including hierarchical models, multilevel models, mixed models and random effects models. Most standard statistical software nowadays contains methods for fitting linear mixed regression models which are appropriate for continuous panel data where the mean of the response variable is a linear function of the explanatory variables. A number of software packages also allow the fitting of selected GLMMs where the response variable is binary or count data, for example. However, as noted previously, 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). Because a categorical response variable can often be transformed into several dichotomous variables, researchers will often consider a binary mixed model rather than a multinomial mixed model for ease of exposition.

As software routines for estimation of multilevel GLMMs using AGQ have most recently become available through the procedure `gllamm` in STATA, there is a need to assess the computational efficiency of estimation using this procedure in an application to a large longitudinal survey such as HILDA. STATA also contains a suite of “xt” commands that are available for analysing panel data including `xtmixed` to fit linear mixed models to continuous data and `xtlogit` for fitting random effects, conditional fixed-effects and population-averaged logit models to dichotomous data.

In a preliminary analysis of women's employment status we first create two binary variables for full-time employment versus not employed and part-time employment versus not employed, to investigate the odds for each type of employment independently, in relation to the explanatory variables. As `xtlogit` also utilises AGQ to estimate a random effects model for binary data we are able to compare results obtained from `gllamm` and `xtlogit` when a random intercept term is included in the model. In addition, we compare these results with those using `nlmixed` in SAS. All three procedures have options for specifying the number of quadrature points during estimation. STATA provides the command `quadchk` for checking the sensitivity of quadrature approximation with the use of random-effects estimators. It is important to use this as a check for stable coefficient estimation as quadrature approximations can be inaccurate when the panel size is large or the observations within individuals are highly correlated. The default number of quadrature points for `xtlogit` is twelve.

To fit a multinomial logit regression model with random effects to data using `gllamm` is a more complex process. An illustration of this process is provided in the GLLAMM manual for an example on a small dataset in which the response variable has three possible outcomes. In the multinomial logit model for employment status we essentially have two response variables with two dependent random intercept terms. So the longitudinal dataset has to be extended in a way that allows estimation of the random effect corresponding to each response state, before implementing `gllamm`. To do this the dataset was sorted by the unique identifier for each woman and her employment status. Each record was then replaced with three replicates of itself, as there are three categories of employment status. A new variable *possible_estatus* was generated to take on the possible values of employment status and a second variable identifies which of the values in *possible_estatus* is the same as the observed response. The last step before the model can be implemented is to specify equations for the random intercepts using dummy variables. The variable *possible_estatus* was used as the response variable and it was specified through an option of the `gllamm` procedure that the data are in expanded form.

The default number of quadrature points in `gllamm` is eight. Even with this number of points the procedure is very slow for our data which contains 11,265 (3 x 3755) rows of observations. Starting with a smaller number of quadrature points and gradually increasing it will speed up the process, however, stable estimation often requires five or more quadrature points. The provision of good starting values is also important for fast processing. Initial estimates can be obtained and passed on from an analysis of the pooled data that ignores random effects. Due to the expensive nature of computations we have not yet tried to fit the multinomial logit model with random effects to the data using `nlmixed`.

As there are many advantages to a Bayesian approach (see discussion in Section 3.2), we also implement the analysis using the WinBUGS software that is freely available from the internet. This software utilises the Gibbs sampler algorithm to perform MCMC simulation to sample from the posterior distributions of all parameters in the specified model. Similarly to most other numerical integration techniques, it is important to establish that the simulated posterior estimates of the regression coefficients and other parameters in the model, such as variance terms, have converged.

5. Results

5.1 Binary logit model with random effects

The employment status variable was dichotomised by creating two new variables. The first binary variable distinguished between women in full-time employment and those who were not employed; the second variable distinguished between women in part-time employment and those who were not employed. A binary logit model with a random intercept was used to separately analyse the relationship between the odds of being in full-time or part-time employment relative to not being employed, and the selected explanatory variables. The variables for age and age left school were centred and partner's income was divided by $10,000 before including them in the regression analysis.

Table 2a shows the parameter estimates for the log odds of a woman in full-time employment relative to not employed using the AGQ procedure for estimation via `xtlogit` and `gllamm` (STATA) and `nlmixed` (SAS). With 12 quadrature points, the results obtained using xtlogit are vastly different to those obtained using gllamm and nlmixed. In general, xtlogit has produced much lower parameter estimates than gllamm and nlmixed. This is particularly apparent with the estimate for the variance of the random intercept which is 6.35 using xtlogit and 224.71 using gllamm. Given these discrepancies, we ran the analyses using 48 quadrature points. This time the estimates obtained using xtlogit were higher than previously, but they were still much lower than the estimates obtained using gllamm and nlmixed. It is comforting that the results obtained using gllamm and nlmixed using 48 quadrature points are very similar, however, they are still considerably greater than the results obtained using xtlogit. The estimate for variance is now 18.36 using xtlogit and 76.39 using gllamm. It is not clear to us why the results generated by xtlogit are so different to those generated using gllamm. Although the xtlogit procedure with 48 quadrature points only took several minutes to run, compared to 50 minutes using gllamm, the accuracy of the estimates is questionable. It is possible that instability in the quadrature estimation procedure may be caused by high correlation within individuals. This is supported by Table 1 which shows that of the 1395 women who were in full-time employment at wave one, 72 percent were still in full-time employment at wave three. In contrast, of the 1227 women who were in part-time employment at wave one, only 57 percent were still in part-time employment at wave three.

Table 2b shows the parameter estimates for the log odds of a woman in part-time employment relative to not employed. As expected, the parameter estimates for this model appear to be much more stable. The estimates obtained from using xtlogit do increase slightly when the number of quadrature points is increased from 12 to 48 points, however, the estimates obtained from gllamm and nlmixed do not change much at all. For this model with 48 quadrature points xtlogit took less than one minute to run while gllamm took about 36 minutes.

If we consider the gllamm results with 48 quadrature points to be most accurate, the results indicate that there is significant unobserved heterogeneity in both the full-time and part-time binary logit models with the variation being almost four times greater in the full-time model (76.39) than in the part-time model (16.04).

For a response variable that consists of unordered categories or discrete choices such as employment status, it is not usually realistic to assume that the utilities for the different alternatives are independent of each other as we have done here with the binary logit models. It is therefore important to account for this dependency in the multinomial logit model and we discuss the results of this analysis below.

5.2 Multinomial logit model with random effects

In this section we use `gllamm` and MCMC simulation via WinBUGS to estimate the multinomial logit model with dependent multivariate normal random effects for women's employment status. The results for the response outcome of full-time employment relative to not employed, and for the response outcome of part-time employment relative to not employed are presented in Tables 3a and 3b, respectively. These tables show the parameter estimates for Models 1 and 2 as described in Section 3.1.

Model 1 represents the pooled multinomial logit model. Here we have not accounted for unobserved heterogeneity between individuals, however, this model provides us with initial estimates for implementing the more complex Model 2 with random intercept terms. This model took less than one minute to run using gllamm with 8 quadrature points. We also used MCMC simulation with non-informative priors to estimate Model 1. The Gibbs sampler algorithm in WinBUGS was run for 50,000 iterations with the first 10,000 discarded as burn-in. Reasonable convergence of the posterior distributions for all parameters was achieved. The computer processing time taken to fit this model to the data using 50,000 MCMC iterations was eleven hours. Obviously, the implementation of MCMC with such a large number of iterations is unnecessary for a straight-forward model such as this. But putting processing time aside, Tables 3a and 3b nonetheless show that the parameter estimates obtained from gllamm and WinBUGS are almost identical for both response outcomes of full-time and part-time employment.

Finally, we analysed the data using a multinomial logit model with random effects where the random effects were generated from a multivariate normal distribution (model 2). We used both AGQ and MCMC methods of estimation with the results shown in Tables 3a and 3b. To implement estimation using AGQ we first ran xtlogit on both binary response variables to obtain initial start values for the parameter estimates. We then ran gllamm with 8 quadrature points to obtain preliminary estimates for model 2. With the two multivariate normal random intercept terms in the model this took five days of computer processing time. The estimates from this analysis were saved and then fed into the gllamm procedure with 12 quadrature points to obtain more stable parameter estimates. This ran for a further 56 hours before producing the stable estimates shown in Table 3. For the MCMC simulation, we ran 150,000 iterations of the Gibbs sampler algorithm and discarded the first 50,000 as burn-in. This large number of iterations was required to achieve convergence and took 42 hours of processing time.

Comparing the results from these two estimation procedures it is clear that the parameter estimates for the model are very close. But for this model with covarying random effects, the MCMC simulation procedure proved to be less computationally expensive than gllamm by 14 hours. 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, applied to a large dataset with over 3,500 individuals and three repeated observations. However, for standard models with no random effects, such as the pooled multinomial logit model, then gllamm will be faster.

Results show that the estimate of the variance of the random intercept for women who are employed full-time is 38.68, more than twice as high as the estimate of 16.03 for women who are employed part-time. The covariance of the random effect terms for full- and part-time women is a high 19.27 so that the intra-class correlation is 0.77. 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.

Substantive results from the binary random effects models and the multinomial random effects model are similar, although as noted, we think that the parameters in the binary model predicting the odds of full-time employment are not well estimated. Given this we will simply interpret the multinomial logit results based on AGQ with 12 quadrature points and MCMC with 150,000 iterations. Beginning with the equation for the log-odds of full-time employment rather than non-employment, we see that human capital and family factors are both associated with full-time employment. More educated women have significantly greater odds of full-time employment than less educated women with each additional year of school being associated with a 60% increase in the odds of full-time employment (exp(0.49) = 1.63). Conditional on the random effects, women with Bachelor degrees or higher qualifications, have odds of full-time employment that are over 70 times greater than the corresponding odds of women with no tertiary qualifications (exp(4.3) = 73.7), and women with lower tertiary qualifications have over 8 times the odds of full-time employment than women without tertiary qualification.

Under AGQ and MCMC, the chances of full-time employment increase with age, reaching a maximum for women who are about 7.5 years older than the mean age in their survey year, and declining thereafter.

In terms of family variables, there are significant variations by marital status, with single women being significantly less likely than married women to be in full-time employment. As female employment normalises, this finding may reflect a selection effect, in which the factors that select women into full-time employment are also ones that are valued in marital partners.

Having a young child in the home is associated with diminished odds of full-time employment, as is the number of children a woman has had. Finally, 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.

The patterns for part-time employment are similar, although the coefficients are typically smaller in magnitude. Increased education implies increased chances of part-time employment, while having a preschool child, or having more children is associated with increased odds of not being employed, rather than being part-time. Married and cohabiting women are more likely to be employed part-time than single or divorced and separated women are, but unlike full-time employment, there is no association with age, or with partner's income.

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 their 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.

Table 2a: Parameter estimates (standard errors) for the log odds of a woman in full-time employment relative to not employed using the AGQ procedure for estimation via `xtlogit` and `gllamm` (STATA) and nlmixed (SAS)

Parameters	Parameter estimates (sd) using 12 quadrature points by software procedure			Parameter estimates (sd) using 48 quadrature points by software procedure		
	Xtlogit (12)	Gllamm (12)	Nlmixed (12)	Xtlogit (48)	Gllamm (48)	Nlmixed (48)
Constant	2.27 (0.22)	10.57 (0.83)	7.28 (0.87)	3.35 (0.36)	6.27 (0.83)	6.29 (0.75)
Age	0.007 (0.009)	0.13 (0.02)	0.07 (0.04)	0.02 (0.01)	0.06 (0.31)	0.06 (0.03)
Age^2	-0.001 (0.001)	-0.001 (0.002)	-0.003 (0.003)	-0.002 (0.001)	-0.003 (0.003)	-0.003 (0.002)
Age left school	0.27 (0.06)	1.51 (0.15)	0.96 (0.24)	0.40 (0.09)	0.73 (0.21)	0.75 (0.19)
Preschool child	-2.91 (0.19)	-11.89 (0.87)	-8.30 (0.85)	-4.06 (0.31)	-6.96 (0.76)	-6.91 (0.69)
Number of children:						
No children	-	-	-	-	-	-
1-2 children	-2.31 (0.21)	-12.05 (0.93)	-7.84 (0.95)	-3.58 (0.35)	-7.06 (0.87)	-7.10 (0.77)
3+ children	-2.72 (0.24)	-13.39 (1.03)	-8.71 (1.04)	-4.15 (0.40)	-7.92 (0.96)	-7.92 (0.85)
Education:						
Degree	2.47 (0.18)	10.13 (0.81)	6.74 (0.78)	3.63 (0.30)	6.57 (0.73)	6.69 (0.67)
Diploma	1.14 (0.15)	4.43 (0.39)	2.97 (0.55)	1.68 (0.24)	3.06 (0.54)	2.96 (0.48)
Year 12	-	-	-	-	-	-
Marital status:						
Married	-	-	-	-	-	-
Single	-0.85 (0.21)	-2.53 (0.44)	-2.26 (0.70)	-1.16 (0.33)	-1.95 (0.62)	-1.83 (0.58)
Sep/Div	0.06 (0.19)	0.27 (0.35)	0.18 (0.61)	0.11 (0.30)	0.14 (0.57)	0.12 (0.53)
Partner's Income	-0.02 (0.01)	-0.01 (0.03)	-0.006 (0.03)	-0.02 (0.02)	-0.01 (0.03)	-0.01 (0.03)
Between individual Variance	6.35 (1.04)	224.71 (34.30)	153.84 (12.92)	18.36 (1.05)	76.39 (9.57)	79.92 (8.42)

Table 2b: Parameter estimates (standard errors) for the log odds of a woman in part-time employment relative to not employed using the AGQ procedure for estimation via `xtlogit` and `gllamm` (STATA) and nlmixed (SAS)

Parameters	Parameter estimates (sd) using 12 quadrature points by software procedure			Parameter estimates (sd) using 48 quadrature points by software procedure		
	Xtlogit (12)	Gllamm (12)	Nlmixed (12)	Xtlogit (48)	Gllamm (48)	Nlmixed (48)
Constant	0.90 (0.23)	1.47 (0.36)	1.42 (0.36)	1.29 (0.33)	1.45 (0.37)	1.44 (0.37)
Age	-0.02 (0.009)	-0.01 (0.01)	-0.01 (0.01)	-0.02 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Age^2	-0.003 (0.001)	-0.004 (0.001)	-0.004 (0.001)	-0.004 (0.001)	-0.004 (0.001)	-0.004 (0.001)
Age left school	0.26 (0.05)	0.38 (0.08)	0.37 (0.08)	0.34 (0.07)	0.37 (0.08)	0.37 (0.08)
Preschool child	-1.62 (0.15)	-2.07 (0.23)	-2.01 (0.23)	-1.93 (0.21)	-2.02 (0.23)	-2.02 (0.23)
Number of children:						
No children	-	-	-	-	-	-
1-2 children	-0.27 (0.22)	-0.63 (0.34)	-0.60 (0.34)	-0.52 (0.31)	-0.62 (0.34)	-0.61 (0.34)
3+ children	-0.36 (0.24)	-0.82 (0.38)	-0.79 (0.38)	-0.67 (0.34)	-0.81 (0.38)	-0.81 (0.38)
Education:						
Degree	1.58 (0.18)	2.28 (0.29)	2.19 (0.29)	2.04 (0.26)	2.21 (0.29)	2.22 (0.29)
Diploma	0.82 (0.13)	1.19 (0.22)	1.14 (0.21)	1.06 (0.19)	1.15 (0.22)	1.14 (0.22)
Year 12	-	-	-	-	-	-
Marital status:						
Married	-	-	-	-	-	-
Single	-0.64 (0.21)	-0.78 (0.32)	-0.76 (0.32)	-0.74 (0.30)	-0.76 (0.33)	-0.76 (0.33)
Sep/Div	-0.58 (0.18)	-0.73 (0.28)	-0.67 (0.28)	-0.68 (0.25)	-0.71 (0.28)	-0.69 (0.28)
Partner's Income	0.004 (0.01)	0.003 (0.02)	0.003 (0.02)	0.003 (0.01)	0.003 (0.02)	0.003 (0.02)
Between individual variance	5.41 (1.05)	16.01 (1.44)	15.75 (1.43)	12.41 (1.06)	16.04 (1.44)	16.05 (1.44)

Table 3a: Parameter estimates for multinomial logit model with multivariate normal random intercept: estimates for outcome of full-time employment relative to not employed. Models 1 and 2 estimated using AGQ in Stata and MCMC in WinBUGS

	Model 1		Model 2		Model 3	
Parameters	Gllamm (sd) 8 quad pts	MCMC (sd) 50,000 its 10,000 b-in	Gllamm (sd) 12 quad pts	MCMC (sd) 150,000 its 50,000 b-in	Gllamm (sd) 12 quad pts	MCMC (sd)
Constant	1.48 (0.10)	1.50 (0.11)	4.82 (0.44)	4.85 (0.47)		
Age	0.002 (0.004)	0.003 (0.004)	0.06 (0.02)	0.06 (0.02)		
Age^2	-0.001 (0.0003)	-0.001 (0.0003)	-0.004 (0.001)	-0.004 (0.002)		
Age left school	0.17 (0.02)	0.17 (0.02)	0.48 (0.11)	0.49 (0.12)		
Preschool child	-1.74 (0.09)	-1.74 (0.09)	-3.74 (0.31)	-3.75 (0.31)		
Number of children:						
No children	-	-	-	-		
1-2 children	-1.32 (0.10)	-1.34 (0.10)	-5.36 (0.44)	-5.43 (0.45)		
3+ children	-1.60 (0.11)	-1.62 (0.11)	-6.27 (0.49)	-6.35 (0.51)		
Education:						
Degree	1.39 (0.08)	1.39 (0.08)	4.25 (0.35)	4.36 (0.37)		
Diploma	0.63 (0.06)	0.63 (0.06)	2.10 (0.27)	2.15 (0.29)		
Year 12	-	-	-	-		
Marital status:						
Married	-	-	-	-		
Single	-0.71 (0.10)	-0.72 (0.10)	-1.61 (0.37)	-1.61 (0.39)		
Sep/Divo	-0.06 (0.84)	-0.06 (0.08)	0.04 (0.32)	0.04 (0.34)		
Partner's Income	-0.03 (0.008)	-0.03 (0.007)	-0.04 (0.02)	-0.04 (0.02)		
Between individual variance for ft state			38.46 (3.02)	38.68 (3.13)		
Covariance with pt state			18.97 (1.75)	19.27 (1.93)		
Computer processing time	0.41sec	11 hours	56 hours	42 hours		

Table 3b: Parameter estimates for multinomial logit model with multivariate normal random intercept: estimates for outcome of part-time employment relative to not employed. Models 1 and 2 estimated using AGQ in Stata and MCMC in WinBUGS

	Model 1		Model 2		Model 3	
Parameters	Gllamm (sd) 8 quad pts	MCMC (sd) 50,000 its 10,000 b-in	Gllamm (sd) 12 quad pts	MCMC (sd) 150,000 its 50,000 b-in	Gllamm (sd) 12 quad pts	MCMC (sd)
Constant	0.39 (0.11)	0.41 (0.11)	2.66 (0.36)	2.68 (0.37)		
Age	-0.02 (0.004)	-0.02 (0.004)	-0.001 (0.01)	0.001 (0.01)		
Age^2	-0.002 (0.0003)	-0.002 (0.0003)	-0.004 (0.001)	-0.004 (0.001)		
Age left school	0.15 (0.02)	0.15 (0.02)	0.38 (0.08)	0.39 (0.08)		
Preschool child	-1.04 (0.08)	-1.03 (0.07)	-2.13 (0.22)	-2.14 (0.22)		
Number of children:						
No children	-	-	-	-		
1-2 children	-0.06 (0.10)	-0.08 (0.11)	-1.36 (0.33)	-1.39 (0.32)		
3+ children	-0.06 (0.11)	-0.08 (0.12)	-1.60 (0.36)	-1.64 (0.36)		
Education:						
Degree	0.91 (0.08)	0.91 (0.08)	2.42 (0.27)	2.48 (0.27)		
Diploma	0.49 (0.06)	0.49 (0.06)	1.27 (0.20)	1.30 (0.20)		
Year 12	-	-	-	-		
Marital status:						
Married	-	-	-	-		
Single	-0.46 (0.10)	-0.46 (0.10)	-0.86 (0.29)	-0.85 (0.30)		
Sep/Divo	-0.35 (0.08)	-0.35 (0.08)	-0.56 (0.25)	-0.56 (0.25)		
Partner's Income	0.005 (0.006)	0.005 (0.006)	0.007 (0.01)	0.008 (0.01)		
Between individual variance for pt state			15.87 (1.31)	16.03 (1.37)		
Covariance with ft state			18.97 (1.75)	19.27 (1.93)		

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