Modeling employment dynamics with state dependence and unobserved heterogeneity

Victoria Prowse

Department of Economics, Cornell University

10 April 2012

Modeling Employment Dynamics with State Dependence and Unobserved Heterogeneity

Victoria Prowse
Department of Economics
Cornell University
prowse@cornell.edu

April 10, 2012

Abstract

We extend existing work on the dynamics of labor force participation by distinguishing between full-time and part-time employment and by allowing unobserved heterogeneity in the effects of previous employment outcomes, children and education on labor supply behavior. In addition, unobserved heterogeneity may feature autocorrelation and correlated random effects. Our results reveal significant variation in the effects of children and education on labor supply behavior. Moreover, the omission of random coefficients and autocorrelation biases estimates of state dependencies. On average, temporary shocks that increase the rate of part-time employment lead subsequently to lower rates of non-employment than do shocks that temporarily increase the rate of full-time work.

Key Words: Discrete Labor Supply, Repeated Multinomial Choice; Maximum Simulated Likelihood Estimation.

JEL Classification: C15; C25; J6; J22.

1 Introduction

Labor supply behavior measured at the individual level displays a great deal of persistence (see, for example, Francesconi, 2002, and Booth *et al.*, 1999). Persistence is observed both in participation decisions and in the hours of work of those in employment. In other words, we observe persistence on the extensive margin and on the intensive margin. It is well established, see for example Heckman (1981a) and Heckman (1981b), that persistence in labor supply behavior can be generated by two different mechanisms. On one hand, individual characteristics may lead an individual to choose repeatedly the same employment state. Relevant characteristics consist of observables, such as educational qualifications and household structure variables, and unobservables including unobserved preferences and ability. Alternatively, persistence in labor supply behavior may arise from state dependencies, whereby an individual's previous labor supply behavior has a causal effect on his or her current labor supply incentives. State dependencies may be generated by, for example, changes in preferences or constraints caused by previous working behavior. For the purpose of policy evaluation, it is critical to determine the relative contributions of state dependence and individual characteristics to the observed persistence in labor supply behavior. Indeed, if labor supply choices are driven entirely by observed or unobserved individual characteristics then the effect of a policy intervention, such as a wage subsidy or an in-work benefit, will cease the moment the policy is withdrawn. In contrast, if past labor market outcomes exert a causal effect on current labor supply behavior then the policy intervention will affect labor market outcomes beyond the duration of the policy.

There exist several studies of labor force participation dynamics. Notably, Heckman (1981a) studied the dynamics of women's labor force participation decisions, while controlling for persistent unobserved individual characteristics. The results show that unobserved individual characteristics contribute significantly to the observed persistence in women's labor force participation behavior but causal effects, or state dependencies, were also found to be present. A number of other studies report similar results, see *inter alia*, Booth *et al.* (1999) and Heckman and Willis (1977). Keane (1993) provided the first model of labor force participation with autocorrelated unobservables, while Hyslop (1999) extended the literature further by allowing both autocorrelated unobservables and correlated random effects, operationalized by including non-contemporaneous measures of observed individual characteristics, including measures of fertility at different points in the life-cycle. Keane and Sauer (2010) in turn extend the work of Hyslop (1999) by including classification error in the dependent variable and by introducing an alternative treatment of the initial conditions.

The primary contribution of this paper is to use Monte Carlo simulations to explore the effects on estimates of state dependencies of different assumptions regarding the distribution of the unobservables that drive labor supply behavior. To this end, we estimate a discrete, dynamic labor supply model that permits more general structures of unobservables than implemented in previous studies. Specifically, as in Hyslop (1999), we consider unobservables that may be: i) autocorrelated; and ii) time invariant and correlated with time varying observables, including children. In addition, we include unobserved heterogeneity in the effects of previous employment outcomes, children and educational qualifications on labor supply behavior. These additional sources of heterogeneity are potentially important determinants of the dynamics of individual labor supply, and their omission may have substantive implications for estimates of state dependencies.

This paper makes two further contributions. First, we analyze the dynamics of individual labor supply in a multinomial choice framework, rather than the more often used binary choice model. While the generalization to a multinomial framework introduces concerns pertaining to identification and furthers computational complexity, this extension provides additional insight as it allows a study of the intertemporal dependencies associated with full-time and part-time employment. This mode of analysis therefore allows us to assess the likely employment trajectories induced by labor market policies that target specifically either full-time or part-time employment. Such results are of clear importance to policy makers who must decide how best to allocate limited resources. This analysis would not be possible using a binary model of labor market participation, such as the reduced form approach of Heckman (1981a) or the structural approach adopted by Eckstein and Wolpin (1989). Second, drawing on the unobserved heterogeneity in the effects of children on labor supply behavior permitted by our model, we are able to explore whether the relatively high rates of non-employment observed among women with young children are due to a common effect of young children on labor supply behavior or whether instead young children affect the labor supply behavior of only a subset of women.

The central econometric framework takes the form of a dynamic mixed multinomial logit model that features random coefficients, autocorrelated unobserved heterogeneity and time invariant unobservables. We adopt a correlated random effects specification for the time invariant unobservables, and thereby permit unobservables to be correlated with individuals' time varying characteristics, including children. In this respect, our specification is less restrictive than a standard random effects model, which would require that unobservables occur independently of individuals' observed characteristics. Parameter estimates are obtained using Maximum Simulated Likelihood estimation. In a further round of empirical analysis, presented in Appendix C.1, we estimate two alternative model specifications, namely a model that attempts to proxy for possible sources of endogeneity and a model that is reduced form in the potentially endogenous variables, and we show that in both cases our key empirical findings continue to hold.

The empirical analysis is conducted using an eighteen year longitudinal sample taken from the British Household Panel Survey. The sample comprises married and cohabiting women and spans the years 1991-2009 inclusive. Three employment states are distinguished, namely full-time work, part-time work and non-employment. For the sample of women under consideration all three employment states are quantitatively important. Furthermore, there is a growing literature that documents the relatively low status of part-time jobs in the United Kingdom; notably Connolly and Gregory (2008) and Manning and Petrongolo (2008) show that part-time jobs are typically poorly paid and are concentrated in menial occupations. Within the context of this literature it is important to establish whether part-time jobs are also associated with lower labor market attachment than full-time jobs.

We draw on the multinomial structure of our model to investigate the effects of shocks that increase temporarily either full-time or part-time work. Considering the sample average, we find that a temporary shock that increases the rate of full-time employment has essentially no implications for the rate of part-time work in the years subsequent to the shock. Meanwhile, a shock that temporarily increases the rate of part-time employment has a positive effect on the subsequent rate of full-time work. Due to the asymmetric nature of the cross-state dependencies and the higher own-state dependence in part-time employment as compared to full-time employment, on average, temporary shocks that increase the rate of part-time employment lead subsequently to lower rates of non-employment than do shocks that temporarily increase the rate of full-time work. For women with young children we find that full-time employment provides a significant stepping-stone into part-time employment. However the reverse is not true; for women with young children part-time employment does not have a causal effect on subsequent full-time employment.

Our results further show significant, additional, variation in preferences for full-time and part-time work, relative to non-employment, among women with young children. We explore the implications of this variation for employment dynamics following the birth of a child. Our results show that the birth of a child is not associated with an increased likelihood of non-employment for women who have a high unobserved preference for full-time work in the event that they have a young child. Thus, the high rates of non-employment among women with children are due to changes in labor supply behavior among a subset of women with children, specifically those women who have a low unobserved preference for full-time work in the event that they have a young child.

Irrespective of the assumed distribution of the unobservables, we find that significant positive own-state dependencies are present in both full-time and part-time work. This result is in line with existing work on dynamic labor supply including Keane (1993) and Hyslop (1999). A comparison of our results across the different specifications of unobservables reveals that estimates of state dependencies are sensitive to the assumed distribution of the unobservables. As has been frequently found in studies of labor force participation, state dependencies are overestimated if persistent unobservables are ignored. Less predictably, the estimated state dependence in full-time employment tends to increase as the distribution of the unobservables is generalized from a specification allowing time invariant random intercepts to more general specifications allowing autocorrelated unobservables and random coefficients. We conclude that estimating dynamic labor supply models and ignoring autocorrelation and variation in the effects of observed individual characteristics on labor supply behavior may bias significantly estimates of the long-term effectiveness of labor market policies. The biases induced by ignoring autocorrelation or variation in the effects of observed individual characteristic pertain predominantly to the long-run effects of policies that facilitate full-time, rather than part-time, work.

The next section outlines a model that describes an individual's choice between full-time employment, part-time employment and non-employment. Section 3 introduces a dynamic mixed multinomial logit model of labor supply behavior. Section 4 provides an overview of the British Household Panel Survey, and summarizes the main features of the estimation sample. Section 5 contains the results, including comparisons of estimated state dependencies as implied by models that feature different assumptions concerning the distribution of the unobservables. Section 6 concludes. The appendices can be found within the accompanying Supplementary Materials.

2 A Dynamic Multi-state Labor Supply Model

We develop and estimate a discrete choice model of women's labor supply dynamics. Specifically, we model transitions between the three most important labor market states for women, namely full-time employment, part-time employment and non-employment. The model proceeds as follows. In year t individual i chooses between full-time employment (f), part-time employment (p) and non-employment (n) so as to maximize her current payoff. The individual receives a payoff $V^j(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,j,t})$ if she chooses employment state j at time t for $j = f, p, n$. Payoffs are functions of the relevant elements of the individual's employment history, $\Omega_{i,t-1}$, individual characteristics observed by both the individual and the econometrician, denoted $X_{i,t}$ and henceforth referred to as explanatory variables, and individual characteristics that are known to the individual but which are unobserved to the econometrician, denoted $\varrho_{i,j,t}$ for $j = f, p, n$. The variables $\Omega_{i,t-1}$, $X_{i,t}$ and $\varrho_{i,j,t}$ may be vectors. Conditional on observed characteristics and the individual's employment history, optimizing behavior on the part of the individual implies the following labor supply probabilities

$$P_{i,f,t}(\Omega_{i,t-1}, X_{i,t}) = P\left(\begin{array}{c} V^f(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,f,t}) \geq V^p(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,p,t}) \\ V^f(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,f,t}) \geq V^n(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,n,t}) \end{array} \middle| \; \Omega_{i,t-1}, X_{i,t} \right), \quad \text{(1a)}$$

$$P_{i,p,t}(\Omega_{i,t-1}, X_{i,t}) = P\left(\begin{array}{c} V^p(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,p,t}) > V^f(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,f,t}) \\ V^p(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,p,t}) \geq V^n(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,n,t}) \end{array} \middle| \; \Omega_{i,t-1}, X_{i,t} \right), \quad \text{(1b)}$$

$$P_{i,n,t}(\Omega_{i,t-1}, X_{i,t}) = P\left(\begin{array}{c} V^n(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,n,t}) > V^f(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,f,t}) \\ V^n(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,n,t}) > V^p(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,p,t}) \end{array} \middle| \; \Omega_{i,t-1}, X_{i,t} \right), \quad \text{(1c)}$$

where $P_{i,j,t}(\Omega_{i,t-1}, X_{i,t})$ is the probability of individual i choosing employment state j at time t and $P()$ denotes a probability.

The term "payoff" in this context refers to the individual's utility associated with a particular employment state, taking into account any costs and benefits, as well as the income, associated with the employment state. Payoffs will depend on both the current period rewards to contemporaneous labor supply choices and, in the event that the individual is forward looking, the expected future benefits to current actions, including higher future wages arising from positive wage-based rewards to experience (see, for example, Eckstein and Wolpin, 1989; Francesconi, 2002).

The above formulation is sufficiently general to allow dependencies between an individual's past and current labor supply decisions due to habit formation in labor supply behavior (Bover, 1991; Kubin and Prinz, 2002; Woittiez and Kapteyn, 1998), wage based rewards for human capital accumulated via labor market experience (Altug and Miller, 1998; Eckstein and Wolpin, 1989; Imai and Keane, 2004; Wolpin, 1992) and job search costs (Heckman and MaCurdy, 1980; Hyslop, 1999). Job search costs generate dependencies between labor supply choices in consecutive years, while habit formation and the accumulation of human capital have the potential to create dependencies in labor supply behavior spanning several years.

Before proceeding, we highlight a limitation of our analysis: we do not attempt to model the demand side of the labor market and, therefore, we neglect any constraints on the available of employment opportunities. This feature of our analysis should be borne in mind when interpreting the estimated dynamic responses of labor supply behavior to temporary employment shocks (see Section 5.2). Specifically, to the extent that adjustments in labor supply behavior cause responses on the demand side of the labor market, our estimation results will be unrepresentative of the full effects of employment shocks on labor supply behavior.

3 Estimation Strategy

The central econometric framework takes the form of a dynamic mixed multinomial logit model. Such a model is obtained by adopting a specification for the payoff functions appearing in the above labor supply probabilities and then placing appropriate distributional assumptions on the unobserved individual characteristics. This section proceeds by discussing the specification of payoffs, the derivation of the likelihood function, and issues surrounding identification. Finally, the chosen empirical specification is presented together with the proposed Maximum Likelihood estimation method.

3.1 Specification of Payoffs

An examination of Equations (1a)-(1c) reveals that labor supply probabilities can be expressed in terms of the two indices $V^f(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,f,t}) - V^n(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,n,t})$ and $V^p(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,p,t}) - V^n(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,n,t})$. (The third index $V^f(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,f,t}) - V^p(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,p,t})$ is redundant as it is equal to the difference between the other two indices.) The following specification is adopted

$$V^j(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,j,t}) - V^n(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,n,t}) = \Omega_{i,t-1}\gamma_j + X_{i,t}b_j + h_j(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,j,t}) \text{ for } j = f, p, \quad (2)$$

where γ_j and b_j for $j = f, p$ are suitably dimensioned vectors of unknown parameters. The first two terms on the right hand side of the above represent the observed components of the individual's payoff from state j for $j = f, p$ relative to non-employment, while $h_j(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,j,t})$ for $j = f, p$ are functions that describe the components of the individual's payoffs from full-time and part-time work, relative to non-employment, that arise from the presence of the unobserved individual characteristics.

The coefficient vectors b_f and b_p appearing in Equation (2) thus measure the marginal effects of the individual characteristics in $X_{i,t}$, such as education and household structure variables, on the observed components of the individual's payoffs from, respectively, full-time work and part-time work relative to her payoff from non-employment. Meanwhile, the coefficient vectors γ_f and γ_p in Equation (2) measure the marginal effects of the individual's employment history, $\Omega_{i,t-1}$, on the observed components of her payoffs from, respectively, full-time work and part-time work relative to her payoff from non-employment. State dependencies are present if any elements of γ_f or γ_p are different from zero. The econometric analysis is conducted using panel data where information about an individual's employment history is restricted to the duration of the individual's presence in the panel. Thus, prior to estimation, restrictions on the specification of $\Omega_{i,t-1}$ are required. In this study attention is restricted to the case where only the individual's labor market outcomes in the past two years affect her payoffs in the current year. Specifically $\Omega_{i,t-1} = [Y_{i,f,t-1}, Y_{i,p,t-1}, Y_{i,f,t-2}, Y_{i,p,t-2}]$, where $Y_{i,j,t}$ is an indicator taking the value one if individual i was in employment state j at time t and zero otherwise. Suppose labor market outcomes are observed in years $t = 1, ..., T$. Equation (2) then holds for $t = 3, ..., T$. This specification should not be overly restrictive as the strongest intertemporal dependencies in labor supply incentives are likely to occur over short time horizons.

We note here two further features of our specification of the payoff functions. First, the specification of payoffs detailed by Equation (2) should be interpreted as an approximation to the state-specific value functions occurring in the underlying dynamic programming problem (and therefore in the choice probabilities (1a) - (1c)). Second, the explanatory variables $X_{i,t}$ do not include employment state-specific variables, such as wages or measures of occupational status, because such quantities are unobserved for all employment states not chosen by the individual at time t. Instead, $X_{i,t}$ includes variables that are generally deemed to be the underlying determinants of payoff-relevant employment state-specific outcomes. In consequence, the posited specification of payoffs is such that the financial incentives associated with employment choices are not modeled directly, i.e., income does not appear directly in the payoffs. One obvious limitation of this approach is that we are unable to determine the employment effect of a policy that changes the financial incentives associated with either employment or non-employment, for example a tax reform. However, this specification is adequate here as the focus of our study is on the implications of assumptions regarding the distribution of unobservables for estimates of state dependencies, rather than the behavioral effect of a specific policy intervention.

An initial conditions problem arises when estimating this model. Given the dynamic structure of the model and the above described specification of the individual's employment history, $\Omega_{i,t-1}$, the individual's employment outcome in the year $t = 1$ depends on her employment outcomes in the years $t = 0$ and $t = -1$, which are unobserved to the econometrician. Likewise, the individual's employment outcome in the year $t = 2$ depends on her unobserved employment outcome in the year $t = 0$. Therefore, employment outcomes in the years $t = 1$ and $t = 2$, referred to as the initial conditions and denoted IC_i, cannot be modeled in the same way as subsequent employment outcomes. When estimating the parameters of the above model, we adopt the treatment of the initial conditions proposed by Wooldridge (2005). According to this approach, the distribution of the unobservables and individual likelihood contributions are defined conditional on the initial conditions. The Wooldridge (2005) approach to the initial conditions problem provides a computational advantage, relative to the approach of Heckman (1981b), in the form of reducing the number of unknown parameters. We explain immediately below how we accommodate a dependence of the unobservables on the initial conditions.

The unobserved characteristics $\varrho_{i,j,t}$ for $j = f, p$ are henceforth taken to represent unobserved characteristics that affect the difference between the individual's payoff from employment state j and her payoff from non-employment. In the econometric analysis, we adopt a correlated random effects specification. Specifically, the adopted specification of the unobservables allows time invariant random intercepts, autocorrelated unobservables and time invariant random coefficients. Furthermore, we allow the time invariant random intercepts to be correlated with time varying observed individual characteristics and the initial conditions. Mathematically,

$$h_j(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,j,t}) = \Omega_{i,t-1}\omega_{i,j} + W_{i,t}\pi_{i,j} + \zeta_{i,j,t} + \nu_{i,j} + \xi_{i,f,t} \quad \text{for} \quad j = f, p; t = 3, ..., T, \tag{3}$$

where $W_{i,t}$ denotes selected elements of $X_{i,t}$, and $\zeta_{i,f,t}$ and $\zeta_{i,p,t}$ follow first order autoregressive processes

$$\zeta_{i,j,t} = \rho_j \zeta_{i,j,t-1} + \varsigma_{i,j,t} \quad \text{for} \quad j = f, p; \; t = 3, ..., T. \tag{4}$$

In the above ρ_j for $j = f, p$ are autocorrelation coefficients and $(\{\xi_{i,j,t}, \varsigma_{i,j,t}\}_{t=3}^{T}, \omega_{i,j}, \pi_{i,j}, \nu_{i,j})$ for $j = f, p$ are unobserved individual characteristics.

The pairs $(\xi_{i,f,t}, \xi_{i,p,t})$ for $t = 3, ..., T$ are assumed to occur independently of the other unobservables and independently over time, and thus represent time varying shocks to individuals' payoffs. The remaining unobserved individual characteristics consist of four distinct components: (i) $\omega_{i,f}$ and $\omega_{i,p}$ are the random components of the coefficients on the individual's employment history, $\Omega_{i,t-1}$; (ii) $\pi_{i,f}$ and $\pi_{i,p}$ represent the random components of the coefficients on the explanatory variables, $W_{i,t}$; (iii) $\zeta_{i,f,t}$ and $\zeta_{i,p,t}$ represent the autocorrelated random components of the employment state-specific intercepts; and (iv) $\nu_{i,f}$ and $\nu_{i,p}$ are the unobserved time invariant components of the employment state-specific intercepts.

We assume that, conditional on $\nu_{i,j}$ for $j = f, p$, the observed individual characteristics $X_{i,t}$ and the initial conditions IC_i are strictly exogenous. Mathematically, we require that $(\{\xi_{i,j,t}, \varsigma_{i,j,t}\}_{t=3}^{T}, \omega_{i,j}, \pi_{i,j})$ occur independently of $X_{i,s}$ and IC_i for all i, t, s and j. However, we capture the endogeneity of observed individual characteristics and the initial conditions by permitting a dependence of the time invariant unobserved components of the employment state-specific intercepts, that is $\nu_{i,f}$ and $\nu_{i,p}$, on the individual's observed characteristics and the initial conditions. Specifically, based on Chamberlain (1984), we adopt the following correlated random effects specification

$$\nu_{i,j} = \overline{Z}_i\lambda_j + IC_i(\vartheta_j + \psi_{i,j}) + \widetilde{\nu}_{i,j} \quad \text{for} \quad j = f, p, \tag{5}$$

where $\overline{Z}_i$ denotes the vector of sample averages of individual i's time varying characteristics, specifically children and unearned income, λ_j and ϑ_j for $j = f, p$ are suitably dimensioned vectors of unknown parameters and $\psi_{i,j}$ for $j = f, p$ are the random components of the coefficients on the initial conditions, IC_i. In our empirical implementation, IC_i consists of five variables indicating if the woman worked full-time, worked part-time or was non-employed in both $t = 1$ and $t = 2$, worked both full-time and part-time in her first two years in the sample or worked full-time and was non-employed in her first two years in the sample. According to Equation (5), the unobserved employment state-specific intercept $\nu_{i,j}$ is decomposed into a component $\overline{Z}_i\lambda_j + IC_i(\vartheta_j + \psi_{i,j})$, which reflects the contribution of observed individual characteristics and the initial conditions, and a second component $\widetilde{\nu}_{i,j}$ which is unrelated to observables. We assume that both $\psi_{i,j}$ and $\widetilde{\nu}_{i,j}$ occur independently of $X_{i,t}$ and IC_i for all i, t and j.

Intuitively, this correlated random effects specification allows selected sources of unobserved heterogeneity to be correlated with observed individual characteristics and the initial conditions, while maintaining that the initial conditions and the past, present and future values of the individual's observed characteristics are independent of the remaining unobservables. In consequence, observed individual characteristics are assumed to be strictly exogenous with respect to only a subset of the unobservables that drive labor supply behavior. Provided that the individual-level sample means of the time varying characteristics capture fully the unobservables that drive both labor supply and fertility our correlated random effects specification will account for the endogeneity of fertility. However, in the event that there remain further variables that influence labor supply and fertility the children variables may still be endogenous. In a further round of empirical analysis, presented in detail in Appendix C.1, we demonstrate that our results are robust to the aforementioned exogeneity assumptions. Specifically, we estimate two alternative model specifications, namely a model that attempts to proxy for possible sources of endogeneity and a model that is reduced form in the potentially endogenous variables, and we show that in both cases our key empirical findings continue to hold.

We do not attempt to estimate a fixed effects version of our model as this would introduce many largely unresolved issues. In particular, if any time invariant unobservables appearing in our model were treated as fixed effects then this would give rise to the well-known incidental parameters problem (Neyman and Scott, 1948), and lead the Maximum Likelihood Estimator to be biased, and inconsistent as the number of individuals goes to infinity with the number of time periods held fixed. Fernández-Val (2009) shows for a dynamic probit model that bias correction can reduce substantially finite sample bias (see Carro, 2007, and Hahn and Kuersteiner, 2004, for further results in this area). However, the empirical properties of bias corrected estimators have not been established in the current setting, where we have a non-linear, specifically multinomial, dynamic model with individual-specific intercepts and individual-specific coefficients on observed characteristics.

3.2 Derivation of the Likelihood Function

The following definitions are required prior to deriving individual i's contribution to the likelihood. Define $\varrho_{i,j}$ as $\varrho_{i,j,t}$ stacked over $t = 3, ..., T$ for $j = f, p$. Similarly, let X_i denote $X_{i,t}$ stacked over $t = 3, ..., T$. We use $G(\varrho_{i,f}, \varrho_{i,p}|X_i, IC_i)$ to denote the distribution of $(\varrho_{i,f}, \varrho_{i,p})$ conditional on observed individual characteristics, X_i, and the initial conditions, IC_i. Define the one by three dimensional vectors $A_f = (1, 0, 0)$, $A_p = (0, 1, 0)$ and $A_n = (0, 0, 1)$ and let $A_{i,t} = A_j$ if individual i chose state j at time t for $j = f, p, n$. Additionally define the two by three dimensional matrix $B_{i,t}$ as follows

$$B_{i,t} = \begin{cases} (A_p', A_n')' \text{ if } Y_{i,f,t} = 1 \\ (A_f', A_n')' \text{ if } Y_{i,p,t} = 1 \quad \text{for} \quad t = 3, ..., T. \\ (A_f', A_p')' \text{ if } Y_{i,n,t} = 1 \end{cases} \tag{6}$$

Lastly, let $V_{i,t}$ denote $V^j(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,j,t})$ stacked vertically over $j = f, p, n$.

Individual i's contribution to the likelihood takes the following form

$$\begin{aligned} \mathcal{L}_i &= \int\limits_{\varrho_{i,f},\varrho_{i,p}} \mathbf{I}(A_{i,3}V_{i,3} \geq \max\{B_{i,3}V_{i,3}\} \cap A_{i,4}V_{i,4} \geq \max\{B_{i,4}V_{i,4}\} \cap ... \\ &\qquad ... \cap A_{i,T}V_{i,T} \geq \max\{B_{i,T}V_{i,T}\}) dG(\varrho_{i,f}, \varrho_{i,p}|X_i, IC_i), \qquad \text{(7a)} \\ &= \int\limits_{\varrho_{i,f},\varrho_{i,p}} \prod_{t=3}^{T} \mathbf{I}(A_{i,t}V_{i,t} \geq \max\{B_{i,t}V_{i,t}\}) dG(\varrho_{i,f}, \varrho_{i,p}|X_i, IC_i), \qquad \text{(7b)} \end{aligned}$$

where $\mathbf{I}(.)$ is an indicator of whether the statement in parentheses is true and the integrals in the two above equations are over the entire support of $(\varrho_{i,f}, \varrho_{i,p})$.

3.3 Identification and the Distribution of Unobservables

Identification of multinomial choice models requires well-known scale and location normalizations (see Ben-Akiva and Lerman, 1985; Bunch, 1991; Keane, 1992). By specifying the problem in terms of differences in payoffs the required location normalizations have been imposed. However, depending on the distribution of the unobservables, an identifying scale normalization might be required as multiplying all payoffs, including the components of payoffs attributable to unobservables, by a positive constant does not change optimal behavior. In all that follows, $G(\varrho_{i,f}, \varrho_{i,p}|X_i, IC_i)$ is taken to be the distribution of the unobserved individual characteristics after the minimum normalizations required to ensure identification have been imposed.

The functions $h_j(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,j,t})$ for $j = f, p$ and the distribution function $G(\varrho_{i,f}, \varrho_{i,p}|X_i, IC_i)$ together dictate both the structure of persistence in unobservables and the joint distribution of unobservables occurring in a particular year. As discussed above, allowing persistence in unobservables is necessary for determining correctly the nature of state dependence in labor supply behavior. Meanwhile, Hausman and Wise (1978) show that estimates of marginal effects, substitution patterns and elasticities are not robust to the assumed intratemporal distribution of the unobservables. It is therefore desirable to work with a flexible distribution of unobservables. However, even after imposing all necessary identifying scale and location normalizations, care is required when working with flexible forms of the above described structure of the unobservables. Indeed, unlike in the binary case, in the current multinomial labor supply model some of the more obvious, fully parametric, specifications of $h_j(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,j,t})$ for $j = f, p$ and distribution of the unobserved individual characteristics, $G(\varrho_{i,f}, \varrho_{i,p}|X_i, IC_i)$, generate models that are identified purely by the functional form of the distribution of the unobserved individual characteristics, and therefore are nonparametrically unidentified. This results follows from Matzkin (1993), who considers identification of polychotomous choice models in which neither the observable components of the payoff functions nor the distribution of the unobservable random terms are specified parametrically. A lack of nonparametric identification is conceptually unappealing. Furthermore, Keane (1992) presents Monte Carlo evidence that illustrates the very poor empirical performance of multinomial choice models in which parameters are identified only by the functional form of the distribution of the unobservables. Thus, in the subsequent analysis, attention is restricted to model specifications in which the distribution of unobservables is nonparametrically identified.

The possibility of an absence of nonparametric identification can be understood by manipulating the individual likelihood contributions displayed above in Equation (7b). Let $\overline{\varrho}_{i,j,t}$ denote $\varrho_{i,j,t}$ net of the additive transient unobservable $\xi_{i,j,t}$ for $j = f, p$ and $t = 3, ..., T$. Further, define $\overline{\varrho}_{i,j}$ as $\overline{\varrho}_{i,j,t}$ stacked over t. In Section 3.1 we assumed that the pairs $(\xi_{i,f,t}, \xi_{i,p,t})$ for $t = 3, ..., T$ are strictly exogenous and occur independently of the other unobservables and independently over time. Therefore

$$G(\varrho_{i,f}, \varrho_{i,p}|X_i, IC_i) = G_{\overline{\varrho}}(\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p}|X_i, IC_i) \prod_{t=3}^{T} G_{\xi}^{t}(\xi_{i,f,t}, \xi_{i,p,t}), \tag{8}$$

where $G_{\overline{\varrho}}(\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p}|X_i, IC_i)$ denotes the joint distribution of $(\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p})$ conditional on X_i and IC_i, and $G_{\xi}^{t}(\xi_{i,f,t}, \xi_{i,p,t})$ denotes the joint distribution of $(\xi_{i,f,t}, \xi_{i,p,t})$. Combining Equation (8) with Equation (7b) gives

$$\mathcal{L}_i = \int\limits_{\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p}} \prod_{t=3}^{T} \left(\int\limits_{\xi_{i,f,t}, \xi_{i,p,t}} \mathbf{I}(A_{i,t}V_{i,t} \geq \max\{B_{i,t}V_{i,t}\}|\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p}) dG_{\xi}^{t}(\xi_{i,f,t}, \xi_{i,p,t}) \right) dG_{\overline{\varrho}}(\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p}|X_i, IC_i). \tag{9}$$

In a nonparametric setting each of the distribution functions $G_{\xi}^{t}(\xi_{i,f,t}, \xi_{i,p,t})$ for $t = 3, ..., T$ can be varied independently of $G_{\overline{\varrho}}(\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p}|X_i, IC_i)$. In other words there may be unknown parameters in $G^t_{\xi}(\xi_{i,f,t}, \xi_{i,p,t})$ that affect the probability that $A_{i,t}V_{i,t} \geq \max\{B_{i,t}V_{i,t}\}$ conditional on the non-transient unobservables $(\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p})$ but which do not enter $G_{\overline{\varrho}}(\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p}|X_i, IC_i)$. In this case the bivariate distribution functions, which appear in parentheses in Equation (9), are nonparametrically unidentified as the same observed variables affect both the probability that $A_{i,t}V_{i,t} > B_{i,t,1}V_{i,t}$ and the probability that $A_{i,t}V_{i,t} > B_{i,t,2}V_{i,t}$, where $B_{i,t,k}$ for $k = 1, 2$ denotes the k^{th} row of $B_{i,t}$. Obtaining models that are nonparametrically identified thus requires that the distribution of the unobservables be restricted such that $G^t_{\xi}(\xi_{i,f,t}, \xi_{i,p,t})$ for $t = 3, ..., T$ cannot be varied independently of $G_{\overline{\varrho}}(\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p}|X_i, IC_i)$. Therefore, nonparametric identification requires that all unknown parameters appearing in the distribution of the unobservables must be identified from intertemporal rather than cross-sectional variation in behavior. In Section 3.4 below we explain how our adopted empirical specification ensures that we work with distributions of the unobservables that are nonparametrically identified.

Before proceeding, we make two further comments about identification. First, Equation (9) shows that the lack of nonparametric identification is related to the absence of employment state-specific explanatory variables. If, in contrast to the specification given in Equation (2), the payoffs included, for example, employment state-specific incomes or other characteristics of the employment states, parameters would, under appropriate regularity conditions, be nonparametrically identified (Harris and Keane, 1998, and Keane, 1992, provide further discussion of this issue). Second, we note that the lack of nonparametric identification is specific to discrete choice models with three or more alternatives; in the corresponding binary choice model nonparametric identification is less problematic as choice probabilities depend on a single index.

3.4 Empirical Specification

In accordance with the above described requirements for nonparametric identification, the time varying shocks to individuals' payoffs $(\xi_{i,f,t}, \xi_{i,p,t})$ for $t = 3, ..., T$ are assumed to have distributions that do not contain unknown parameters. In what follows, $\xi_{i,f,t}$ and $\xi_{i,p,t}$ are defined respectively as $\epsilon_{i,f,t} - \epsilon_{i,n,t}$ and $\epsilon_{i,p,t} - \epsilon_{i,n,t}$ for $t = 3, ..., T$ where $\epsilon_{i,j,t}$ for $j = f, p, n$ and are mutually independent and independent of $\{X_{i,s}\}^T_{s=3}$ and IC_i. Furthermore $\epsilon_{i,j,t}$ for $j = f, p, n$ are assumed to have type I extreme value distributions. We note that one could instead assume $\epsilon_{i,j,t} \sim N(0, 1)$. The latter assumption would also ensure that the distribution of the transient unobservables does not contain unknown parameters, but would yield a dynamic mixed multinomial probit model instead of a dynamic mixed multinomial logit model. The choice between a normal distribution and a type I extreme value distribution is not substantiative in this application as these two different distributional assumptions imply only a small difference in the distribution of the (suitably rescaled) error differences that appear in Equation (2).

It follows that, conditional on $(\Omega_{i,t-1}, X_{i,t}, \overline{\varrho}_{i,f,t}, \overline{\varrho}_{i,p,t})$, the individual's choice probabilities are independent over time and take the familiar multinomial logit form

$$P_{i,j,t}(\Omega_{i,t-1}, X_{i,t}, \overline{\varrho}_{i,f,t}, \overline{\varrho}_{i,p,t}) = \frac{\exp(\Omega_{i,t-1}\gamma_j + X_{i,t}b_j + \overline{h}_j(\Omega_{i,t-1}, X_{i,t}, \overline{\varrho}_{i,j,t}))}{1 + \sum_{k=f,p} \exp(\Omega_{i,t-1}\gamma_k + X_{i,t}b_k + \overline{h}_k(\Omega_{i,t-1}, X_{i,t}, \overline{\varrho}_{i,k,t}))}$$
$$\text{for } j = f, p; t = 3, ..., T, \tag{10a}$$

$$P_{i,n,t}(\Omega_{i,t-1}, X_{i,t}, \overline{\varrho}_{i,f,t}, \overline{\varrho}_{i,p,t}) = \frac{1}{1 + \sum_{k=f,p} \exp(\Omega_{i,t-1}\gamma_k + X_{i,t}b_k + \overline{h}_k(\Omega_{i,t-1}, X_{i,t}, \overline{\varrho}_{i,k,t}))}$$
$$\text{for } t = 3, ..., T, \tag{10b}$$

where, for $j = f, p$ and $t = 3, ..., T$, $\overline{h}_j(\Omega_{i,t-1}, X_{i,t}, \overline{\varrho}_{i,j,t})$ denotes $h_j(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,j,t})$ net of the additive transient unobservable $\xi_{i,j,t}$. The expression for individual i's likelihood contribution given above by Equation (7b) can be rewritten as follows

$$\mathcal{L}_i = \int\limits_{\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p}} \prod_{t=3}^{T} \prod_{j=f,p,n} P_{i,j,t}(\Omega_{i,t-1}, X_{i,t}, \overline{\varrho}_{i,f,t}, \overline{\varrho}_{i,p,t})^{Y_{i,j,t}} dG_{\overline{\varrho}}(\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p} | X_i, IC_i). \tag{11}$$

Nonparametric identification requires that all unknown parameters appearing in the distribution of the unobservables must be identified from intertemporal rather than cross-sectional variation in behavior. Consider the case where $\overline{h}_j(\Omega_{i,t-1}, X_{i,t}, \overline{\varrho}_{i,j,t})$ allows only time invariant individual-specific random effects. In this case, two periods of observations subsequent to the initial conditions, i.e., four periods of observations including the two initial periods, is sufficient for nonparametric identification of $G(\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p} | X_i, IC_i)$: with two periods of observations subsequent to the initial conditions the joint distribution of the non-transitory unobservables in adjacent time periods can be obtained, and with the restriction that non-transitory unobservables consist of time invariant random effects the distribution of the random effects is thus obtained (see Walker *et al.*, 2007). By analogy, if $\overline{h}_j(\Omega_{i,t-1}, X_{i,t}, \overline{\varrho}_{i,j,t})$ additionally allows autocorrelation in the employment state-specific intercepts then nonparametric identification of $G(\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p} | X_i, IC_i)$ requires $T \geq 5$; an extra year of observations is required in order to separate the autocorrelated and time invariant unobservables. The introduction of random coefficients does not require a longer panel for nonparametric identification provided that random coefficients on the time dummies and any other variables that, for all individuals, are non-zero in a maximum of one year between $t = 3$ and T are excluded. This ensures that all random coefficients with a distribution that contains unknown parameters affect payoffs in at least two years between $t = 3$ and $t = T$.

Six different specifications of the unobservables are considered. The specifications vary in the richness of the permitted unobservables, and therefore cross-specification comparisons are informative about the importance of the various types of unobserved heterogeneity under consideration. The first specification, presented primarily for comparative purposes, consists of a standard multinomial logit model. The second and third specifications allow the employment state-specific intercepts to include time invariant individual effects. In both specifications, the means of the employment-state specific intercepts may depend on the individual-level sample averages of the child variables and unearned income and on the initial conditions, and therefore correlated random effects are permitted. In the second specification the random components of the employment state-specific intercepts are jointly normally distributed with mean zero and an unrestricted covariance matrix. Meanwhile, in the third specification we assume a distribution generated by a mixture of two normal distributions with different means and covariance matrices. The fourth specification allows the employment state-specific intercepts to contain time invariant components, as in the second specification, and autocorrelated components, where the autocorrelation processes are jointly normal and the initial conditions of the autocorrelation processes ensure stationary. The fifth specification allows time invariant individual effects, as in the second specification, and random coefficients on the individual's previous employment outcomes, the initial conditions and selected explanatory variables. The two random coefficients on a particular variable, for example the k^{th} elements of $\pi_{i,f}$ and $\pi_{i,p}$, are assumed to be jointly normally distributed with zero mean and an unrestricted covariance matrix, and all pairs of random coefficients are mutually independent and independent of the random components of the employment state-specific intercepts. Allowing correlations between all pairs of random coefficients leads to a prohibitively large number of parameters. The sixth specification is the most general specification under consideration and augments the fifth specification by permitting autocorrelation, as previously described, in the employment state-specific intercepts. The notes accompanying Table 3 provide further details concerning the implemented distributions of the unobservables.

We refrain from considering latent class models. According to this approach, each individual is one of a finite number of distinct types, and each type is characterized by a particular vector of unobserved attributes. Latent class models thus provide a means of including permanent unobservables but without the need to specify a particular distribution. However, such models quickly proliferate parameters as the number of types or latent attributes increases. Another alternative, nested models, have be used extensively in multinomial choice problems in order to capture cross-alternative correlations in unobservables, particularly in applications where the choice set is large. However, in the current application nested models do not provide a natural means of modeling the unobservables. In particular, the application of a nested model requires that choice alternatives be assigned to nests prior to estimation. However, given the choice alternatives of full-time work, part-time work and non-employment, there is no entirely plausible allocation of choice alternatives to nests. Indeed, there are reasons for grouping part-time employment with both full-time employment and non-employment. Finally, neither latent class models nor nested models can accommodate straightforwardly autocorrelation.

3.5 Estimation Methodology and Performance

Given a sample of N individuals and assuming independence over individuals, the likelihood function is the product of the individual likelihood contributions for the sample members, given above in Equation (11). However, due to the integration with respect to the unobserved individual characteristics, analytic expressions for the individual likelihood contributions are unavailable for all but the simplest specifications of unobserved heterogeneity. Let h_i denote $\overline{h}_j(\Omega_{i,t-1}, X_{i,t}, \overline{\varrho}_{i,j,t})$ stacked over $j = f, p$ and then over $t = 3, ..., T$ and define the $2(T-2)$ by $2(T-2)$ conditional covariance matrix $\Upsilon_i = VAR\left[h_i|X_i, IC_i\right]$. The dimension of the integral occurring in the individual's likelihood contribution is equal to the rank of Υ_i, which in turn depends on the assumed distribution of the unobservables. Specifications in which unobservables take the form of time invariant random intercepts require integration over two dimensions while each pair of random coefficients adds two to the dimension of the integral, up to a maximum of $2(T-2)$. Specifications that include autocorrelation involve $2(T-2)$ dimensional integrals. For two dimensional problems fast and accurate quadrature methods are available to evaluate the individual likelihood contributions (Geweke, 1996, provides a survey). However numerical methods are unable to evaluate the likelihood contributions with sufficient speed and accuracy to be effective in problems where the dimension of integration is greater than two (see Bhat, 2001; Hajivassiliou and Ruud, 1994). Consequently, in the context of the current application, numerical methods to evaluate the likelihood contributions are unavailable when unobservables feature random coefficients on several variables or when T is moderately large and unobservables are autocorrelated.

For models where an analytic expression for the likelihood is unavailable we use simulation techniques to evaluate the likelihood contributions. Simulation methods replace the intractable integral in the likelihood function by a sum over likelihood functions evaluated at different draws from the distribution of unobserved heterogeneity. Let $(\overline{\varrho}^r_{i,f}, \overline{\varrho}^r_{i,p})$ denote the r^{th} draw from the distribution $G(\overline{\varrho}_{i,f}, \overline{\varrho}_{i,p}|X_i, IC_i)$ for individual i. Individual i's likelihood contribution is simulated as follows

$$\mathcal{L}^s_i = \frac{1}{R}\sum_{r=1}^{R}\prod_{t=3}^{T}\prod_{j=f,p,n} P_{i,j,t}(\Omega_{i,t-1}, X_{i,t}, \overline{\varrho}^r_{i,f,t}, \overline{\varrho}^r_{i,p,t})^{Y_{i,j,t}}. \tag{12}$$

Continuing to assume independence over individuals, the simulated likelihood is the product of the simulated individual likelihood contributions for the sample members. Maximum Simulated Likelihood estimates are obtained by maximizing the log simulated likelihood function. By the strong law of large numbers the Maximum Simulated Likelihood estimates converge almost surely to the true parameters as $R \to \infty$ and $N \to \infty$. Moreover, if R increases at a fast enough rate relative to N, Maximum Simulated Likelihood estimation is asymptotically equivalent to Maximum Likelihood estimation. In particular, with pseudo random draws, $\sqrt{N}/R \to 0$ as $N \to \infty$ is required (Hajivassiliou and Ruud, 1994).

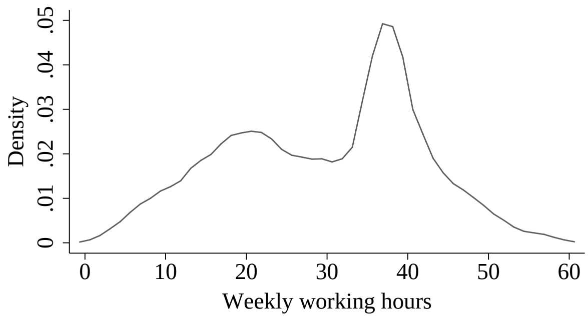
In this application, the likelihood is simulated using antithetic variates rather than pseudo random draws. Antithetic variates are a variance reduction technique which reduces simulation noise by using draws from the distribution of the unobservables with more even coverage than pseudo random draws (see Train, 2003, for a description of the construction of antithetic variates). Hajivassiliou (1999) presents Monte Carlo evidence which shows that the use of antithetic variates in Maximum Simulated Likelihood problems approximately halves the number of draws required to obtain a given level of accuracy. We note that Halton draws are not appropriate in this application due to the high correlation, and therefore poor multidimensional coverage, of the draws which occurs in high dimensional problems, such as the one in hand. Indeed, Hess and Polak (2003) show that the poor multidimensional coverage of high dimensional Halton draws can cause serious problems in the estimation of models with high-dimensional integrals.

Monte Carlo simulations, presented in Appendix A, illustrate the severity of the numerical problems afflicting a dynamic mixed multinomial logit model in which identification is reliant on the functional form of the distribution of the unobservables. In Appendix B we present Monte Carlo evidence demonstrating the satisfactory empirical properties of the Maximum Simulated Likelihood estimator of the parameters of the two most complex specifications of unobservables under consideration. In summary, for a specification in which unobservables include random coefficients but exclude autocorrelated unobservables evaluation of the likelihood using 500 antithetic draws yields parameter estimates with tolerably small amounts of bias. A specification including autocorrelation displays a moderate amount of simulation bias when 500 or 2,000 antithetic draws are used, but biases are relatively small when estimation uses 5,000 antithetic draws. Therefore all of our empirical analysis uses 5,000 antithetic draws.

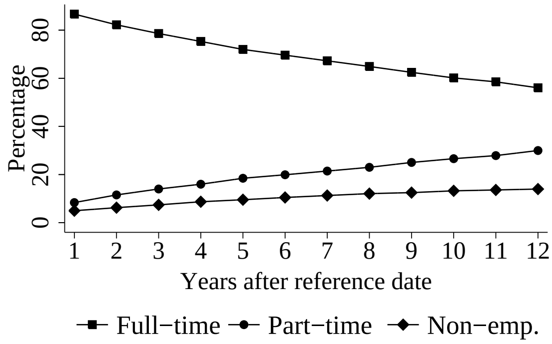
4 Data and Sample

The data source used for the empirical analysis is the British Household Panel Survey (BHPS). The BHPS is an ongoing annual panel survey that started in 1991 with a nationally representative sample of approximately 5,500 households in Great Britain. The sample used for analysis is a weakly balanced panel covering the years 1991 - 2008. We construct our sample such that each individual is present for exactly 13 years. Attention is restricted to married or cohabiting, non-retired women aged between 18 and 65 years. Single mothers and single adult households are therefore excluded from the sample. Women who satisfy the sample selection criteria for more than thirteen consecutive years enter our sample at a date randomly selected from those dates that provide at least thirteen consecutive observations, and leave the sample after thirteen years. The final sample consists of 1,288 different women and 16,744 person-year observations. The previously described method for constructing the sample was chosen for three reasons. First, the weakly balanced panel structure allows us to employ the treatment of the initial conditions proposed by Wooldridge (2005) (see the final paragraph of this section for further discussion of this approach). Second, as noted above in Section 3.4, robust identification of the parameters of model specifications that feature both autocorrelation and time invariant random intercepts requires a minimum of five repeated observations. A panel length of thirteen observations per individual therefore provides a sufficient number of repeated observations to allow us to distinguish empirically the various sources of persistence in behavior. Third, random selection of the sample entry date for individuals who provide in excess of thirteen consecutive observations ensures that we have enough observations in each calender year to be able to control effectively for common time effects.

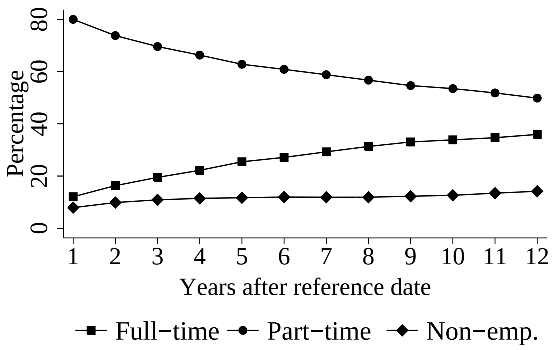
The chosen measure of employment status is based on reported usual weekly hours of work. Figure 1(a) shows the density of the observed usual hours of work of the sampled women in employment, that is those with strictly positive usual hours of work. There are pronounced peaks at around 20 and 38 hours of work per week representing the hours of work frequently associated with, respectively, part-time and full-time work. For the purpose of the empirical analysis, and in accordance with the conventional British definitions of full-time and part-time work, women reporting usual weekly hours of work of between zero and 30 hours are classified as part-time employed, and women reporting usual weekly hours of work of over 30 hours are classified as full-time employed. Non-employment corresponds to zero usual weekly hours of work. Classification error in employment status should be minimal as observations of usual hours of work refer to usual working hours at the exact time of the annual survey, rather than being a retrospective report of usual working hours at some pervious date. Figures 1(b)- 1(d) illustrate the high level of persistence in women's employment outcomes. Around 85% of women who were working full-time one year previously are in full-time employment in



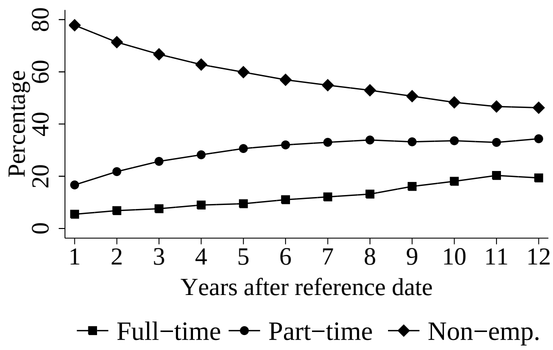
(a) Density of observed usual weekly working hours for women in employment.



(b) Labor market outcomes of women who were working full-time t years previously.



(c) Labor market outcomes of women who were working part-time t years previously.



(d) Labor market outcomes of women who were non-employed t years previously.

Notes: The sample used to construct Figure 1(a) has been truncated at 60 hours per week which excludes 0.5% of the observations.

Figure 1: Density of observed hours of work, and observed persistence in employment outcomes.

the current year. Similarly, approximately 80% of women who were working part-time or who were non-employed one year previously are in the same employment state in the current year. There is also evidence of persistence over a longer time horizon. For example, around 55% of women who were working full-time 12 years previously are currently in full-time work. The corresponding figures for part-time work and non-employment are 50% and 46% respectively.

The explanatory variables used in the empirical analysis are the conventional variables used in studies of women's labor supply behavior: education; age; child-related variables; and unearned income, which includes the husband's earnings. Arguably the most important of the child-related variables is an indicator of the woman having given birth to a child during the ten months prior to the annual survey or during the two months following the annual survey (in the presentation of the results this variable is denoted "YOUNGEST CH. 0-1 YEAR" and is referred to as a "child aged under 1 year"). Our indicator of birth is thus constructed such that recent births and shortly impending births are treated in the same; we proceed in this way in order to capture women's entitlement to maternity leave under United Kingdom legislation. In addition, throughout the empirical analysis we include a full set of year dummies in order to control for fluctuations in labor market conditions. Table 1 contains further details concerning the explanatory variables.

Finally, we comment on the nexus of our weakly balanced panel structure, the use of the Wooldridge (2005) approach to the initial conditions and the adopted correlated random effects specification. Given our weakly balanced panel structure, all individuals are observed for exactly thirteen consecutive years, however individuals differ in the date at which they enter the sample, e.g., some individuals are observed from 1991-2003 inclusive, while others are observed from 1995-2007. The construction of Equation (5) assumes implicitly that the link between the random intercepts, $\nu_{i,j}$ for $j = f, p$, and individual-specific averages of time varying characteristics, $\overline{Z}_i$, and the initial conditions, IC_i is common across individuals. Therefore, in the context of our weakly balanced panel structure we require that the relationship between the random intercepts $\nu_{i,j}$ for $j = f, p$ and the relevant observables does not depend on the specific years in which the individual was present in the sample.

5 Results

The dynamic mixed multinomial logit model is estimated with six different specifications of unobserved individual characteristics, as described above in Section 3.4. The parameter estimates and average marginal effects obtained from Specification VI, the most general specification under consideration, are discussed in Section 5.1. In sections 5.2 and 5.3 we explore respectively the nature of state dependence in women's labor supply behavior and the extent of any heterogeneity in labor supply dynamics following the birth of a child, again based on Specification VI. In Section 5.4 we investigate the importance of allowing autocorrelation and random coefficients by making comparisons of the results obtained from Specification IV with those obtained from Specifications I-V, which impose more restrictive distributions of unobservables.

5.1 Parameter Estimates and Average Marginal Effects

Specification VI is the most general specification under consideration. This specification allows random intercepts with both time invariant and autocorrelated components, and time invariant random coefficients. The time invariant components of the random intercepts are allowed to be correlated with the individual's observed characteristics and the initial conditions. The time invariant random coefficients appear on the indicator of having a degree, the indicator of the woman's youngest child being aged under one year, and on the variables describing the initial conditions. Experimentation with various specifications of the random coefficients revealed that there are no random coefficients with significant amounts of variation on any other explanatory variables.

The last two columns of Table 2 show the coefficients on the individual's employment history and individual characteristics appearing in the observed components of the payoffs from full-time and part-time employment. The coefficient estimates are as expected and are not discussed. Instead, we focus our discussion on the last two columns of Table 4, which show how the coefficients translate into average marginal effects. The average marginal effects for Specification VI reveal that an increase in qualifications from no qualifications to A Levels a or higher qualification below degree level significantly increases the probability full-time work, while women with a higher qualification below degree level are significantly more likely to work part-time than otherwise identical women without educational

Variable	Year																	
	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Highest Educational Qualification:																		
DEGREE	0.13	0.13	0.14	0.14	0.15	0.16	0.16	0.16	0.16	0.16	0.17	0.17	0.17	0.18	0.19	0.19	0.19	0.18
HIGHER QUAL. BELOW DEGREE LEVEL	0.15	0.16	0.16	0.18	0.18	0.20	0.21	0.23	0.24	0.26	0.28	0.29	0.31	0.32	0.33	0.36	0.38	0.41
A LEVELS	0.10	0.11	0.10	0.11	0.12	0.12	0.12	0.11	0.11	0.11	0.10	0.10	0.10	0.11	0.10	0.10	0.11	0.08
GCSES	0.27	0.27	0.27	0.26	0.26	0.25	0.25	0.24	0.23	0.22	0.21	0.21	0.20	0.19	0.19	0.17	0.16	0.17
UNEARNED INCOME	13.36	12.56	12.16	11.99	12.12	12.39	12.75	12.98	13.51	13.61	13.98	14.18	14.32	14.40	16.08	16.59	17.63	17.64
AGE	36.09	36.54	36.71	37.26	37.36	37.48	38.48	39.48	40.46	41.49	42.48	43.47	44.48	44.52	44.52	44.85	44.86	45.67
YOUNGEST CH. 0-1 YEARS	0.08	0.12	0.05	0.07	0.05	0.06	0.06	0.06	0.04	0.04	0.04	0.04	0.03	0.03	0.02	0.02	0.03	0.01
YOUNGEST CH. 1-2 YEARS	0.14	0.13	0.13	0.10	0.13	0.11	0.10	0.10	0.10	0.10	0.08	0.08	0.07	0.07	0.07	0.06	0.04	0.06
YOUNGEST CH. 3-4 YEARS	0.06	0.06	0.10	0.10	0.08	0.08	0.10	0.09	0.08	0.08	0.08	0.07	0.06	0.07	0.09	0.08	0.10	0.07
YOUNGEST CH. 5-6 YEARS	0.04	0.04	0.06	0.08	0.07	0.07	0.07	0.07	0.08	0.08	0.06	0.06	0.06	0.06	0.05	0.08	0.10	0.08
YOUNGEST CH. 7-11 YEARS	0.15	0.15	0.13	0.14	0.14	0.13	0.13	0.14	0.15	0.15	0.16	0.17	0.16	0.17	0.19	0.17	0.17	0.21
YOUNGEST CH. 12-15 YEARS	0.13	0.11	0.11	0.10	0.10	0.09	0.10	0.10	0.10	0.10	0.11	0.10	0.11	0.11	0.11	0.13	0.12	0.13
PROTESTANT	0.66	0.65	0.63	0.65	0.64	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.62	0.61	0.63	0.59	0.57
CATHOLIC	0.12	0.12	0.13	0.13	0.13	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.11	0.11	0.10
FAMILY VALUES I Family suffers when woman works full-time	0.32	0.34	0.34	0.34	0.32	0.32	0.33	0.33	0.34	0.34	0.32	0.32	0.31	0.32	0.34	0.36	0.34	0.27
FAMILY VALUES II Husband and wife should contribute to household income	0.43	0.44	0.44	0.45	0.42	0.43	0.42	0.42	0.40	0.40	0.40	0.40	0.37	0.36	0.35	0.37	0.36	0.36
Observations	272	501	696	869	1055	1288	1288	1288	1288	1288	1288	1288	1288	1016	787	592	419	233

Notes: DEGREE, HIGHER QUAL. BELOW DEGREE LEVEL, A LEVELS and GCSES are indicators of a woman's highest qualification being, respectively, a university degree, a non-degree level higher qualification, A levels or equivalent qualifications (A Levels are usually taken at age 18 years) or grade A-C GCSEs or equivalent qualifications (GCSEs are usually taken at age 16 years). UNEARNED INCOME refers to a woman's annual net unearned income including her partner's income expressed in pounds sterling and deflated to year 1991 prices using the Retail Price Index. AGE is the woman's age in years. YOUNGEST CH. $a-b$ YEARS is an indicator of the youngest child in the household being aged between a and b years at 2 months after the date of the annual survey. PROTESTANT and CATHOLIC are indicators of the woman's religious denomination being, respectively, protestant and catholic. FAMILY VALUES I is an indicator that takes the value one if the woman agrees with the statement "all in all, family life suffers when the woman has a full-time job" and zero otherwise. FAMILY VALUES II is an indicator that takes the value one if the woman agrees with the statement "both husband and wife should contribute to the household income" and zero otherwise.

Table 1: Sample means of the explanatory variables in years 1991-2008.

qualifications. Young children have a strong negative effects on the probabilities of both full-time and part-time employment. Specifically, women whose youngest child is aged one year or under are on average 34.36(1.90) percentage points less likely to be working full-time and 9.02(2.88) percentage points less likely to be working part-time than otherwise identical women without children. The effect of children on a woman's probability of engaging in full-time work decreases quickly as the age of the woman's youngest child increases, while a youngest child aged between 1 and 7 years has a significant positive effect the probability of part-time employment.

We find that unearned income has a negative effect on the probability of full-time work and on the probability of part-time work, but neither effect is significant. This result is not surprising as, via the correlated random effects specification (see Equation (5)), the individual-specific average of unearned income is included in the payoffs, in addition to the contemporaneous value of unearned income. Therefore, the marginal effects of unearned income reported for Specification VI in Table 4 refer to the effect of transitory, rather than permanent, unearned income. Consistent with the theoretically negative effect of life-cycle unearned income on labor supply, the coefficients on the individual-level average of unearned income in the payoffs from full-time and part-time work (not reported) are both significantly negative (based on Specification VI, p values are 0.001 and 0.016 for the coefficients on individual-level average income in the payoffs from full-time and part-time employment, and $p = 0.001$ for the joint hypotheses that both coefficient equal zero).

The results for Specification VI in Table 4 further show that, on average over the sampled women, working full-time rather than being non-employed in the previous year increases the probability of working full-time in the current year by 43.93(4.39) percentage points. Similarly, working part-time rather than being non-employed increases the probability of working part-time in the current year by 23.40(2.93) percentage points. These results confirm the presence of significant state dependence in women's labor supply behavior. The nature of the intertemporal dependencies in labor supply behavior is explored in further detail below in Section 5.2.

In terms of the distribution of the unobservables, the results in Table 3 that pertain to Specification VI reveal negative first order autocorrelation in the unobservables affecting payoffs from full-time employment and positive first order autocorrelation in the unobservables affecting payoffs from part-time employment. (A likelihood ratio test for the joint significance of ρ_f and ρ_p reveals that the null hypothesis of zero autocorrelation in the time-varying component of unobservables is rejected at all conventional significance levels.) Women with young children have very large and significant amounts of variation in their unobserved payoffs from working full-time. There is also significant variation in women's unobserved preferences for part-time employment if they have a young child, but far less than for full-time employment. This unobserved variation in payoffs might reflect unobserved variation in child-care costs or unobserved variation in productivity in home production. Similarly, women with a degree level qualification have a significantly higher level of unobserved variation in their payoffs from working part-time than women with other levels of qualifications. This is consistent with a relatively high level of heterogeneity in the labor market returns to a university education in the event that the woman works part-time. The coefficients on lagged employment behavior display relatively small and generally insignificant amounts of variation. We conclude our discussion of the parameter estimates for Specification IV by noting that we reject conclusively the null hypothesis of zero correlation between

Variable	Spec. I		Spec. II		Spec. III		Spec. IV		Spec. V		Spec. VI	
	f	p	f	p	f	p	f	p	f	p	f	p
$Y_{i,f,t-2}$	2.35 (0.16)	1.17 (0.12)	1.57 (0.18)	0.71 (0.14)	1.63 (0.18)	0.72 (0.14)	2.08 (0.40)	1.10 (0.24)	1.55 (0.24)	0.69 (0.19)	2.30 (0.42)	1.15 (0.28)
$Y_{i,p,t-2}$	1.11 (0.15)	1.36 (0.09)	0.76 (0.17)	0.91 (0.11)	0.82 (0.17)	0.91 (0.11)	1.01 (0.27)	1.14 (0.20)	0.83 (0.21)	0.91 (0.15)	1.08 (0.29)	1.09 (0.20)
$Y_{i,f,t-1}$	4.09 (0.16)	1.72 (0.12)	3.12 (0.19)	1.18 (0.14)	3.16 (0.19)	1.22 (0.14)	4.50 (0.68)	1.65 (0.47)	3.37 (0.25)	1.25 (0.21)	5.25 (0.66)	1.37 (0.40)
$Y_{i,p,t-1}$	2.47 (0.14)	3.07 (0.09)	1.96 (0.17)	2.59 (0.11)	1.99 (0.17)	2.60 (0.11)	2.70 (0.51)	2.91 (0.37)	1.85 (0.20)	2.65 (0.13)	2.71 (0.46)	2.90 (0.31)
Highest Educational Qualification:												
DEGREE	0.61 (0.13)	0.24 (0.11)	0.94 (0.24)	0.37 (0.19)	0.93 (0.24)	0.34 (0.19)	1.07 (0.27)	0.45 (0.21)	0.90 (0.27)	0.41 (0.22)	1.12 (0.35)	0.50 (0.27)
HIGHER QUAL. BELOW DEGREE LEVEL	0.55 (0.11)	0.42 (0.09)	0.92 (0.19)	0.67 (0.15)	0.91 (0.19)	0.65 (0.15)	0.97 (0.22)	0.73 (0.18)	0.86 (0.22)	0.71 (0.19)	1.10 (0.29)	0.88 (0.24)
A LEVELS	0.42 (0.14)	0.23 (0.13)	0.77 (0.24)	0.44 (0.20)	0.78 (0.24)	0.43 (0.20)	0.87 (0.27)	0.50 (0.22)	0.69 (0.26)	0.44 (0.23)	0.79 (0.34)	0.52 (0.28)
GCSES	0.37 (0.11)	0.25 (0.09)	0.55 (0.19)	0.38 (0.15)	0.55 (0.19)	0.36 (0.15)	0.57 (0.22)	0.41 (0.17)	0.46 (0.22)	0.38 (0.19)	0.62 (0.28)	0.49 (0.23)
UNEARNED INCOME/100	−1.47 (0.28)	−0.67 (0.26)	−0.56 (0.49)	−0.39 (0.49)	−0.56 (0.49)	−0.35 (0.50)	−0.64 (0.59)	−0.33 (0.55)	−0.65 (0.54)	−0.52 (0.53)	−0.96 (0.72)	−0.63 (0.64)
AGE/10	−0.88 (0.23)	0.16 (0.23)	−1.54 (0.45)	0.07 (0.39)	−1.50 (0.44)	0.11 (0.39)	−1.62 (0.50)	0.08 (0.41)	−1.82 (0.49)	−0.19 (0.43)	−2.39 (0.63)	−0.30 (0.51)
YOUNGEST CH. 0-1 YEAR	−4.42 (0.16)	−2.28 (0.17)	−5.28 (0.25)	−2.72 (0.23)	−5.19 (0.25)	−2.66 (0.23)	−5.94 (0.70)	−2.91 (0.49)	−6.08 (0.43)	−2.97 (0.30)	−8.35 (0.85)	−3.95 (0.55)
YOUNGEST CH. 1-2 YEARS	−0.55 (0.16)	0.72 (0.15)	−1.67 (0.26)	0.24 (0.22)	−1.58 (0.26)	0.29 (0.23)	−1.46 (0.34)	0.38 (0.25)	−1.88 (0.28)	0.07 (0.24)	−2.54 (0.43)	−0.32 (0.31)
YOUNGEST CH. 3-4 YEARS	−0.37 (0.18)	0.53 (0.15)	−1.42 (0.27)	0.19 (0.23)	−1.35 (0.27)	0.25 (0.23)	−1.23 (0.34)	0.32 (0.25)	−1.61 (0.29)	0.04 (0.25)	−2.24 (0.42)	−0.26 (0.30)
YOUNGEST CH. 5-6 YEARS	0.21 (0.18)	0.77 (0.15)	−0.72 (0.26)	0.59 (0.22)	−0.66 (0.26)	0.64 (0.22)	−0.45 (0.31)	0.75 (0.24)	−0.85 (0.28)	0.49 (0.23)	−1.26 (0.38)	0.31 (0.28)
YOUNGEST CH. 7-11 YEARS	0.19 (0.14)	0.41 (0.13)	−0.46 (0.22)	0.41 (0.20)	−0.41 (0.22)	0.44 (0.20)	−0.29 (0.26)	0.49 (0.22)	−0.54 (0.24)	0.34 (0.21)	−0.81 (0.32)	0.25 (0.25)
YOUNGEST CH. 12-15 YEAR	0.50 (0.16)	0.26 (0.14)	0.08 (0.21)	0.27 (0.18)	0.13 (0.21)	0.29 (0.18)	0.23 (0.24)	0.33 (0.20)	0.02 (0.22)	0.22 (0.19)	0.01 (0.29)	0.23 (0.23)
INTERCEPT	−3.11 (0.33)	−2.62 (0.31)	−2.70 (0.50)	−2.40 (0.43)	−2.72 (0.58)	−2.77 (1.00)	−3.27 (0.65)	−2.54 (0.50)	−2.41 (0.55)	−2.20 (0.47)	−3.79 (0.78)	1.84 (0.48)
Log Likelihood	-6913.55		-6825.68		-6823.30		-6822.82		-6791.79		-6778.67	
Pseudo R^2	54.25%		54.82%		54.84 %		54.84%		55.05%		55.13%	
AIC	13987.09		13845.35		13852.60		13849.65		13813.57		13797.35	
BIC	14591.79		14578.55		14631.15		14620.64		14682.83		14704.39	
Joint Significance of Correlated Random Effects	-		$p = 0.000$		$p = 0.000$		$p = 0.019$		$p = 0.000$		$p = 0.001$	

Notes: Standard errors in parentheses. Estimates of the coefficients on the year dummies and the initial conditions are omitted. Columns headed f and p contain the coefficients describing payoffs from respective full-time employment and part-time employment. AIC=-2Log likelihood+2Parameters; BIC=-2Log likelihood+ $\ln(NT)$Parameters; Pseudo R^2=1-Restricted Log likelhood/Unrestrcited Log likelihood. See notes to Table 1 for variable definitions.

Table 2: Estimates of the coefficients appearing in the observed components of payoffs and model specification statistics for Specifications I-VI of the dynamic mixed multinomial logit model.

	Spec. II	Spec. III	Spec. IV	Spec. V	Spec. VI
ΣIntercept 1	$\begin{pmatrix} \underset{(0.39)}{2.61} & . \\ \underset{(0.25)}{1.43} & \underset{(0.22)}{1.22} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.62)}{2.81} & . \\ \underset{(1.07)}{1.52} & \underset{(1.59)}{1.21} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.65)}{2.75} & . \\ \underset{(0.44)}{1.55} & \underset{(0.36)}{1.28} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.47)}{2.57} & . \\ \underset{(0.30)}{1.54} & \underset{(0.26)}{1.03} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.97)}{4.53} & . \\ \underset{(0.62)}{2.68} & \underset{(0.48)}{1.84} \end{pmatrix}$
ΣIntercept 2		$\begin{pmatrix} \underset{(0.52)}{1.65} & . \\ \underset{(0.28)}{0.88} & \underset{(0.64)}{0.47} \end{pmatrix}$			
μ_2		$\begin{pmatrix} \underset{(0.94)}{0.94} \\ \underset{(1.06)}{1.06} \end{pmatrix}$			
α		$\underset{(0.03)}{0.63}$			
ρ_f			$\underset{(0.19)}{-0.16}$		$\underset{(0.10)}{-0.12}$
ρ_p			$\underset{(0.29)}{0.12}$		$\underset{(0.19)}{0.31}$
Σ_ζ			$\begin{pmatrix} \underset{(1.59)}{2.39} & . \\ \underset{(0.04)}{0.96} & \underset{(0.83)}{0.73} \end{pmatrix}$		$\begin{pmatrix} \underset{(1.87)}{5.64} & . \\ \underset{(0.11)}{0.89} & \underset{(0.75)}{1.32} \end{pmatrix}$
$\Sigma_{Y_{i,f,t-2}}$				$\begin{pmatrix} \underset{(0.42)}{0.30} & . \\ \underset{(0.23)}{0.02} & \underset{(0.03)}{0.00} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.64)}{0.66} & . \\ \underset{(0.39)}{0.20} & \underset{(0.23)}{0.07} \end{pmatrix}$
$\Sigma_{Y_{i,p,t-2}}$				$\begin{pmatrix} \underset{(0.37)}{0.18} & . \\ \underset{(0.33)}{0.25} & \underset{(0.31)}{0.34} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.56)}{0.23} & . \\ \underset{(0.41)}{0.18} & \underset{(0.34)}{0.23} \end{pmatrix}$
$\Sigma_{Y_{i,f,t-1}}$				$\begin{pmatrix} \underset{(0.49)}{0.63} & . \\ \underset{(0.47)}{0.68} & \underset{(0.60)}{1.12} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.19)}{0.02} & . \\ \underset{(0.39)}{0.09} & \underset{(0.59)}{0.50} \end{pmatrix}$
$\Sigma_{Y_{i,p,t-1}}$				$\begin{pmatrix} \underset{(0.15)}{0.06} & . \\ \underset{(0.11)}{-0.13} & \underset{(0.24)}{0.28} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.18)}{0.06} & . \\ \underset{(0.17)}{-0.14} & \underset{(0.32)}{0.34} \end{pmatrix}$
Σ_{DEGREE}				$\begin{pmatrix} \underset{(0.72)}{0.53} & . \\ \underset{(0.54)}{0.68} & \underset{(0.53)}{1.21} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.77)}{0.76} & . \\ \underset{(0.82)}{1.15} & \underset{(0.65)}{1.74} \end{pmatrix}$
Σ_{CHILD}				$\begin{pmatrix} \underset{(2.88)}{7.71} & . \\ \underset{(1.68)}{4.42} & \underset{(1.35)}{2.53} \end{pmatrix}$	$\begin{pmatrix} \underset{(5.43)}{13.47} & . \\ \underset{(2.94)}{7.42} & \underset{(2.04)}{4.28} \end{pmatrix}$

Notes: Standard errors in parentheses. Specification I has no unknown parameters in the distribution of the unobservables. In Specifications II and IV-VI, ΣIntercept 1 is the covariance matrix of the time invariant components of the random intercepts. Specification III has time invariant random intercepts with a distribution obtained from the mixture of two bivariate normal distributions: with probability α the random intercepts have mean zero and variance ΣIntercept 1 and with probability $(1-\alpha)$ the random intercepts have mean μ_2 and variance ΣIntercept 2. In specifications allowing autocorrelation in the random intercepts, ρ_f and ρ_p are the first order autocorrelation coefficients and Σ_ζ is the covariance matrix of the innovations in the autoregressive processes. Σ_{DEGREE} and Σ_{CHILD} are the covariance matrices of the random coefficients on the indicated variables. The covariance matrices of the random coefficients on the initial conditions in Specifications V and VI are not reported, and the coefficients associated with the correlated random effects are omitted.

Table 3: Estimates of parameters appearing in the distribution of unobservables for Specifications II-VI of the dynamic mixed multinomial logit model.

the time-invariant random intercepts and observed individual characteristics.

5.2 Labor Supply following Employment Shocks

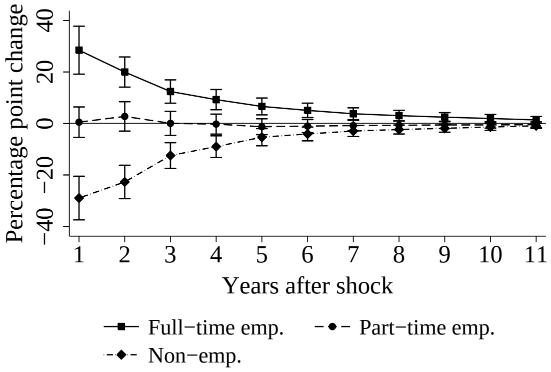
In this section we explore the nature of state dependence in labor supply behavior by investigating how labor supply behavior changes in response to temporary, exogenous, employment shocks. Specifically, we consider shocks to employment behavior which, for the duration of one year, place non-employed women in either full-time or part-time employment. The shocks themselves last only one year and

Variable	Spec. I		Spec. II		Spec. III		Spec. IV		Spec. V		Spec. VI	
	f	p	f	p	f	p	f	p	f	p	f	p
$n_{t-1} \to f_{t-1}$	52.39 (2.27)	−8.62 (1.87)	32.47 (2.40)	2.40 (2.09)	33.07 (3.79)	−8.80 (2.89)	42.38 (4.34)	−13.82 (3.70)	34.22 (2.92)	−11.06 (2.31)	43.93 (4.39)	−21.69 (3.90)
$n_{t-1} \to p_{t-1}$	4.95 (1.70)	39.88 (1.72)	−0.35 (1.79)	1.79 (2.05)	0.30 (3.37)	28.36 (5.90)	3.65 (2.47)	27.71 (2.73)	−2.43 (2.47)	29.67 (3.30)	1.94 (2.32)	23.40 (2.93)
NO EDUC. → GCSES	1.57 (0.75)	0.51 (0.86)	2.68 (1.37)	1.37 (1.38)	2.82 (1.30)	0.71 (1.21)	2.05 (1.14)	1.21 (1.25)	2.54 (1.43)	1.01 (1.47)	2.14 (1.25)	1.68 (1.32)
NO EDUC. → A LEVELS	2.10 (0.90)	0.02 (1.04)	4.54 (1.75)	1.75 (1.53)	4.58 (1.58)	−0.10 (1.57)	4.00 (1.57)	0.26 (1.61)	4.19 (1.78)	0.21 (1.62)	3.12 (1.37)	1.04 (1.68)
NO EDUC. → HIGHER QUAL BELOW DEGREE LEVEL	2.03 (0.75)	1.31 (0.78)	4.22 (1.46)	1.46 (1.30)	4.21 (1.30)	1.68 (1.23)	3.30 (1.22)	2.18 (1.20)	3.91 (1.42)	2.16 (1.47)	3.17 (1.25)	2.94 (1.39)
NO EDUC. → DEGREE	3.73 (0.81)	−1.12 (0.95)	6.71 (1.68)	1.68 (1.60)	6.71 (1.69)	−2.31 (1.53)	6.17 (1.49)	−1.83 (1.46)	6.33 (1.75)	−1.53 (1.58)	5.47 (1.50)	−0.96 (1.53)
UNEARNED INCOME+£1000	−8.55 (2.00)	1.12 (2.45)	−2.69 (3.84)	3.84 (4.95)	−2.93 (3.44)	−0.46 (4.02)	−3.13 (3.70)	0.28 (4.91)	−2.55 (3.56)	−1.92 (4.36)	−3.15 (3.68)	−1.36 (4.99)
AGE + 1 YEAR	−0.21 (0.04)	0.19 (0.05)	−0.39 (0.07)	0.07 (0.08)	−0.35 (0.09)	0.28 (0.10)	−0.38 (0.08)	0.31 (0.09)	−0.38 (0.08)	0.23 (0.09)	−0.37 (0.08)	0.26 (0.09)
NO CHILDREN → CHILD AGED≤1 YEAR	−31.87 (1.18)	−7.60 (2.13)	−35.28 (1.82)	1.82 (2.63)	−35.28 (2.87)	−6.93 (3.14)	−33.36 (1.69)	−5.94 (2.49)	−35.26 (2.53)	−7.68 (5.60)	−34.36 (1.90)	−9.02 (2.88)
NO CHILDREN → 1 YEAR <CHILD AGED≤2 YEARS	−9.75 (1.12)	12.06 (1.30)	−18.84 (2.24)	2.24 (2.50)	−18.26 (2.84)	15.83 (3.80)	−15.50 (2.02)	14.97 (2.15)	−19.12 (2.25)	14.74 (2.39)	−16.57 (2.34)	11.42 (2.69)
NO CHILDREN → 2 YEAR <CHILD AGED≤4 YEARS	−6.76 (1.33)	8.38 (1.44)	−16.07 (2.37)	2.37 (2.59)	−15.65 (2.64)	13.59 (3.42)	−13.08 (2.36)	12.57 (2.56)	−16.36 (2.36)	12.42 (2.49)	−14.79 (2.30)	10.43 (2.49)
NO CHILDREN → 4 YEAR <CHILD AGED≤7 YEARS	−3.36 (1.11)	7.15 (1.25)	−12.23 (2.02)	2.02 (2.12)	−11.87 (2.76)	13.39 (3.38)	−9.44 (2.16)	12.15 (2.28)	−12.43 (2.09)	12.59 (2.21)	−11.28 (2.06)	11.03 (2.42)
NO CHILDREN → 7 YEAR <CHILD AGED≤11 YEARS	−1.04 (0.89)	3.23 (0.97)	−8.15 (1.81)	1.81 (1.76)	−7.68 (2.10)	8.74 (2.46)	−6.07 (1.75)	7.78 (1.88)	−8.17 (1.69)	8.27 (1.75)	−7.61 (1.79)	7.56 (1.96)
NO CHILDREN → 11 YEAR <CHILD AGED≤16 YEARS	2.74 (0.97)	−0.52 (1.03)	−1.21 (1.63)	1.63 (1.54)	−1.01 (1.53)	2.67 (1.60)	−0.32 (1.32)	2.21 (1.61)	−1.41 (1.57)	2.34 (1.40)	−1.36 (1.39)	2.34 (1.45)

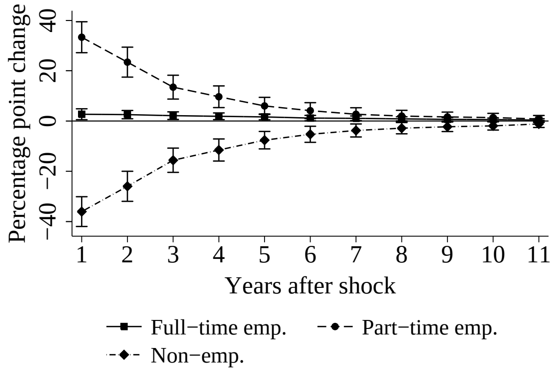
Notes: Standard errors in parentheses. Marginal effects, expressed in percentage points, were computed by simulating, for each individual in the sample, employment behavior before and after a change in the relevant characteristic, and then averaging the responses over time and over individuals. Columns headed f contain the marginal effects for full-time employment and columns headed p contain marginal effects for part-time employment. See notes to Table 1 for variable definitions.

Table 4: Marginal effects for Specifications I-VI of the dynamic mixed multinomial logit model.

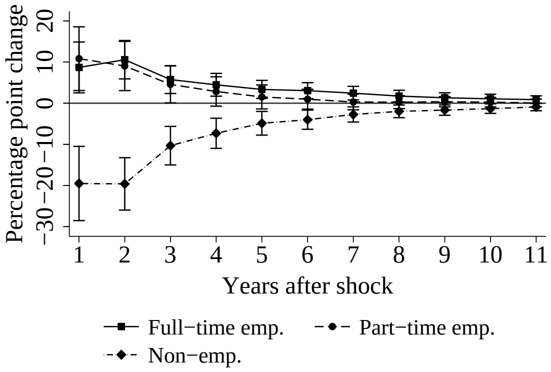
therefore labor supply behavior subsequent to the shocks is affected only via the effect of the individual's previous employment outcome on her current payoffs. These simulation experiments are designed to illustrate transparently the strength of state dependencies implied by our various model specifications, but do not correspond directly to any particular policy environment. That being said, many active labor market policies feature time-limited components (see, for example, the polices discussed by Autor and Houseman (2010), Card and Hyslop, 2005, de Graaf-Zijl *et al.*, 2011, and Gerfin *et al.*, 2005), and therefore our results are indicative of the implications of assumptions regarding persistent unobserved heterogeneity for conclusions concerning policy effectiveness.



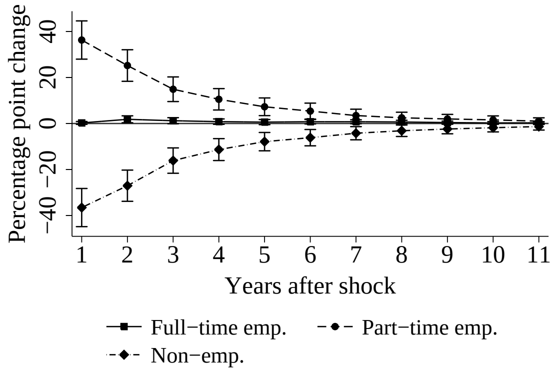
(a) Temporary shock moves non-employed women into full-time work: All women non-employed at $t = 0$.



(b) Temporary shock moves non-employed women into part-time work: All women non-employed at $t = 0$.



(c) Temporary shock moves non-employed women into full-time work: Women with young children non-employed at $t = 0$.



(d) Temporary shock moves non-employed women into part-time work: Women with young children non-employed at $t = 0$.

Notes: "Women with young children" refers to the women who gave birth to a child one year after the shock (i.e., at $t = 1$). Vertical bars represent 95% confidence intervals. Confidence intervals were constructed from repeated evaluations of the effects of the policy interventions where each evaluation used a new parameter vector obtained by sampling from the asymptotic distribution of the MLEs.

Figure 2: Impulse response functions based on Specification VI.

Figure 2(a) shows the average effect on the labor supply behavior of initially non-employed women of a temporary shock that moves non-employed women into full-time work. We see that this shock causes a significant increase in full-time work of 28.5 percentage points in the year immediately after the shock. The temporary shock continues to have a significant positive, but smaller, effect on full-time employment in subsequent years. This increase in full-time employment is balanced predominantly by a reduction in non-employment; the effect of the shock on part-time work is generally negative but is insignificant. Similarly, Figure 2(b) shows the average effect on the labor supply behavior of initially non-employed women of a temporary shock that moves non-employed women into part-time work. Such a shock causes a significant increase in part-time work, and a much smaller, yet significant, increase in full-time work, together balanced by a reduction in non-employment. Specifically, the one year own-state dependence effect for part-time employment is 33.3 percentage points, which is around 5 percentage points larger than the corresponding own-state dependence effect for full-time employment. Further, one year after a temporary shock that moves initially non-employed women into part-time work the rate of full-time employment is 2.7 percentage points higher than in the absence of any shocks, and this effect is significant at the 1.538% level. Due to the asymmetric nature of the cross-state dependencies and the higher own-state dependence in part-time employment as compared to full-time employment, a shock that increases part-time employment produces a larger reduction in non-employment than does a shock that increases full-time employment. This result highlights the value of our multinomial approach to modeling labor supply; a binary model of labor force participation would be uninformative about the relative merits of labor market policies that facilitate either full-time or part-time employment.

Figures 2(c) and 2(d) meanwhile show the dynamic labor supply responses to employment shocks for initially non-employed women who give birth to a child one year after the shock, henceforth referred to as "women with young children". From Figure 2(c) we see that a shock that places non-employed women with young children in full-time employment causes the rate of full-time employment among those affected to increase by 8.7 percentage points one year after the shock, a markedly smaller increase in full-time employment than for the sample average. Additionally, and again in contrast to the results for the sample average, part-time employment increases significantly for this group of women. In fact, a shock that places non-employed women with young children in full-time employment causes the rate of part-time work one year after the shock to increases by slightly more than the increase in full-time work. Thus, for women with young children, full-time employment provides an important stepping-stone into part-time employment. Finally, Figure 2(d) shows that a shock that places non-employed women in part-time employment cause an increase in part-time employment of 36.3 percentage points among women with young children, however cross-state dependencies are absent in this case. Overall, we find that among women with young children, persistence in employment, i.e., full-time and part-time work combined, is higher following a shock that moves non-employed women into part-time work than following a shock that moves non-employed women into full-time work. Difference between the own-state and cross-state dependencies in labor supply behavior for women with young children and for sample average suggests that maximizing the effectiveness of policies incentivizing either full-time or part-time employment requires tailoring of polices according to demographic characteristics.

5.3 Heterogeneity in Labor Supply Dynamics after Child Birth

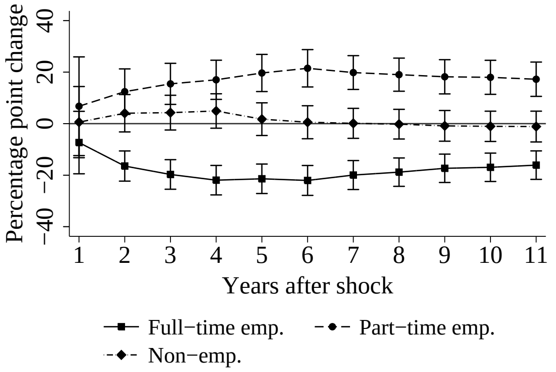
We use the parameter estimates for Specification VI to explore the extent of heterogeneity in labor supply dynamics following the birth of a child. As discussed in Section 5, Table 3 shows that there are significant amounts of variation in the effects of having a child aged under one year on a woman's payoffs from both full-time and part-time work. Together with the significant state dependence effects documented above, heterogeneity in the effects of having a child aged under one year suggests that there may be persistent differences in labor supply behavior following the birth of a child.

Figure 3 shows the estimated effect a having a child on subsequent employment behavior for women at different points in the distribution of unobserved preferences for full-time and part-time work in the event that they have a child aged under one year. Figure 3(a) shows that for women who have a high unobserved preference for full-time work in the event that they have a child aged under one year, having a young child has very little immediate effect on labor supply behavior. As the child becomes older these women become more likely to work part-time and less likely to work full-time, as compared to if they had not had a child. Non-employment increases slightly 3-6 years following the birth of the child. Thus, we conclude that for women with a very strong preference for full-time work in the event that they have a child aged under one year, there is a substitution away from full-time work and towards part-time work, but no pronounced movement away from employment in general.

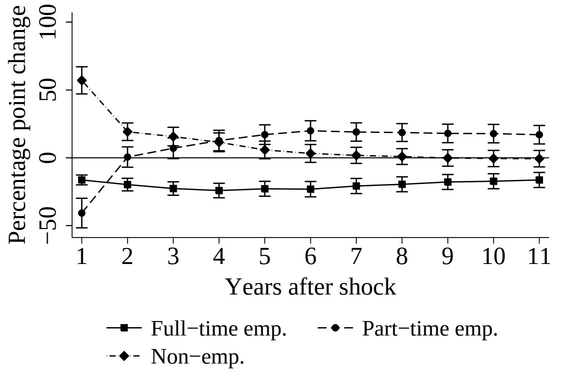
We see from Figure 3(b) that the picture is dramatically different for women who have a relatively low preference for full-time work in the event that they have a child aged under one year. For such women, the birth of a child is accompanied by a large and significant substitution away from both full-time and part-time work and into non-employment. For such women, two years after the shock the rate of part-time employment is higher than if the women had not had a child, however it takes 6 years before the rate of non-employment among women with a low preference of full-time work in the event that they have a child aged under one year is within two percentage points of the rate of non-employment among women with a high preference of full-time work in the event that they have a child aged under one year. Figures 3(c) and 3(d) illustrate the change in labor supply behavior over time caused by the birth of a child for women with high and low preferences for part-time work in the event that they have a child aged under one year. We see that the variation in employment responses according to the unobserved tastes for part-time employment in the event that the woman has a child aged under one year is very similar to the variation on employment responses according to tastes for full-time employment in the same circumstances. This latter result reflects the high correlation between the incremental unobserved components of preferences for full-time and part-time work that occur due to the presence of a child aged under one year.

5.4 Comparisons with More Restrictive Specifications

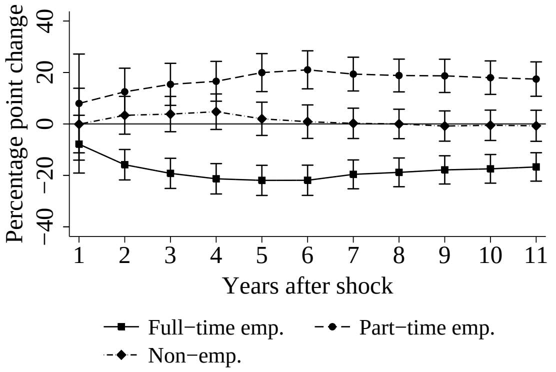
Comparisons are now made with specifications that impose more restrictive distributions of unobservables than Specification VI. Recall that the primary motivation for allowing generality, in the form of autocorrelation and random coefficients, in the distribution of unobservables was that imposing an overly restrictive distribution of persistent unobservables would likely lead to inconsistent estimates of state dependencies. Therefore, when comparing the various specifications, attention is focused on



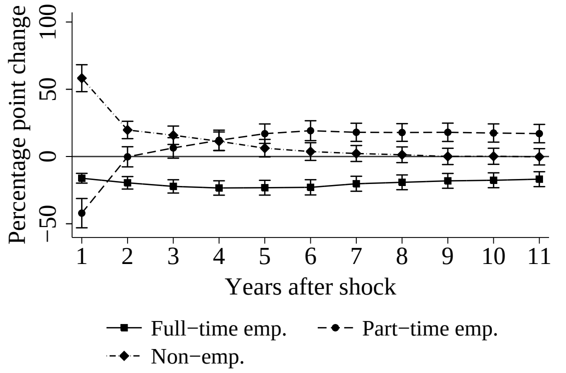
(a) Effect of having a child at $t = 1$ - High unobserved preference for full-time work.



(b) Effect of having a child at $t = 1$ - Low unobserved preference for full-time work.



(c) Effect of having a child at $t = 1$ - High unobserved preference for part-time work.



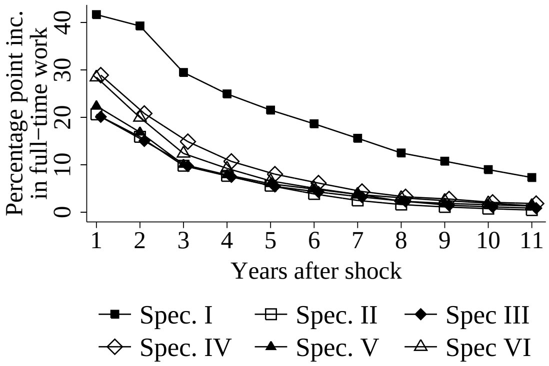
(d) Effect of having a child at $t = 1$ - Low unobserved preference for part-time work.

Notes: Vertical bars represent 95% confidence intervals, constructed as described in the notes accompanying Figure 2. High and low unobservables refer to the 90^{th} and 10^{th} percentiles of the distribution of unobservables. Other unobservables are drawn from the appropriate conditional distribution. Effects were estimated by averaging over the sample distribution of all observed individual characteristics, except children.

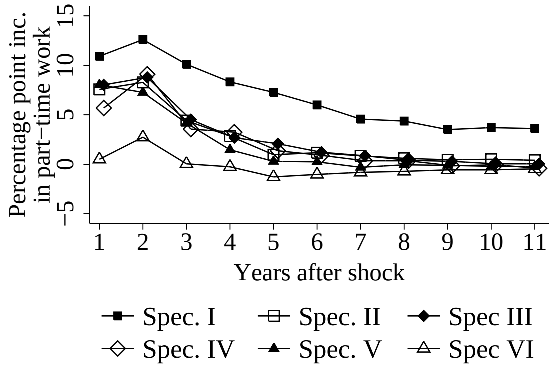
Figure 3: Heterogeneity in labor supply dynamics after child birth.

differences between specifications in estimates of impulse responses functions. However, for completeness, at the end of this subsection we discuss briefly model selection criteria and cross-specification differences in average marginal effects.

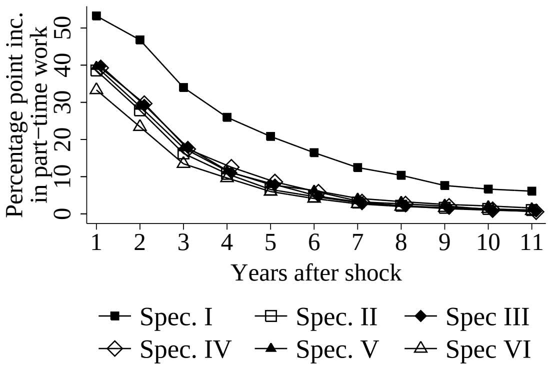
Figures 4 and 5 show the dynamic responses to employment shocks as implied by each of the six model specifications under consideration. As in Section 5.2, the employment shocks under consideration cause women who are non-employed at $t = 0$ to work, depending on the shock, either full-time or part-time. Also as previously, all shocks last only one year and therefore labor supply behavior subsequent to the shocks is affected only via the effect of the individual's previous employment outcome on her current payoffs. We present state dependence effects averaged over the sample and for women who gave birth to a child one year after the employment shock, referred to as "women with young children". Figure 4 shows that on average Specification I implies, for both full-time and part-time work, substantially larger own-state and cross-state dependencies than Specification VI; as expected



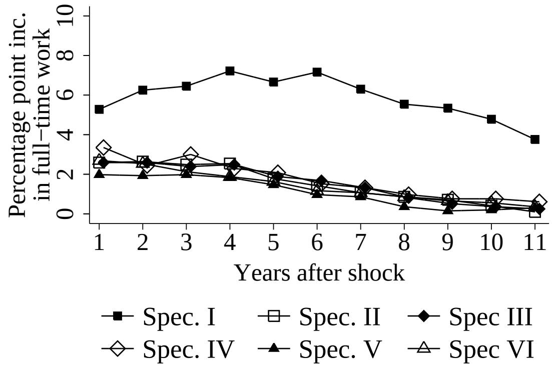
(a) Temporary shock moves non-employed women into full-time work - own-state effect.



(b) Temporary shock moves non-employed women into full-time work - cross-state effect.



(c) Temporary shock moves non-employed women into part-time work - own-state effect.

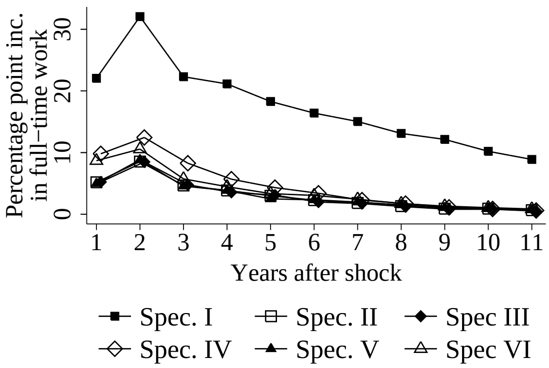


(d) Temporary shock moves non-employed women into part-time work - cross-state effect.

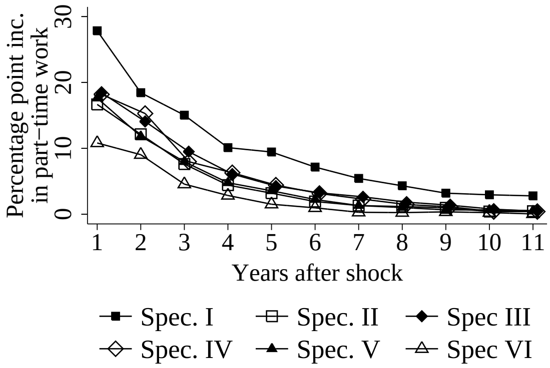
Figure 4: Comparison of impulse response functions based on Specifications I-VI: Average effects for women non-employed at the time of the shock.

completely ignoring persistent unobservables leads to an overestimate of the state dependence in labor supply behavior. Looking across all of the own-state and cross-state dependence effects, there is very little difference between the results implied by Specifications II and III. In other words, generalizing the distribution of the time invariant random intercepts to be non-normal does not impact on estimates of intertemporal dependencies.

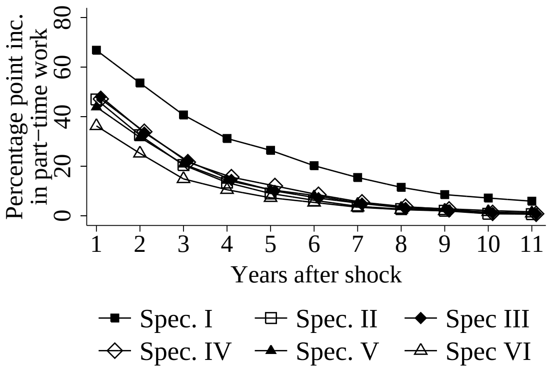
Focusing first on the effects of a shock that places non-employed women in full-time employment and considering the sample average, we see that the own-state dependencies impled by Specifications IV and VI are larger than those implied by any of Specifications II, III or V. For example, according to Specification VI the one year own-state dependence effect for full-time employment is 28.5 percentage points, while Specification V, which excludes autocorrelation, suggest a one year own-state dependence effect of around 22.4 percentage points. Table 5 shows that many of the differences between the own state dependencies implied by Specification VI and those implied by more restrictive specifications are significant. Thus we conclude that permitting both random coefficients and autocorrelated unobservables is necessary to estimate accurately the degree of own-state dependence in full-time employment.



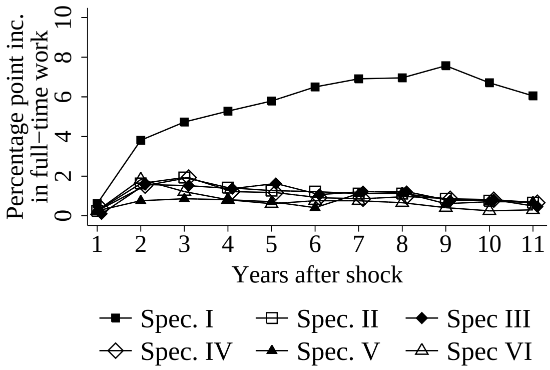
(a) Temporary shock moves non-employed women into full-time work - own-state effect - young child.



(b) Temporary shock moves non-employed women into full-time work - cross-state effect - young child.



(c) Temporary shock moves non-employed women into part-time work - own-state effect - young child.



(d) Temporary shock moves non-employed women into part-time work - cross-state effect - young child.

Figure 5: Comparison of impulse response functions based on Specifications I-VI: Average effects for women non-employed at the time of the shock and who give birth to a child at one year after the shock.

There also exist differences between specifications in estimates of the cross-state effect full-time employment on subsequent part-time employment. Specifically, Specification VI suggests that full-time employment does not facilitate part-time employment while the other specifications show a positive stepping-stone effect. Table 5 shows that Specification IV implies a significantly lower cross state effect of previous full-time employment on current part-time employment than Specification V. For part-time work, the own-state dependencies implied by Specifications II and VI, as well as the three intermediate specifications, are very similar. The cross-state dependencies also show little variation. In summary, the modeling of unobserved heterogeneity has greater implications for estimation of own-state and cross-state dependencies for full-time employment than for part-time employment.

Figure 5 shows the own-state and cross-state dependence effects induced by shocks that move non-employed women into either full-time or part-time employment, focusing on women who gave birth to a child one year after the employment shock. As in Section 5.2, the illustrated employment effects in Figures 5(a)-5(d) are obtained by averaging over the sample distribution of all other individual characteristics. Figure 5(a) reveals that one year after an employment shock that moves non-employed

Labor Supply Response	Years since Employment Shock										
	1	2	3	4	5	6	7	8	9	10	11
Own-state Effects											
Difference between Spec. II and Spec. VI											
Δ Full-time emp. (Sample average)	2.28	2.87	3.44	2.19	2.16	2.19	2.33	1.66	1.57	1.48	1.75
Δ Part-time emp. (Sample average)	-0.87	-0.77	-0.74	-0.34	-0.17	0.09	0.09	0.15	0.16	0.30	0.21
Δ Full-time emp. (Young child)	2.05	1.09	1.32	1.25	1.77	1.17	1.45	1.07	0.72	0.89	0.99
Δ Part-time emp. (Young child)	-1.18	-0.93	-0.94	-0.71	-0.52	-0.23	0.05	0.19	0.26	0.38	0.36
Difference between Spec. IV and Spec. VI											
Δ Full-time emp. (Sample average)	0.70	0.68	0.65	0.69	0.78	0.76	0.98	0.91	0.97	0.81	0.86
Δ Part-time emp. (Sample average)	0.01	-0.07	0.01	0.32	0.40	0.64	0.75	1.01	1.00	1.09	0.96
Δ Full-time emp. (Young child)	0.23	0.36	0.22	0.38	0.35	0.36	0.37	0.32	0.29	0.38	0.43
Δ Part-time emp. (Young child)	-0.15	-0.23	-0.24	0.07	0.17	0.40	0.62	0.86	0.87	1.00	0.95
Difference between Spec. V and Spec. VI											
Δ Full-time emp. (Sample average)	2.97	2.11	2.16	1.28	1.04	0.88	1.11	0.80	0.91	0.54	0.78
Δ Part-time emp. (Sample average)	-1.41	-0.69	-0.71	-0.41	-0.38	-0.25	-0.21	-0.30	-0.22	-0.05	-0.13
Δ Full-time emp. (Young child)	2.59	2.38	2.18	2.25	1.27	0.86	0.78	0.93	0.46	0.25	0.58
Δ Part-time emp. (Young child)	-0.98	-0.51	-0.55	-0.52	-0.38	-0.10	-0.08	-0.11	-0.01	0.08	-0.01
Cross-state Effects											
Difference between Spec. II and Spec. VI											
Δ Part-time emp. (Sample average)	-1.24	-1.00	-1.08	-0.93	-0.95	-1.13	-1.08	-0.96	-0.85	-0.65	-0.64
Δ Full-time emp. (Sample average)	0.07	-0.08	-0.05	-0.27	-0.16	0.00	-0.02	-0.03	-0.08	-0.22	-0.23
Δ Part-time emp. (Young child)	-0.48	-0.43	-0.61	-0.68	-0.69	-0.72	-0.49	-0.55	-0.36	-0.41	-0.29
Δ Full-time emp. (Young child)	0.09	-0.32	-0.04	-0.53	-0.52	-0.26	-0.76	-0.45	-0.69	-0.33	-0.47
Difference between Spec. IV and Spec. VI											
Δ Part-time emp. (Sample average)	-0.14	-0.41	-0.45	-0.37	-0.45	-0.44	-0.52	-0.67	-0.61	-0.40	-0.53
Δ Full-time emp. (Sample average)	0.05	-0.26	-0.27	-0.38	-0.21	-0.14	-0.04	-0.02	-0.09	-0.15	-0.09
Δ Part-time emp. (Young child)	0.06	-0.37	-0.27	-0.34	-0.25	-0.26	-0.18	-0.15	-0.05	-0.03	0.02
Δ Full-time emp. (Young child)	-0.23	-0.32	-0.41	-0.66	-0.78	-0.58	-0.70	-0.75	-0.75	-0.33	-0.43
Difference between Spec. V and Spec. VI											
Δ Part-time emp. (Sample average)	-2.14	-1.39	-2.02	-1.04	-0.93	-0.74	-0.62	-0.64	-0.53	-0.35	-0.44
Δ Full-time emp. (Sample average)	1.56	0.52	0.94	0.50	0.37	0.47	0.39	0.04	-0.27	-0.43	-0.25
Δ Part-time emp. (Young child)	-0.92	-0.13	-0.57	-0.68	-0.67	-0.50	-0.31	-0.50	-0.33	-0.16	-0.32
Δ Full-time emp. (Young child)	0.51	-0.15	0.94	0.54	0.15	0.09	-0.18	-0.10	-0.54	-0.06	0.16

Notes: Standard errors are bootstrapped. Δ denotes the change relative to the baseline case, where no shock occurred. "Young child" refers to women who had a young child one year after the employment shock (i.e., at $t = 1$). Specification I is omitted because the predictions from this specification are always significantly different to those from Specification VI. Specification III is omitted because results are almost identical to those obtained from Specification II.

Table 5: t tests for significance of differences in the own and cross-state effects of employment shocks.

women into full-time employment the estimated rate of full-time employment is higher according to Specification VI than according to either specification II or Specification V. Table 5 shows that these differences are significant, a result which again illustrates the importance of random coefficients.

Table 4 shows that estimates of average marginal effects of changes in individual characteristics are rather robust to the assumed distribution of the unobservables. Thus the sensitivity of our results to the assumed distribution of unobservables does not extend to estimates of the average effect of observed individual characteristics on labor supply behavior; this is not surprising as the estimated state dependencies are generated in part by dynamic selection on unobservables, while the remaining marginal effects are static in nature. Finally, we note that model selection criteria, presented in Table 2, are inconclusive regarding the preferred specification of unobservables: the Akaike Information Criterion (Akaike, 1973) suggests that Specification VI is preferred, while the Bayesian Information Criterion (Schwartz, 1978), which imposes a greater penalty for model complexity, selects Specification I.

In Appendix C.2 we consider the role played by the correlated random effects, which are permitted in Specifications II-VI. In summary, we show that the omission of correlated random effects leads to an overstatement of the own state dependence in full-time employment. In addition, we find that estimates of labor supply behavior following the birth of a child are also dependent on whether or not correlated random effects are permitted.

6 Conclusion

This paper has extended the literature on binary models of labor force participation dynamics by including a distinction between full-time and part-time work and by considering more general distributions of unobserved individual characteristics. Within this setting and using a panel sample of British women, we have found significant autocorrelation and significant variation in the effects of education and children on labor supply behavior. We have shown that excluding either of these two features of the distribution of unobservables impacts significantly on estimates of state dependencies. In particular, working with a specification of unobservables that allows correlated time invariant individual-specific random effects, but no further generality in the distribution of unobservables, results in significant downward biases in the estimated effect of a woman's previous employment behavior on her current choice between full-time work, part-time work and non-employment. More general specifications, that allow either autocorrelation in the employment state-specific intercepts or variation in the effects of children and education on labor supply preferences, perform better. However, there remains a downward bias relative to when both autocorrelation and random coefficients are permitted. While our approach is entirely reduced form in nature, our results suggest that the biases that arise as a result of imposing overly restrictive distributions of unobservables are large enough to make the choice of distribution of unobservables important when conducting policy evaluation.

Leveraging the multinomial nature of our model, we have investigated the relative persistence in employment following temporary employment shocks that increase specifically either full-time or part-time employment. On average, over our sample of married or cohabiting women, we have shown that temporary shocks that increase the rate of part-time employment are followed by higher rates of employment, that is full-time and part-time employment combined, than are temporary shocks that increase the rate of full-time employment. This result is notable in the context of the debate surrounding the status of part-time employment in the United Kingdom. In particular, our results suggest that, while part-time jobs tend to be relatively poorly paid and are concentrated disproportionably at low levels of the occupational hierarchy, part-time employment does not appear to entail lower labor market attachment than full-time employment.

Supplementary Materials

Appendices: Appendices A and B provide evidence from Monte Carlo simulation on the performance of the employed Maximum Simulated Likelihood estimator. In Appendix C we present the results of robustness checks, and we explore the role played by the correlated random effects that are permitted in the primary empirical analysis.

Acknowledgements

I express my thanks for useful comments to the following: Richard Blundell; Steve Bond; Martin Browning; Ian Crawford; Kathryn Graddy; Peter Haan; George Jakubson; Andrey Launov; Valérie Lechene; Robert Moffitt; Bent Nielsen; and the referees, editor and associate editor of the *Journal of Business & Economic Statistics*. I have also benefited from discussions with participants in seminars at CAM, IZA, Oxford, Surrey, Sussex, and at EEA and Econometric Society conferences. Any remaining errors are my own.

References

Akaike, H. (1973), Information Theory as an Extension of the Maximum Likelihood Principle, in B. Petrov and F. Csaki (Editors), *Second International Symposium on Information Theory*, pp. 267–281, Akademiai Kiado, Budapest.

Altug, S. and Miller, R. (1998), The Effect of Work Experience on Female Wages and Labour Supply, *Review of Economic Studies*, **vol. 65**(1): pp. 45–85.

Autor, D. H. and Houseman, S. N. (2010), Do Temporary-Help Jobs Improve Labor Market Outcomes for Low-Skilled Workers? Evidence from "Work First", *American Economic Journal: Applied Economics*, **vol. 2**(3): pp. 96–128.

Ben-Akiva, M. and Lerman, S. R. (1985), *Discrete Choice Analysis*, Cambridge, Massachusetts: MIT Press.

Bhat, C. R. (2001), Quasi-random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model, *Transportation Research B: Methodological*, **vol. 35**(7): pp. 677–693.

Booth, A., Jenkins, S. and Serrano, C. (1999), New Men and New Women? A Comparison of Paid Work Propensities from a Panel Data Perspective, *Oxford Bulletin of Economics and Statistics*, **vol. 61**(2): pp. 167–197.

Bover, O. (1991), Relaxing Intertemporal Separability: A Rational Habits Model of Labor Supply Estimated from Panel Data, *Journal of Labor Economics*, **vol. 9**(1): pp. 85–100.

Bunch, D. S. (1991), Estimability in the Multinomial Probit Model, *Transportation Research B: Methodological*, **vol. 25**(1): pp. 1–12.

Card, D. and Hyslop, D. R. (2005), Estimating the Effects of a Time-limited Earnings Subsidy for Welfare-leavers, *Econometrica*, **vol. 73**(6): pp. 1723–1770.

Carro, J. (2007), Estimating Dynamic Panel Data Discrete Choice Models with Fixed Effects, *Journal of Econometrics*, **vol. 140**(2): pp. 503–528.

Chamberlain, G. (1984), Panel Data, in Griliches and Intriligator (Editors), *Handbook of Econometrics*, vol. 2, chap. 22, Amsterdam: North Holland.

Connolly, S. and Gregory, M. (2008), Moving Down: Women's Part-Time Work and Occupational Change in Britain 1991-2001, *Economic Journal*, **vol. 118**: pp. F52–F76.

de Graaf-Zijl, M., van den Berg, G. and Heyma, A. (2011), Stepping Stones for the Unemployed: The Effect of Temporary Jobs on the Duration until (Regular) Work, *Journal of Population Economics*, **vol. 24**(1): pp. 107–139.

Eckstein, Z. and Wolpin, K. (1989), The Specification and Estimation of Dynamic Stochastic Discrete Choice Models: A Survey, *Journal of Human Resources*, **vol. 24**(4): pp. 562–598.

Fernández-Val, I. (2009), Fixed Effects Estimation of Structural Parameters and Marginal Effects in Panel Probit Models, *Journal of Econometrics*, **vol. 150**(1): pp. 71–85.

Francesconi, M. (2002), A Joint Dynamic Model of Fertility and Work of Married Women, *Journal of Labor Economics*, **vol. 20**(2): pp. 336–380.

Gerfin, M., Lechner, M. and Steiger, H. (2005), Does Subsidised Temporary Employment get the Unemployed Back to Work? An Econometric Analysis of Two Different Schemes, *Labour Economics*, **vol. 12**(6): pp. 807–835.

Geweke, J. F. (1996), Monte Carlo Simulation and Numerical Integration, in H. Kendrick, D. Amman and J. Rust (Editors), *Handbook of Computational Economics*, vol. 13, pp. 731–800, Amsterdam: North Holland.

Hahn, J. and Kuersteiner, G. (2004), Bias Reduction for Dynamic Nonlinear Panel Models with Fixed Effects, *Econometric Theory*, **vol. 1**(1): pp. 1–40.

Hajivassiliou, V. (1999), Some Practical Issues in Maximum Simulated Maximum Likelihood, in R. Mariano, T. Schuermann and M. Weeks (Editors), *Simulation-Based Inference in Econometrics: Methods and Applications*, pp. 71–99, Cambridge University Press.

Hajivassiliou, V. and Ruud, P. A. (1994), Classical Estimation Methods for LDV Models Using Simulation, in C. Engle and D. McFadden (Editors), *Handbook of Econometrics*, pp. 2383–2441, Amsterdam: North Holland.

Harris, K. M. and Keane, M. P. (1998), A Model of Health Plan Choice: Inferring Preferences and Perceptions from a Combination of Revealed Preference and Attitudinal Data, *Journal of Econometrics*, **vol. 89**(1-2): pp. 131–157.

Hausman, J. A. and Wise, D. A. (1978), A Conditional Probit Model for Qualitative Choice: Discrete Decisions Recognizing Interdependence and Heterogeneous Preferences, *Econometrica*, **vol. 46**(2): pp. 403–26.

Heckman, J. (1981a), Statistical Models for Discrete Panel Data, in C. F. Manski and D. McFadden (Editors), *Structural Analysis of Discrete Data with Econometric Applications*, pp. 114–178, MIT Press.

Heckman, J. (1981b), The Incedental Parameter Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process, in C. F. Manski and D. McFadden (Editors), *Structural Analysis of Discrete Data with Econometric Applications*, pp. 179–195, MIT Press.

Heckman, J. and MaCurdy, T. (1980), A Life-cycle Model of Female Labor Supply, *Review of Economic Studies*, **vol. 47**(1): pp. 47–74.

Heckman, J. J. and Willis, R. (1977), A Beta-logistic Model for the Analysis of Sequential Labor Force Participation by Married Women, *Journal of Political Economy*, **vol. 85**(1): pp. 27–58.

Hess, S. and Polak, J. (2003), An Alternative Method to the Scrambled Halton Sequence for Removing Correlation Between Standard Halton Sequences in High Dimensions, Tech. rep., European Regional Science Association.

Hyslop, D. (1999), State Dependence, Serial Correlation and Heterogeneity in Intertemporal Labor Force Participation of Married Women, *Econometrica*, **vol. 67**(6): pp. 1255–1294.

Imai, S. and Keane, M. P. (2004), Intertemporal Labor Supply and Human Capital Accumulation, *International Economic Review*, **vol. 45**(2): pp. 601–641.

Keane, M. (1993), Simulation Estimation for Panel Data Models with Limited Dependent Variables, in G. Maddala, C. Rao and H. Vinod (Editors), *Handbook of Statistics*, Amsterdam: North Holland.

Keane, M. and Sauer, R. (2010), A Computationally Practical Simulation Estimation Algorithm for Dynamic Panel Data Models with Unobserved Endogenous State Variables, *International Economic Review*, **vol. 51**(4): pp. 925–958.

KEANE, M. P. (1992), A Note on Identification in the Multinomial Probit Model, *Journal of Business and Economic Statistics*, **vol. 10**(2): pp. 193–200.

KUBIN, I. AND PRINZ, A. (2002), Labour Supply with Habit Formation, *Economics Letters*, **vol. 75**(1): pp. 75–79.

MANNING, A. AND PETRONGOLO, B. (2008), The Part-Time Pay Penalty for Women in Britain, *Economic Journal*, **vol. 118**: pp. F28–F51.

MATZKIN, R. (1993), Nonparametric Identification and Estimation of Polychotomous Choice Models, *Journal of Econometrics*, **vol. 58**(1-2): pp. 137–168.

NEYMAN, J. AND SCOTT, E. (1948), Consistent Estimates Based on Partially Consistent Observations, *Econometrica*, **vol. 16**(1): pp. 1–32.

SCHWARTZ, G. (1978), Estimating the Dimension of a Model, *Annals of Statistics*, **vol. 6**: pp. 461–464.

TRAIN, K. (2003), *Discrete Choice Models using Simulation*, Cambridge University Press.

WALKER, J. L., BEN-AKIVA, M. AND BOLDUC, D. (2007), Identification of Parameters in Normal Error Component Logit-Mixture (NECLM) Models, *Journal of Applied Econometrics*, **vol. 22**(6): pp. 1095–1125.

WOITTIEZ, I. AND KAPTEYN, A. (1998), Social Interactions and Habit Formation in a Model of Female Labour Supply, *Journal of Public Economics*, **vol. 70**(2): pp. 185–205.

WOLPIN, K. I. (1992), The Determinants of Black-White Differences in Early Employment Careers: Search, Layoffs, Quits, and Endogenous Wage Growth, *Journal of Political Economy*, **vol. 100**(3): pp. 535–560.

WOOLDRIDGE, J. M. (2005), Simple Solutions to the Initial Conditions Problem in Dynamic, Nonlinear Panel Data Models with Unobserved Heterogeneity, *Journal of Applied Econometrics*, **vol. 20**(1): pp. 39–54.

Modeling Employment Dynamics with State Dependence and Unobserved Heterogeneity

Supplementary Materials

Victoria Prowse
Department of Economics
Cornell University
prowse@cornell.edu

April 10, 2012

Appendix A: Monte Carlo Simulations I

Monte Carlo simulations are used to illustrate the poor numerical properties of the Maximum Likelihood estimator of the parameters of a dynamic mixed multinomial logit model in which there are unobserved individual characteristics that affect payoffs in only one year and have distributions containing unknown parameters which do not appear elsewhere in the distribution of unobservables. Further Monte Carlo simulations show that reliable parameter estimates are obtained if additional structure is imposed on the unobservables.

To maintain consistency, attention is restricted to the three state model of employment dynamics described in the main text, however similar results were obtained for static models and for models with more than three alternatives. The following specification of payoffs is adopted for $t = 3, ..., T$

$$\begin{aligned} V^f(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,f,t}) - V^n(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,n,t}) &= \gamma_{f,f-1}Y_{i,f,t-1} + \gamma_{f,p-1}Y_{i,p,t-1} + \gamma_{f,f-2}Y_{i,f,t-2} \\ &\quad + \gamma_{f,p-2}Y_{i,p,t-2} + \beta_{f,0} + \beta_{f,1}X1_{i,t} + \beta_{f,2}X2_{i,t} + \eta_{i,f,t} + \xi_{i,f,t}, \quad (1a) \\ V^p(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,p,t}) - V^n(\Omega_{i,t-1}, X_{i,t}, \varrho_{i,n,t}) &= \gamma_{p,f-1}Y_{i,f,t-1} + \gamma_{p,p-1}Y_{i,p,t-1} + \gamma_{p,f-2}Y_{i,f,t-2} \\ &\quad + \gamma_{p,p-2}Y_{i,p,t-2} + \beta_{p,0} + \beta_{p,1}X1_{i,t} + \beta_{p,2}X2_{i,t} + \eta_{i,p,t} + \xi_{i,p,t}. \quad (1b) \end{aligned}$$

In the above $Y_{i,j,t}$ is an indicator of individual i being in employment state j at time t, and $X1_{i,t}$ and $X2_{i,t}$ are individual specific variables, constructed to be mutually independent, independent over time and individuals and to have standard normal distributions. Individuals' employment outcomes at $t = 1$ and $t = 2$ are determined randomly and are constructed to be independent of the unobservables that drive subsequent employment outcomes, thus allowing the initial conditions to be ignored. The unobservables $\xi_{i,j,t} = \epsilon_{i,j,t} - \epsilon_{i,n,t}$ for $j = f, p$, and $\epsilon_{i,j,t}$ for $j = f, p, n$ are assumed to be mutually independent, independent over time, independent over individuals and to have type I extreme value distributions. The first component of the unobservables $(\eta_{i,f,t}, \eta_{i,p,t})$ is assumed to be formed as follows

$$\begin{aligned} \eta_{i,f,t} &= \nu_{i,f} + \textstyle\sum_{t=3}^{T} \pi_{i,f,t} I_t \quad \text{for} \quad t = 3, ..., T, \quad (2a) \\ \eta_{i,p,t} &= \nu_{i,p} + \textstyle\sum_{t=3}^{T} \pi_{i,p,t} I_t \quad \text{for} \quad t = 3, ..., T, \quad (2b) \end{aligned}$$

where $(\nu_{i,f}, \nu_{i,p})' \sim N(0, \Sigma)$, I_t for $t = 3, ..., T$ are time dummies and $(\pi_{i,f,t}, \pi_{i,p,t})$ for $t = 3, ..., T$ are random coefficients that are independent over time and individuals with $(\pi_{i,f,t}, \pi_{i,p,t})' \sim N(0, \Xi^t)$ for $t = 3, ..., T$. This specification of the unobservables allows the employment state-specific intercepts to include time invariant individual effects and additionally, via the random coefficients on the time dummies, allows the time-varying components of the unobservables to be correlated over choice alternative and hetroskedastic. When estimating this model, normalizations are imposed on $\Xi^t_{1,1}$ for $t = 3, ..., T$. Without such normalizations, scale identification relies on the slight difference in the shapes of the logistic and normal distributions (see Walker *et al.*, 2007). However, as explained in Section 3.3, even following these normalizations identification remains reliant on the functional form of the distribution of the unobservables. Excluding the random coefficients on the time dummies leads to a model which is nonparametrically identified provided that $T \geq 4$.

Monte Carlo simulations are conducted, first excluding random coefficients on the time dummies and then allowing random coefficient on the time dummies. For each of these two Monte Carlo simulations, the sample size is fixed at 3,000 individuals and we use $T = 4$. For each of the two specifications, 200 data sets were generated and Maximum Simulated Likelihood estimates obtained for each data set. The results are summarized in Table 1. In the simulations in which random

Parameter	Truth	Random Coef. on Time Dummies Excluded			Random Coef. on Time Dummies Permitted		
		E(parameter)	E(σ)	σ(parameter)	E(parameter)	E(σ)	σ(parameter)
$\gamma_{f,f-2}$	1	0.99	0.14	0.14	0.96	0.17	0.15
$\gamma_{f,p-2}$	0.5	0.48	0.14	0.13	0.49	0.22	0.25
$\gamma_{f,f-1}$	2	2.02	0.15	0.15	2.12	0.20	0.22
$\gamma_{f,p-1}$	1	1.00	0.14	0.14	1.11	0.32	0.45
$\beta_{f,0}$	-1	-1.00	0.17	0.18	-1.03	0.51	0.68
$\beta_{f,1}$	-0.8	-0.80	0.09	0.09	-0.78	0.23	0.31
$\beta_{f,2}$	0.5	0.50	0.07	0.07	0.48	0.14	0.18
$\gamma_{p,f-2}$	0.5	0.51	0.12	0.11	0.34	0.63	0.56
$\gamma_{p,p-2}$	1	0.99	0.13	0.11	1.71	2.19	1.76
$\gamma_{p,f-1}$	1	1.02	0.14	0.12	0.91	0.68	0.51
$\gamma_{p,p-1}$	2	2.01	0.12	0.13	3.60	4.63	3.82
$\beta_{p,0}$	0.5	0.50	0.13	0.13	0.41	0.49	0.43
$\beta_{p,1}$	1	1.01	0.08	0.08	2.59	4.63	3.85
$\beta_{p,2}$	-0.5	-0.51	0.06	0.06	-1.39	2.58	2.18
$\Sigma_{1,1}$	1	1.01	0.40	0.39	0.97	0.57	0.56
$\Sigma_{2,1}$	0.5	0.51	0.27	0.27	0.49	1.15	0.82
$\Sigma_{2,2}$	1	1.06	0.33	0.33	11.81	63.40	40.72
$\Xi^3_{1,1}$	4 [Fixed]	-	-	-	4	-	-
$\Xi^3_{2,1}$	1	-	-	-	-0.83	7.46	7.70
$\Xi^3_{2,2}$	2	-	-	-	59.19	314.23	171.98
$\Xi^4_{1,1}$	4 [Fixed]	-	-	-	4	-	-
$\Xi^4_{2,1}$	1	-	-	-	-0.40	6.46	6.10
$\Xi^4_{2,2}$	2	-	-	-	57.53	313.81	178.98
Average Iterations			4.18			38.41	
Maximum Iterations			10			200	

Notes: E(parameter) is the mean parameter estimate, E(σ) is the mean estimated standard error and σ(parameter) is the standard deviation of the parameter estimates over the 200 Monte Carlo replications. Maximum Simulated Likelihood estimation used 5,000 antithetic draws. The number of iterations was limited to 200.

Table 1: Monte Carlo simulations illustrating the empirical properties of the Maximum Likelihood estimator of the parameters of a dynamic mixed multinomial logit model with and without random coefficients on time dummies.

coefficients on time dummies are excluded, average parameter estimates correspond closely to their true values. Similarly, average standard errors are almost identical to the standard deviation of the parameter estimates. Convergence was obtained in all of the 200 Monte Carlo replications, and took an average of 4.18 iterations starting from the true parameter values. In contrast, the Monte Carlo results for the specification in which random coefficients on the time dummies are permitted reveal major problems. In many cases, the average coefficients on the explanatory variables differ substantially from their true values, and average standard errors bear little resemblance to the standard deviation of the parameter estimates. The estimates of the parameters of the covariance matrices reveal even greater problems: in many cases average variances are several times larger than their true values and average standard errors are huge. Furthermore, in around 10% of the Monte Carlo replications, convergence was not obtained within the first 200 iterations. The results of these Monte Carlo simulation are consistent with the findings of Keane (1992), who conducts a similar set of Monte Carlo simulations in a cross-sectional multinomial choice setting.

Appendix B: Monte Carlo Simulations II

Two further Monte Carlo simulations are conducted in order to establish the empirical properties of the Maximum Simulated Likelihood estimator in the context of dynamic mixed multinomial logit models in which the observed components of payoffs are as described by Equations (1a) and (1b) and the unobservables are as in Specifications V and VI, detailed in Section 3.4 of the main text (note that for the purpose of limiting the number of parameters in the Monte Carlo simulations we exclude correlated random effects but continue to allow time invariant employment state-specific intercepts). For each specification of unobservables, 200 data sets were generated, each with the same sample size, attrition pattern and distribution of the initial conditions as observed in the BHPS sample. In order to explore the how the simulation bias varies with R, the number of antithetic draws to evaluate the likelihood function, all simulations are conduced using R =500, 2,000 and 5,000.

Tables 2-3 summarize the coefficient estimates. For Specification V, which permits random coefficients but excludes autocorrelated unobservables, there is a close correspondence between the average coefficient estimates and the true values, and the average standard errors are close to the standard deviation of the parameter estimates. This is true for $R = 500$ as well as for higher values of R. However, when $R = 500$ there is evidence of biases in some of the parameters appearing in the distribution of the unobservables. In particular, some of the estimates of the variances of the random coefficients appear to be biased downwards. These biases are substantially reduced when R is increased to 2,000 and all but eliminated by using $R = 5,000$. The results for Specification VI, which features autocorrelated unobservables in addition to random coefficients, show that there are small biases, specifically up to 6% of the true parameter values, in the coefficient estimates when $R = 5,000$ is used. Similarly, with $R = 5,000$, there are downwards biases in many of the variance parameters appearing in the distribution of the unobservables. For both sets of parameters, lower values of R are associated with substantially larger biases.

Tables 6 and 7 show the impulse response functions for Specifications V and VI respectively, evaluated at the estimated parameter values and at the true parameter values. As described in Section 5.2 of the main text, the impulse response functions show the estimated dynamic response of labor supply to exogeneous shocks that move non-employed women into either full-time or part-time work. The shocks themselves last only one year and therefore behavior subsequent to the shock is affected only via the intertemporal dependencies present in labor supply behavior. For Specification V, which excludes autocorrelated unobservables, the estimated impulse response function obtained using 500 antithetic draws is never more than 0.4 of a percentage point away from the true impulse response function. Therefore, moderately large biases in the parameter estimates translate into very small biases in the estimated impulse response function. Increasing the number of antithetic draws to 2,000 tends to reduce the difference between the estimated and true impulse response functions, while a further increase to 5,000 antithetic draws leads to an additional, albeit small, decreased in the difference between the estimated and true impulse response functions.

The Monte Carlo simulations for Specification VI, which additionally includes autocorrelated unobservables, show that relying on only 500 antithetic draws for the Maximum Likelihood Estimation leads to an impulse response function that diverges by up to 2.2 percentage points from the true impulse response function. For example, an employment shock that temporarily moves non-employed women into full-time work decreases the rate of non-employment by 11.65 percentage points one year after the shock while the corresponding estimated effect is 13.84 percentage points. Increasing the number of antithetic draws to 2,000 approximately halves the magnitude of the difference between the estimated and true impulse response functions. A further increase to 5,000 antithetic draws leads to an additional reduction in the bias of the estimated impulse response function. However, even using 5,000 antithetic draws, which would generally be considered a large number of draws, there are some biases in the estimated impulse response functions, although such biases are tolerably small; using $R = 5,000$, the maximum bias in the estimated impulse response function is only 0.6 of a percentage point, and in relative terms the biases are around 3-6% of the corresponding true quantity.

VARIABLE	TRUTH f	TRUTH p	$R = 500$ f	$R = 500$ p	$R = 2,000$ f	$R = 2,000$ p	$R = 5,000$ f	$R = 5,000$ p
$Y_{i,f,t-2}$	1.00	0.50	0.98 (0.11)[0.15]	0.47 (0.12)[0.10]	0.97 (0.12)[0.14]	0.47 (0.12)[0.13]	0.98 (0.13)[0.12]	0.48 (0.12)[0.12]
$Y_{i,p,t-2}$	0.50	1.00	0.46 (0.10)[0.12]	0.95 (0.14)[0.09]	0.49 (0.11)[0.11]	0.98 (0.11)[0.10]	0.49 (0.12)[0.11]	0.99 (0.11)[0.10]
$Y_{i,f,t-1}$	2.00	1.00	1.94 (0.12)[0.14]	0.94 (0.13)[0.11]	1.97 (0.13)[0.15]	0.98 (0.13)[0.14]	2.00 (0.14)[0.15]	1.00 (0.13)[0.15]
$Y_{i,p,t-1}$	1.00	2.00	0.97 (0.10)[0.16]	1.93 (0.15)[0.10]	0.99 (0.12)[0.13]	1.98 (0.11)[0.12]	1.00 (0.12)[0.13]	1.99 (0.12)[0.13]
$X1_{i,t}$	-0.80	1.00	-0.78 (0.04)[0.05]	0.97 (0.04)[0.04]	-0.79 (0.05)[0.05]	1.00 (0.05)[0.05]	-0.79 (0.05)[0.05]	1.01 (0.05)[0.05]
$X2_{i,t}$	0.50	-0.50	0.48 (0.04)[0.04]	-0.49 (0.04)[0.04]	0.50 (0.04)[0.04]	-0.50 (0.04)[0.04]	0.50 (0.04)[0.04]	-0.50 (0.04)[0.04]
INTERCEPT	-1.00	0.50	-1.01 (0.14)[0.14]	0.48 (0.11)[0.12]	-1.01 (0.15)[0.16]	0.49 (0.13)[0.14]	-1.00 (0.16)[0.15]	0.50 (0.13)[0.12]

Notes: Average standard errors are given in round brackets and the standard deviation of the parameter estimates is given in square brackets. Estimates of the parameters on the initial conditions are omitted. Columns headed f contain the coefficient describing payoffs from full-time employment and columns headed p contain the coefficients describing payoffs from part-time employment. Results are based on 200 Monte Carlo replications.

Table 2: Results of Monte Carlo simulations for Specification V: Estimates of coefficients in the observed component of payoffs.

VARIABLE	TRUTH f	TRUTH p	$R = 500$ f	$R = 500$ p	$R = 2,000$ f	$R = 2,000$ p	$R = 5,000$ f	$R = 5,000$ p
$Y_{i,f,t-2}$	1.00	0.50	0.96 (0.10)[0.12]	0.48 (0.10)[0.12]	0.95 (0.12)[0.13]	0.48 (0.11)[0.12]	0.98 (0.12)[0.15]	0.49 (0.12)[0.14]
$Y_{i,p,t-2}$	0.50	1.00	0.44 (0.09)[0.11]	0.92 (0.09)[0.11]	0.47 (0.11)[0.11]	0.96 (0.10)[0.10]	0.48 (0.11)[0.13]	0.97 (0.11)[0.12]
$Y_{i,f,t-1}$	2.00	1.00	1.98 (0.11)[0.13]	1.01 (0.10)[0.12]	1.97 (0.13)[0.14]	1.00 (0.12)[0.12]	2.00 (0.14)[0.15]	1.00 (0.13)[0.14]
$Y_{i,p,t-1}$	1.00	2.00	0.99 (0.10)[0.12]	1.96 (0.09)[0.12]	1.00 (0.11)[0.13]	1.97 (0.11)[0.13]	1.00 (0.12)[0.13]	1.98 (0.12)[0.13]
$X1_{i,t}$	-0.80	1.00	-0.70 (0.04)[0.05]	0.94 (0.04)[0.05]	-0.75 (0.05)[0.07]	0.96 (0.05)[0.05]	-0.76 (0.06)[0.07]	0.98 (0.05)[0.06]
$X2_{i,t}$	0.50	-0.50	0.43 (0.04)[0.04]	-0.47 (0.04)[0.04]	0.46 (0.04)[0.05]	-0.48 (0.04)[0.04]	0.48 (0.04)[0.05]	-0.49 (0.04)[0.04]
INTERCEPT	-1.00	0.50	-1.02 (0.14)[0.15]	0.26 (0.13)[0.15]	-1.00 (0.16)[0.19]	0.37 (0.14)[0.15]	-0.99 (0.18)[0.19]	0.44 (0.15)[0.16]

Notes: See Table 2.

Table 3: Results of Monte Carlo simulations for Specification VI: Estimates of coefficients in the observed component of payoffs.

	TRUTH		$R = 500$		$R = 2,000$		$R = 5,000$	
$\Sigma_{Intercept\ 1}$	1	.	0.95 (0.19)[0.44]	.	0.99 (0.26)[0.38]	.	0.99 (0.30)[0.40]	.
	0.5	1	0.45 (0.13)[0.29]	0.92 (0.17)[0.33]	0.49 (0.19)[0.27]	0.99 (0.23)[0.33]	0.50 (0.22)[0.29]	1.00 (0.27)[0.31]
$\Sigma_{Y_{i,f,t-2}}$	1	.	0.72 (0.26)[0.42]	.	0.83 (0.32)[0.38]	.	0.95 (0.36)[0.39]	.
	0.5	1	0.28 (0.19)[0.32]	0.72 (0.24)[0.40]	0.35 (0.26)[0.33]	0.85 (0.32)[0.42]	0.44 (0.30)[0.33]	0.92 (0.37)[0.40]
$\Sigma_{Y_{i,p,t-2}}$	1	.	0.66 (0.23)[0.43]	.	0.87 (0.32)[0.33]	.	0.98 (0.35)[0.38]	.
	0.5	1	0.28 (0.17)[0.28]	0.78 (0.20)[0.29]	0.42 (0.23)[0.26]	0.92 (0.25)[0.29]	0.48 (0.25)[0.26]	0.97 (0.27)[0.28]
$\Sigma_{Y_{i,f,t-1}}$	1	.	0.69 (0.25)[0.46]	.	0.91 (0.34)[0.49]	.	0.98 (0.39)[0.41]	.
	0.5	1	0.28 (0.20)[0.35]	0.72 (0.25)[0.40]	0.42 (0.28)[0.38]	0.91 (0.35)[0.43]	0.50 (0.33)[0.39]	1.00 (0.40)[0.47]
$\Sigma_{Y_{i,p,t-1}}$	1	.	0.68 (0.24)[0.45]	.	0.89 (0.32)[0.39]	.	0.96 (0.36)[0.37]	.
	0.5	1	0.30 (0.17)[0.33]	0.79 (0.21)[0.32]	0.42 (0.24)[0.27]	0.93 (0.26)[0.32]	0.49 (0.26)[0.28]	1.00 (0.28)[0.29]
$\Sigma_{X1_{i,t}}$	1	.	0.89 (0.12)[0.13]	.	0.95 (0.13)[0.13]	.	0.96 (0.13)[0.14]	.
	0.5	1	0.42 (0.08)[0.09]	0.88 (0.10)[0.12]	0.47 (0.09)[0.09]	0.97 (0.11)[0.12]	0.47 (0.09)[0.10]	0.99 (0.12)[0.12]
$\Sigma_{X2_{i,t}}$	1	.	0.88 (0.11)[0.14]	.	0.97 (0.13)[0.13]	.	0.99 (0.13)[0.13]	.
	0.5	1	0.42 (0.08)[0.08]	0.89 (0.09)[0.10]	0.47 (0.09)[0.09]	0.97 (0.11)[0.11]	0.49 (0.09)[0.08]	0.99 (0.11)[0.11]

Notes: Average standard errors are given in round brackets and the standard deviation of the parameter estimates is given in square brackets. Results are based on 200 Monte Carlo replications.

Table 4: Results of Monte Carlo simulations for Specification V: Estimates of parameters in the distribution of unobservables.

	TRUTH	$R = 500$	$R = 2,000$	$R = 5,000$
$\Sigma_{Intercept\ 1}$	$\begin{pmatrix} 1 & . \\ 0.5 & 1 \end{pmatrix}$	$\begin{pmatrix} \underset{(0.17)[0.49]}{0.79} & . \\ \underset{(0.13)[0.32]}{0.37} & \underset{(0.16)[0.41]}{0.68} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.24)[0.53]}{0.79} & . \\ \underset{(0.18)[0.35]}{0.39} & \underset{(0.24)[0.47]}{0.71} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.31)[0.53]}{0.82} & . \\ \underset{(0.23)[0.35]}{0.41} & \underset{(0.31)[0.49]}{0.76} \end{pmatrix}$
$\Sigma_{Y_{i,f,t-2}}$	$\begin{pmatrix} 1 & . \\ 0.5 & 1 \end{pmatrix}$	$\begin{pmatrix} \underset{(0.21)[0.38]}{0.53} & . \\ \underset{(0.16)[0.32]}{0.24} & \underset{(0.23)[0.40]}{0.68} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.31)[0.36]}{0.79} & . \\ \underset{(0.25)[0.31]}{0.35} & \underset{(0.31)[0.42]}{0.80} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.35)[0.43]}{0.89} & . \\ \underset{(0.30)[0.38]}{0.45} & \underset{(0.37)[0.47]}{0.94} \end{pmatrix}$
$\Sigma_{Y_{i,p,t-2}}$	$\begin{pmatrix} 1 & . \\ 0.5 & 1 \end{pmatrix}$	$\begin{pmatrix} \underset{(0.20)[0.37]}{0.53} & . \\ \underset{(0.15)[0.24]}{0.23} & \underset{(0.18)[0.28]}{0.65} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.30)[0.44]}{0.77} & . \\ \underset{(0.22)[0.30]}{0.37} & \underset{(0.25)[0.28]}{0.85} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.25)[0.29]}{0.43} & . \\ \underset{(0.28)[0.31]}{0.91} & \underset{(0.37)[0.43]}{0.85} \end{pmatrix}$
$\Sigma_{Y_{i,f,t-1}}$	$\begin{pmatrix} 1 & . \\ 0.5 & 1 \end{pmatrix}$	$\begin{pmatrix} \underset{(0.21)[0.35]}{0.48} & . \\ \underset{(0.17)[0.28]}{0.17} & \underset{(0.23)[0.37]}{0.54} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.30)[0.43]}{0.71} & . \\ \underset{(0.25)[0.37]}{0.29} & \underset{(0.32)[0.48]}{0.75} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.34)[0.43]}{0.83} & . \\ \underset{(0.25)[0.33]}{0.41} & \underset{(0.29)[0.34]}{0.90} \end{pmatrix}$
$\Sigma_{Y_{i,p,t-1}}$	$\begin{pmatrix} 1 & . \\ 0.5 & 1 \end{pmatrix}$	$\begin{pmatrix} \underset{(0.19)[0.36]}{0.43} & . \\ \underset{(0.14)[0.27]}{0.17} & \underset{(0.19)[0.30]}{0.64} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.30)[0.43]}{0.73} & . \\ \underset{(0.22)[0.32]}{0.37} & \underset{(0.26)[0.35]}{0.84} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.14)[0.15]}{0.90} & . \\ \underset{(0.09)[0.10]}{0.45} & \underset{(0.12)[0.13]}{0.94} \end{pmatrix}$
$\Sigma_{x_{i,1,t}}$	$\begin{pmatrix} 1 & . \\ 0.5 & 1 \end{pmatrix}$	$\begin{pmatrix} \underset{(0.10)[0.12]}{0.71} & . \\ \underset{(0.07)[0.08]}{0.36} & \underset{(0.09)[0.11]}{0.80} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.13)[0.12]}{0.84} & . \\ \underset{(0.08)[0.09]}{0.42} & \underset{(0.11)[0.12]}{0.88} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.13)[0.14]}{0.91} & . \\ \underset{(0.09)[0.10]}{0.45} & \underset{(0.12)[0.13]}{0.94} \end{pmatrix}$
$\Sigma_{x_{i,2,t}}$	$\begin{pmatrix} 1 & . \\ 0.5 & 1 \end{pmatrix}$	$\begin{pmatrix} \underset{(0.10)[0.10]}{0.71} & . \\ \underset{(0.07)[0.08]}{0.35} & \underset{(0.09)[0.10]}{0.77} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.12)[0.12]}{0.85} & . \\ \underset{(0.08)[0.08]}{0.42} & \underset{(0.11)[0.09]}{0.88} \end{pmatrix}$	$\begin{pmatrix} \underset{(0.62)[0.75]}{0.99} & . \\ \underset{(0.50)[0.54]}{0.45} & \underset{(0.63)[0.64]}{0.98} \end{pmatrix}$
ρ_f	0.7	$\underset{(0.08)[0.23]}{0.80}$	$\underset{(0.08)[0.21]}{0.75}$	$\underset{(0.09)[0.13]}{0.74}$
ρ_p	0.8	$\underset{(0.03)[0.07]}{0.90}$	$\underset{(0.04)[0.08]}{0.87}$	$\underset{(0.05)[0.09]}{0.83}$
$\Sigma_{\zeta 1,1}$	2	$\underset{(0.10)[0.26]}{0.67}$	$\underset{(0.36)[0.74]}{1.30}$	$\underset{(0.48)[0.68]}{1.56}$
$\Sigma_{\zeta 2,1}$	0.7	$\underset{(0.18)[0.50]}{0.65}$	$\underset{(0.10)[0.22]}{0.67}$	$\underset{(0.11)[0.19]}{0.68}$
$\Sigma_{\zeta 2,2}$	2	$\underset{(0.22)[0.55]}{1.10}$	$\underset{(0.36)[0.60]}{1.63}$	$\underset{(0.45)[0.61]}{1.87}$

Notes: See Table 4.

Table 5: Results of Monte Carlo simulations for Specification VI: Estimates of parameters in the distribution of unobservables.

Employment State	Years since Employment Shock										
	1	2	3	4	5	6	7	8	9	10	11
True dynamic responses											
	Non-employed moved into full-time work at $t = 2$										
Full-time	14.93	10.87	3.94	3.36	1.77	1.42	0.88	0.71	0.49	0.41	0.32
Part-time	-3.41	-4.60	-2.17	-2.32	-1.34	-1.14	-0.73	-0.61	-0.42	-0.36	-0.27
Non-employment	-11.51	-6.27	-1.77	-1.04	-0.43	-0.28	-0.15	-0.10	-0.06	-0.05	-0.05
	Non-employed moved into part-time work at $t = 2$										
Full-time	-3.56	-3.41	-1.47	-1.66	-0.90	-0.77	-0.45	-0.39	-0.29	-0.23	-0.18
Part-time	16.43	10.84	3.67	3.12	1.53	1.17	0.68	0.54	0.38	0.31	0.23
Non-employment	-12.87	-7.43	-2.20	-1.46	-0.63	-0.41	-0.23	-0.15	-0.09	-0.08	-0.05
Estimated Dynamic responses $R = 500$											
	Non-employed moved into full-time work at $t = 2$										
Full-time	15.31	11.08	4.05	3.29	1.74	1.35	0.84	0.66	0.47	0.38	0.29
Part-time	-3.49	-4.56	-2.11	-2.24	-1.27	-1.10	-0.70	-0.58	-0.41	-0.35	-0.27
Non-employment	-11.82	-6.52	-1.94	-1.05	-0.46	-0.25	-0.14	-0.08	-0.05	-0.04	-0.02
	Non-employed moved into part-time work at $t = 2$										
Full-time	-3.28	-3.25	-1.36	-1.56	-0.83	-0.72	-0.43	-0.37	-0.27	-0.22	-0.16
Part-time	16.46	10.88	3.72	3.02	1.49	1.14	0.67	0.53	0.36	0.30	0.20
Non-employment	-13.18	-7.63	-2.36	-1.46	-0.66	-0.42	-0.23	-0.16	-0.09	-0.07	-0.04
Estimated Dynamic responses $R = 2,000$											
	Non-employed moved into full-time work at $t = 2$										
Full-time	14.98	10.90	3.97	3.36	1.77	1.41	0.87	0.70	0.48	0.40	0.29
Part-time	-3.37	-4.59	-2.14	-2.34	-1.33	-1.14	-0.73	-0.62	-0.43	-0.37	-0.27
Non-employment	-11.61	-6.31	-1.83	-1.01	-0.45	-0.27	-0.14	-0.08	-0.05	-0.03	-0.02
	Non-employed moved into part-time work at $t = 2$										
Full-time	-3.47	-3.31	-1.41	-1.59	-0.85	-0.72	-0.44	-0.37	-0.28	-0.23	-0.17
Part-time	16.47	10.80	3.68	3.03	1.49	1.14	0.66	0.53	0.36	0.30	0.21
Non-employment	-13.00	-7.49	-2.26	-1.44	-0.63	-0.42	-0.22	-0.15	-0.09	-0.06	-0.04
Estimated Dynamic responses $R = 5,000$											
	Non-employed moved into full-time work at $t = 2$										
Full-time	14.98	10.89	3.94	3.34	1.78	1.42	0.88	0.71	0.49	0.42	0.32
Part-time	-3.41	-4.61	-2.13	-2.30	-1.33	-1.13	-0.73	-0.61	-0.43	-0.37	-0.28
Non-employment	-11.57	-6.28	-1.81	-1.03	-0.45	-0.28	-0.15	-0.10	-0.06	-0.05	-0.04
	Non-employed moved into part-time work at $t = 2$										
Full-time	-3.52	-3.32	-1.42	-1.61	-0.86	-0.75	-0.44	-0.39	-0.29	-0.23	-0.18
Part-time	16.41	10.78	3.66	3.07	1.50	1.16	0.68	0.54	0.38	0.31	0.24
Non-employment	-12.90	-7.46	-2.24	-1.46	-0.64	-0.41	-0.23	-0.15	-0.09	-0.08	-0.05

Notes: Based on 200 Monte Carlo replications. All figures are percentage point changes for women affected by the employment shock.

Table 6: True and Estimated Impulse Response functions for Specification V using R=500, 2,000 and 5,000.

Employment State	Years since Employment Shock 1	2	3	4	5	6	7	8	9	10	11
	True dynamic responses										
	Non-employed moved to full-time work at $t = 2$										
Full-time	14.40	10.25	3.45	2.96	1.48	1.23	0.71	0.55	0.38	0.31	0.25
Part-time	-2.75	-3.59	-1.55	-1.79	-1.03	-0.96	-0.64	-0.48	-0.36	-0.28	-0.21
Non-employment	-11.65	-6.66	-1.92	-1.18	-0.45	-0.27	-0.07	-0.07	-0.02	-0.03	-0.04
	Non-employed moved to part-time work at $t = 2$										
Full-time	-3.10	-2.07	-1.35	-1.40	-0.75	-0.62	-0.41	-0.33	-0.23	-0.16	-0.12
Part-time	16.00	10.98	3.76	3.09	1.47	1.04	0.63	0.45	0.28	0.23	0.18
Non-employment	-12.90	-7.91	-2.41	-1.69	-0.72	-0.43	-0.21	-0.12	-0.05	-0.07	-0.06
	Estimated Dynamic responses $R = 500$										
	Non-employed moved to full-time work at $t = 2$										
Full-time	16.16	11.34	4.21	3.16	1.65	1.23	0.77	0.59	0.40	0.30	0.23
Part-time	-2.32	-3.34	-1.53	-1.71	-0.96	-0.84	-0.54	-0.45	-0.32	-0.24	-0.18
Non-employment	-13.84	-8.00	-2.68	-1.44	-0.69	-0.39	-0.23	-0.14	-0.08	-0.06	-0.05
	Non-employed moved to part-time work at $t = 2$										
Full-time	-2.88	-2.91	-1.22	-1.36	-0.72	-0.63	-0.37	-0.31	-0.22	-0.18	-0.13
Part-time	17.66	11.66	4.18	3.17	1.60	1.16	0.68	0.51	0.35	0.28	0.19
Non-employment	-14.78	-8.75	-2.97	-1.81	-0.88	-0.53	-0.32	-0.20	-0.13	-0.09	-0.06
	Estimated Dynamic responses $R = 2,000$										
	Non-employed moved to full-time work at $t = 2$										
Full-time	15.16	10.57	3.84	3.06	1.60	1.21	0.73	0.57	0.37	0.32	0.23
Part-time	-2.53	-3.36	-1.53	-1.77	-1.00	-0.87	-0.55	-0.47	-0.31	-0.27	-0.19
Non-employment	-12.62	-7.21	-2.31	-1.29	-0.60	-0.35	-0.19	-0.11	-0.07	-0.05	-0.04
	Non-employed moved to part-time work at $t = 2$										
Full-time	-3.11	-2.92	-1.22	-1.40	-0.76	-0.64	-0.39	-0.32	-0.22	-0.18	-0.14
Part-time	16.88	11.26	3.96	3.13	1.55	1.14	0.67	0.49	0.34	0.26	0.19
Non-employment	-13.77	-8.34	-2.73	-1.73	-0.79	-0.50	-0.28	-0.18	-0.11	-0.08	-0.05
	Estimated Dynamic responses $R = 5,000$										
	Non-employed moved to full-time work at $t = 2$										
Full-time	14.89	10.57	3.77	3.06	1.56	1.20	0.73	0.56	0.38	0.31	0.22
Part-time	-2.65	-3.55	-1.57	-1.79	-0.99	-0.86	-0.55	-0.46	-0.31	-0.26	-0.19
Non-employment	-12.24	-7.02	-2.20	-1.27	-0.57	-0.34	-0.18	-0.10	-0.07	-0.05	-0.03
	Non-employed moved to part-time work at $t = 2$										
Full-time	-3.08	-2.88	-1.23	-1.39	-0.74	-0.64	-0.39	-0.32	-0.23	-0.18	-0.14
Part-time	16.48	11.01	3.84	3.08	1.51	1.13	0.65	0.49	0.34	0.26	0.19
Non-employment	-13.40	-8.14	-2.61	-1.69	-0.77	-0.49	-0.27	-0.17	-0.11	-0.07	-0.05

Notes: See Table 6.

Table 7: True and Estimated Impulse response functions for Specification VI using R=500, 2,000 and 5,000.

Appendix C: Further Empirical Analysis

In this appendix, we present the results of further empirical analysis. Specifically, in Appendix C.1 we explore the robustness of our results to alternative empirical specifications. Meanwhile, in Appendix C.2 we investigate the impact of allowing correlated random effects on the estimated impulse response functions and on our estimates of the labor supply response to the birth of a child. Throughout this discussion, we refer to the specification of the payoffs, including the choice of explanatory variables, adopted in the main text as the "preferred specification".

C.1 Robustness Checks

Our preferred specification allows a correlation between the employment state-specific intercepts and the individual's observed time varying characteristics, specifically children and unearned income, via the correlated random effects. However, we maintain a strict exogeneity assumption. Fornally, we assume that the unobservables $(\{\xi_{i,j,t}, \varsigma_{i,j,t}\}_{t=3}^{T}, \omega_{i,j}, \pi_{i,j}, \psi_{i,j}, \widetilde{\nu}_{i,j})$ occur independently of $X_{i,s}$ and IC_i for all i, $j = f, p$ and $t, s = 3, ..., T$. In this appendix we explore the robustness of our empirical results to this strict exogeneity assumption. In particular, one may be concerned that there exist unobserved individual characteristics that affect both fertility and labor supply behavior, and which are not captured fully by the inclusion of the individual-specific time averages of the child-related variables, i.e., the correlated random effects. The same agrement may be constructed concerning unearned income. The presence of such variables would lead to bias in the coefficients on the child and unearned income variables and may also impact on the estimated impulse response functions and on other quantities that summarize the dynamic aspects of labor supply behavior.

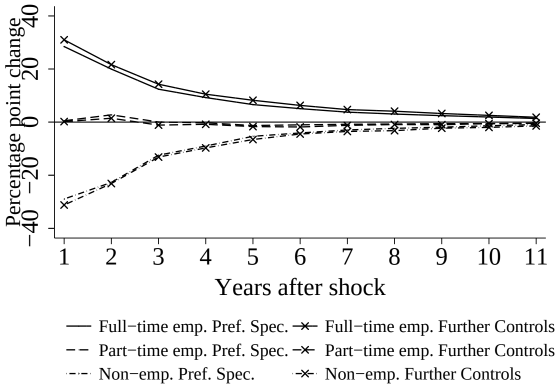
Against this backdrop, we reestimate our dynamic mixed multinomial logit model, including further controls for variables that may affect fertility and/or unearned income as well as labor supply behavior. Henceforth, we refer to this model as the "further controls" model. The further controls model is obtained by adding to the explanatory variables included in the preferred specification additional variables that measure religions denomination (two indicator variables - the first indicating catholic and the second indicating protestant) and also variables that describe the woman's attitude towards work and family (two indicator variables - the first indicating that the woman agrees with the statement "all in all, family life suffers when the woman has a full-time job" and the second indicating that woman agrees with the statement "both husband and wife should both contribute to the household income"). This variables were selected as further controls because they are plausible proxy variables for unobservables that may impact on both fertility and/or unearned income and labor supply behavior.

Figure 1 illustrates the impulse response functions obtained from the preferred specification and from the further controls model, in both cases using the Specification IV of the unobservable, as described in Section 3.4 of the main text. We see a very close correspondence between the estimated impulse response functions obtained from the preferred specification and the further controls model. This results is true for the sample average and for women with young children. Figure 2 shows that our estimates of labor supply dynamics following the birth of a child are also robust to adding further controls to the preferred specification.

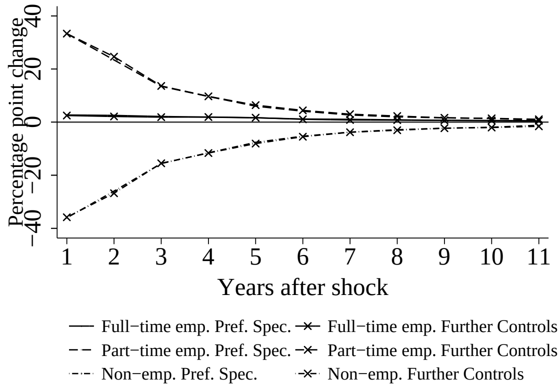
In Table 8 and Table 9 we explore the robustness of our conclusions concerning the specification of the unobservables to the inclusion of further control variables. We focus here on comparisons between Specifications II (time invariant random intercepts), IV (time invariant random intercepts and random coefficients); V (time invariant random intercepts and autocorrelation); and VI (time invariant random intercepts, random coefficients and autocorrelation). As for the preferred specification, we find that the further controls model implies higher own state dependencies in full-time employment when autocorrelation and random coefficients are permitted as compared to when only time invariant random intercepts are allowed. Similarly, according to both the preferred specification and the further controls model, the estimated own state dependencies for part-time employment are similar for Specifications II, IV and V of the unobservables, while Specification VI of the unobservables implies somewhat lower own state dependence in part-time employment. The cross state dependencies implied by the preferred specification and further controls model also show a close correspondence.

As a second robustness check we estimate a version of our dynamic labor supply model in which payoffs are reduced form in the potentially endogenous variables, specifically children and unearned income. In this model, henceforth referred to as the "reduced form" model, the observed component of payoffs are determined by education, age, common time effects and previous employment outcomes, but measures of fertility, and unearned income and excluded. We view the variables that are included in the reduced form model as potential determinants of fertility and unearned income, as well as possible drivers of labor supply behavior. This approach is discussed in the context of fertility by, for example, Mincer (1963) and Moffitt (1984). The reduced form approach allows us to extract entirely from concerns surrounding the possible endogeneity of fertility and unearned income, but has the obvious cost of precluding an analysis of the effects of child-related variables and unearned income on labor supply dynamics.

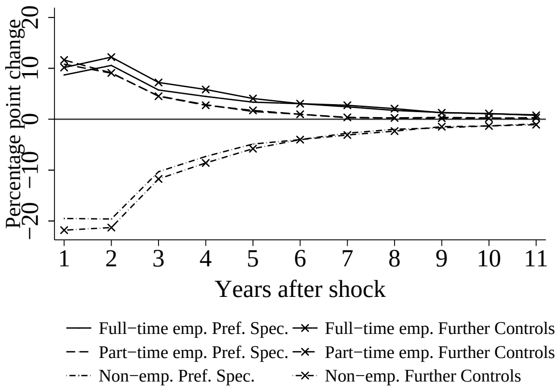
Table 3 shows that the estimated impulse response functions, which summarize how labor supply behavior responds to temporary employment shocks, obtained from the preferred specification and from the reduced form specification are rather similar. One relatively minor exception is that the reduced form model suggests a larger degree of own state dependence in full-time employment than does our preferred specification. However, given the markedly different nature of the explanatory variables included in the preferred specification and in the reduced form model, this difference may be considered satisfactorily small. Moreover, we do not find any such difference when the look at labor supply behavior following an employment shock that temporarily places non-employed women in part-time employment. Finally, we note that Table 8 and Table 9 show that our results concerning the impact of the specification of the unobservables on conclusions concerning the dynamics of labor supply behavior also continue of apply when we use the reduced form model.



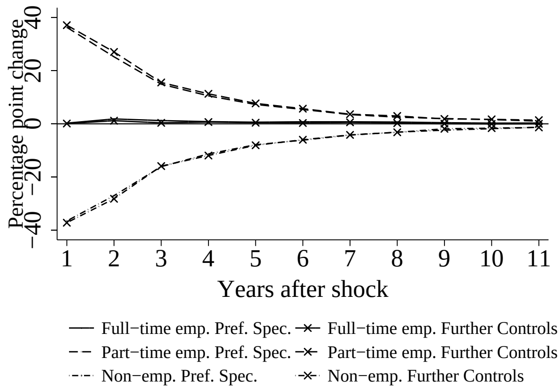
(a) Temporary shock moves non-employed women into full-time work: All women non-employed at $t = 0$.



(b) Temporary shock moves non-employed women into part-time work: All women non-employed at $t = 0$.



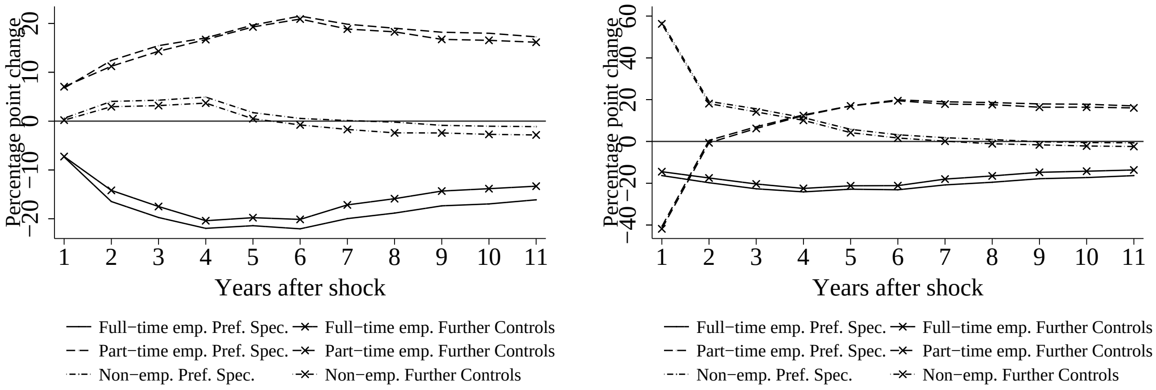
(c) Temporary shock moves non-employed women into full-time work: Women with young children non-employed at $t = 0$.



(d) Temporary shock moves non-employed women into part-time work: Women with young children non-employed at $t = 0$.

Notes: "Women with young children" refers to the women who gave birth to a child one year after the shock (i.e., at $t = 1$).

Figure 1: Robustness checks 1: Impulse response functions obtained from Specification VI estimated with explanatory variables as in the preferred specification and with further controls for family values and religious denomination.

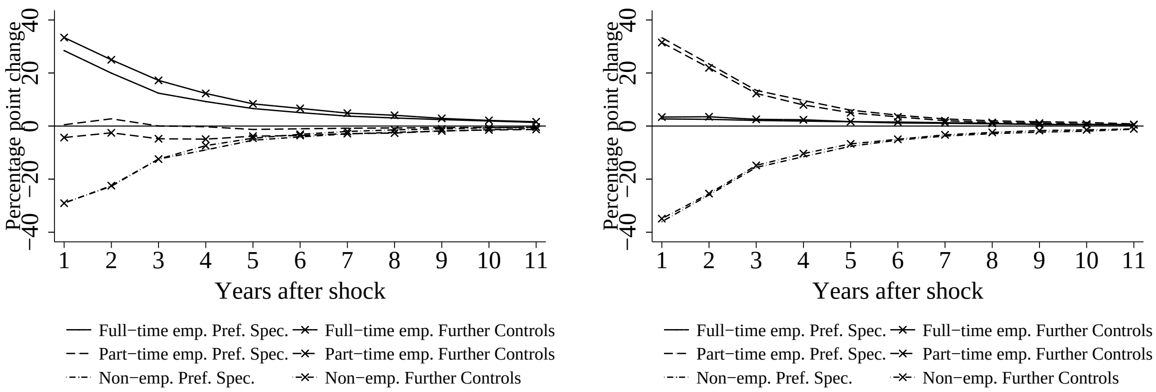


(a) Effect of having a child at $t = 1$ - High unobserved preference for full-time work.

(b) Effect of having a child at $t = 1$ - Low unobserved preference for full-time work.

Notes: High and low unobservables refer to the 90th and 10th percentiles of the distribution of unobservables. Other unobservables are drawn from the appropriate conditional distribution. Effects were estimated by averaging over the sample distribution of all observed individual characteristics, except children.

Figure 2: Robustness checks 3: Heterogeneity in labor supply dynamics after child birth from Specification VI estimated with explanatory variables as in the preferred specification and with further controls for family values and religious denomination.



(a) Temporary shock moves non-employed women into full-time work: All women non-employed at $t = 0$.

(b) Temporary shock moves non-employed women into part-time work: All women non-employed at $t = 0$.

Notes: See Figure 1.

Figure 3: Robustness checks 2: Impulse response functions obtained from Specification VI estimated with explanatory variables as in the preferred specification and via a model that is reduced form in children and unearned income.

Model	Years since Employment Shock										
	1	2	3	4	5	6	7	8	9	10	11
	Effect on Full-time Employment (Percentage Points)										
Sp. II: Preferred	20.63	15.90	9.81	7.67	5.59	3.86	2.49	1.63	1.12	0.76	0.46
Sp. II: Further Controls	21.54	15.19	9.71	7.27	5.54	4.22	2.79	1.83	1.63	1.07	0.66
Sp. II: Reduced Form	25.10	21.80	14.53	11.64	8.59	6.66	5.23	3.56	2.59	1.98	1.47
Sp. IV: Preferred	28.91	20.83	14.89	10.72	8.03	6.15	4.37	3.25	2.79	2.08	1.83
Sp. IV: Further Controls	26.88	18.9	11.43	7.83	5.39	4.17	2.69	1.98	1.47	0.91	0.86
Sp. IV: Reduced Form	30.28	23.93	16.26	10.42	7.52	5.44	3.96	2.59	2.34	1.73	1.22
Sp. V: Preferred	22.41	16.87	10.06	7.88	6.00	4.88	3.76	2.34	1.88	1.58	1.32
Sp. V: Further Controls	24.39	18.45	11.38	8.69	6.81	5.64	4.01	2.85	2.39	2.08	1.52
Sp. V: Reduced Form	26.32	21.65	14.38	10.87	8.13	6.30	4.62	3.86	2.79	1.88	1.47
Sp. VI: Preferred	28.46	19.97	12.40	9.25	6.61	5.08	3.76	3.05	2.44	1.93	1.37
Sp. VI: Further Controls	31.00	21.65	14.28	10.52	8.23	6.30	4.73	4.12	3.25	2.54	1.83
Sp. VI: Reduced Form	33.38	25.00	17.23	12.30	8.38	6.66	4.88	4.07	2.90	2.13	1.63
	Effect on Part-time Employment (Percentage Points)										
Sp. II: Preferred	7.57	8.28	4.42	2.85	0.97	1.17	0.86	0.61	0.46	0.51	0.41
Sp. II: Further Controls	8.54	8.99	4.52	2.44	1.42	1.32	0.91	0.46	0.61	0.41	0.36
Sp. II: Reduced Form	0.97	-0.56	-2.59	-2.59	-3.00	-2.39	-2.34	-1.42	-1.32	-1.27	-0.97
Sp. IV: Preferred	5.69	9.10	3.56	3.25	1.37	0.91	0.36	0.36	-0.15	-0.05	-0.41
Sp. IV: Further Controls	3.66	6.05	2.69	2.74	1.37	1.17	0.76	0.86	0.86	0.56	0.15
Sp. IV: Reduced Form	-3.46	-0.15	-4.22	-3.30	-3.46	-2.85	-2.24	-1.27	-1.32	-1.12	-1.02
Sp. V: Preferred	8.03	7.27	4.17	1.47	0.30	0.25	-0.30	-0.05	-0.10	-0.20	-0.25
Sp. V: Further Controls	7.47	6.10	3.30	1.37	-0.15	-0.36	-0.41	-0.46	-0.25	-0.25	-0.36
Sp. V: Reduced Form	0.76	-0.56	-2.34	-2.44	-2.74	-2.59	-2.08	-2.13	-1.78	-1.22	-0.91
Sp. VI: Preferred	0.51	2.74	0.05	-0.25	-1.27	-1.02	-0.81	-0.71	-0.56	-0.56	-0.46
Sp. VI: Further Controls	0.20	1.47	-1.12	-0.81	-1.68	-1.83	-1.22	-0.91	-0.97	-0.56	-0.41
Sp. VI: Reduced Form	-4.32	-2.54	-4.78	-4.93	-3.81	-3.56	-2.85	-2.64	-1.83	-1.47	-1.27
	Effect on Non-employment (Percentage Points)										
Sp. II: Preferred	-28.20	-24.19	-14.23	-10.52	-6.55	-5.03	-3.35	-2.24	-1.58	-1.27	-0.86
Sp. II: Further Controls	-30.08	-24.19	-14.23	-9.71	-6.96	-5.54	-3.71	-2.29	-2.24	-1.47	-1.02
Sp. II: Reduced Form	-26.07	-21.24	-11.94	-9.04	-5.59	-4.27	-2.90	-2.13	-1.27	-0.71	-0.51
Sp. IV: Preferred	-34.60	-29.93	-18.45	-13.97	-9.40	-7.06	-4.73	-3.61	-2.64	-2.03	-1.42
Sp. IV: Further Controls	-30.54	-24.95	-14.13	-10.57	-6.76	-5.34	-3.46	-2.85	-2.34	-1.47	-1.02
Sp. IV: Reduced Form	-26.83	-23.78	-12.04	-7.11	-4.07	-2.59	-1.73	-1.32	-1.02	-0.61	-0.20
Sp. V: Preferred	-30.44	-24.14	-14.23	-9.35	-6.30	-5.13	-3.46	-2.29	-1.78	-1.37	-1.07
Sp. V: Further Controls	-31.86	-24.54	-14.68	-10.06	-6.66	-5.28	-3.61	-2.39	-2.13	-1.83	-1.17
Sp. V: Reduced Form	-27.08	-21.09	-12.04	-8.43	-5.39	-3.71	-2.54	-1.73	-1.02	-0.66	-0.56
Sp. VI: Preferred	-28.96	-22.71	-12.45	-8.99	-5.34	-4.07	-2.95	-2.34	-1.88	-1.37	-0.91
Sp. VI: Further Controls	-31.20	-23.12	-13.16	-9.71	-6.55	-4.47	-3.51	-3.20	-2.29	-1.98	-1.42
Sp. VI: Reduced Form	-29.07	-22.46	-12.45	-7.37	-4.57	-3.10	-2.03	-1.42	-1.07	-0.66	-0.36

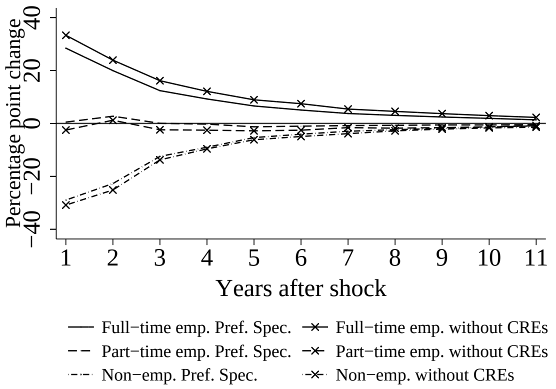
Table 8: Impulse response functions for a temporary shock that moves non-employed women into full-time work. Results are presented for Specifications II, IV, V and VI of the unobservables and estimated: using the preferred specification of the explanatory variables; with further controls for family values and religious denomination; and via a reduced form specification of the explanatory variables.

Model	Years since Employment Shock										
	1	2	3	4	5	6	7	8	9	10	11
	Effect on Full-time Employment (Percentage Points)										
Sp. II: Preferred	2.59	2.64	2.49	2.54	1.78	1.42	1.07	0.86	0.71	0.41	0.10
Sp. II: Further Controls	2.74	2.69	2.18	1.88	1.63	1.32	0.86	0.81	1.22	0.61	0.25
Sp. II: Reduced Form	3.40	4.42	3.35	3.25	2.13	1.98	1.73	1.37	0.91	0.51	0.30
Sp. IV: Preferred	3.35	2.44	3.00	2.29	2.08	1.52	1.32	0.97	0.76	0.76	0.61
Sp. IV: Further Controls	2.54	2.44	2.18	1.93	1.58	1.47	1.32	1.12	0.71	0.61	0.46
Sp. IV: Reduced Form	3.20	3.20	3.00	2.13	1.78	1.37	1.02	0.76	0.66	0.46	0.51
Sp. V: Preferred	1.98	1.93	1.98	1.83	1.47	0.97	0.86	0.36	0.15	0.20	0.30
Sp. V: Further Controls	2.64	2.18	2.18	1.88	1.42	1.27	0.91	0.61	0.56	0.41	0.51
Sp. V: Reduced Form	3.56	4.17	3.46	2.69	1.98	1.73	1.27	1.27	0.76	0.41	0.20
Sp. VI: Preferred	2.69	2.54	2.13	1.88	1.63	1.17	1.07	0.86	0.66	0.56	0.36
Sp. VI: Further Controls	2.49	2.13	1.88	1.93	1.68	1.07	0.81	0.76	0.66	0.61	0.51
Sp. VI: Reduced Form	3.40	3.51	2.54	2.39	1.68	1.52	1.27	1.02	0.56	0.66	0.61
	Effect on Part-time Employment (Percentage Points)										
Sp. II: Preferred	38.57	27.85	16.26	10.77	6.55	4.67	3.05	2.18	1.63	1.32	1.02
Sp. II: Further Controls	39.58	28.56	16.72	10.72	7.16	4.67	3.30	2.03	1.32	1.07	0.76
Sp. II: Reduced Form	36.33	25.61	14.28	9.10	5.69	3.20	1.88	0.91	0.61	0.46	0.51
Sp. IV: Preferred	39.28	29.67	17.43	12.55	8.59	5.84	3.20	2.64	2.03	1.12	0.56
Sp. IV: Further Controls	35.82	26.32	14.89	9.91	6.40	4.22	2.44	2.03	1.83	1.07	0.56
Sp. IV: Reduced Form	32.11	24.09	11.84	8.38	4.57	3.05	1.83	1.02	0.51	0.25	-0.05
Sp. V: Preferred	39.63	28.91	17.73	11.53	7.83	6.30	4.17	3.30	2.54	2.13	1.58
Sp. V: Further Controls	39.33	28.91	17.68	11.64	8.38	5.74	3.86	3.00	2.29	1.78	1.02
Sp. V: Reduced Form	35.92	25.56	14.63	9.30	6.61	4.17	2.95	1.78	1.22	1.07	1.02
Sp. VI: Preferred	33.33	23.42	13.47	9.65	6.00	4.12	2.69	1.98	1.63	1.37	0.81
Sp. VI: Further Controls	33.33	24.64	13.62	9.71	6.40	4.42	3.00	2.29	1.63	1.42	1.07
Sp. VI: Reduced Form	31.50	21.95	12.30	7.98	5.03	3.46	2.03	1.37	1.12	0.76	0.46
	Effect on Non-employment (Percentage Points)										
Sp. II: Preferred	-41.16	-30.49	-18.75	-13.31	-8.33	-6.10	-4.12	-3.05	-2.34	-1.73	-1.12
Sp. II: Further Controls	-42.33	-31.25	-18.90	-12.60	-8.79	-6.00	-4.17	-2.85	-2.54	-1.68	-1.02
Sp. II: Reduced Form	-39.74	-30.03	-17.63	-12.35	-7.83	-5.18	-3.61	-2.29	-1.52	-0.97	-0.81
Sp. IV: Preferred	-42.63	-32.11	-20.43	-14.84	-10.67	-7.37	-4.52	-3.61	-2.79	-1.88	-1.17
Sp. IV: Further Controls	-38.36	-28.76	-17.07	-11.84	-7.98	-5.69	-3.76	-3.15	-2.54	-1.68	-1.02
Sp. IV: Reduced Form	-35.32	-27.29	-14.84	-10.52	-6.35	-4.42	-2.85	-1.78	-1.17	-0.71	-0.46
Sp. V: Preferred	-41.62	-30.84	-19.72	-13.36	-9.30	-7.27	-5.03	-3.66	-2.69	-2.34	-1.88
Sp. V: Further Controls	-41.97	-31.10	-19.87	-13.52	-9.81	-7.01	-4.78	-3.61	-2.85	-2.18	-1.52
Sp. V: Reduced Form	-39.48	-29.73	-18.09	-11.99	-8.59	-5.89	-4.22	-3.05	-1.98	-1.47	-1.22
Sp. VI: Preferred	-36.03	-25.97	-15.60	-11.53	-7.62	-5.28	-3.76	-2.85	-2.29	-1.93	-1.17
Sp. VI: Further Controls	-35.82	-26.78	-15.50	-11.64	-8.08	-5.49	-3.81	-3.05	-2.29	-2.03	-1.58
Sp. VI: Reduced Form	-34.91	-25.46	-14.84	-10.37	-6.71	-4.98	-3.30	-2.39	-1.68	-1.42	-1.07

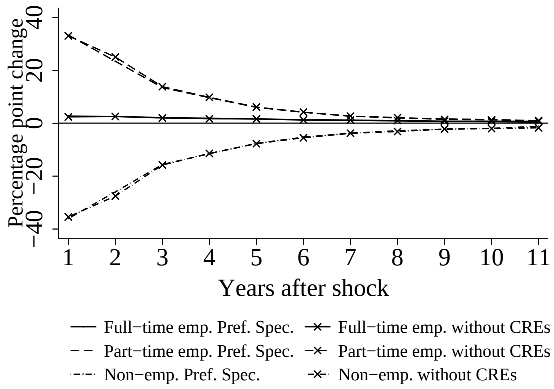
Table 9: Impulse response functions for a temporary shock that moves non-employed women into part-time work. Results are presented for Specifications II, IV, V and VI of the unobservables and estimated: using the preferred specification of the explanatory variables; with further controls for family values and religious denomination; and via a reduced form specification of the explanatory variables.

C.2 Role of the Correlated Random Effects

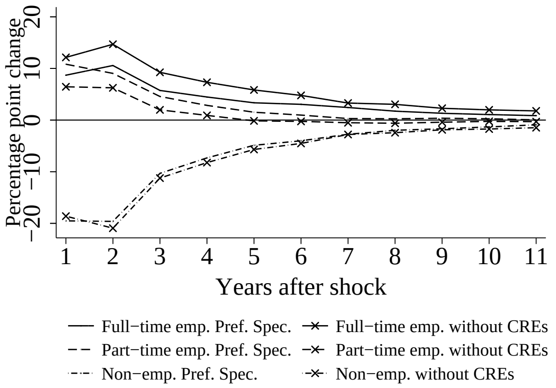
Finally, we investigate the impact of allowing correlated random effects. Figure 4 shows the estimated impulse response functions and estimated labor supply responses to the birth of a child, based on the preferred specification and on an alternative specification in which correlated random effects are excluded. In both cases, we use Specification VI of the unobservables, as described in Section 3.4 of the main text. We find that labor supply behavior following a temporary shock that moves non-employed women into full-time work is somewhat sensitive to the inclusion of correlated random effects. In particular, the omission of correlated random effects leads to an overstatement of the own state dependence in full-time employment. In addition, we find that estimates of labor supply behavior following the birth of a child are also dependent on whether or not correlated random effects are permitted. Specifically, the omission of correlated random effects leads to an understatement of the rate of part-time employment and an overstatement of the rate of full-time employment following the birth of a child, with the sensitivity to the inclusion of correlated random effects being larger for women with a high unobserved preference for full-time work in the event that they have a young child than for women with an low unobserved preference for full-time work in the event that they have a young child.



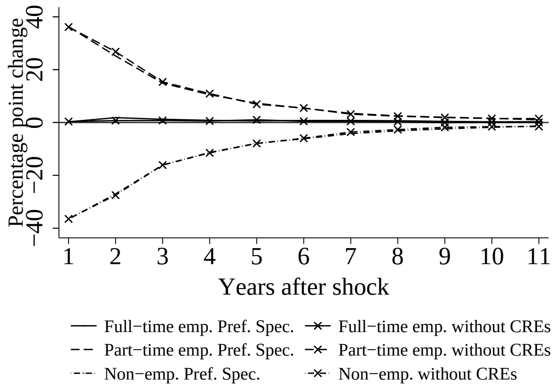
(a) Temporary shock moves non-employed women into full-time work: All women non-employed at $t = 0$.



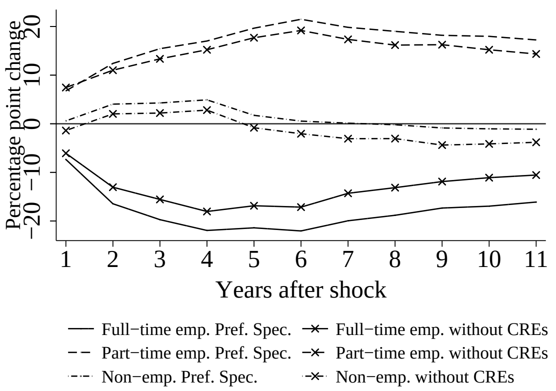
(b) Temporary shock moves non-employed women into part-time work: All women non-employed at $t = 0$.



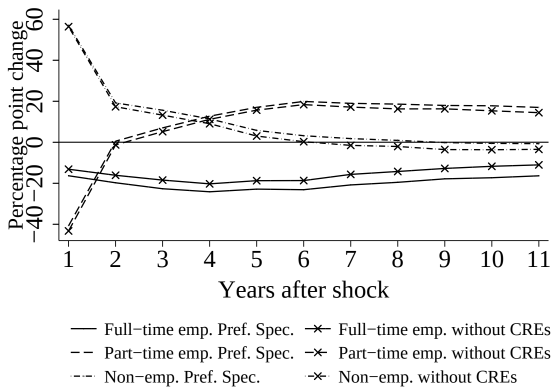
(c) Temporary shock moves non-employed women into full-time work: Women with young children non-employed at $t = 0$.



(d) Temporary shock moves non-employed women into part-time work: Women with young children non-employed at $t = 0$



(e) Effect of having a child at $t = 1$ - High unobserved preference for full-time work.



(f) Effect of having a child at $t = 1$ - Low unobserved preference for full-time work.

Notes: See Figure 1 and Figure 3.

Figure 4: Behavioral effect of allowing correlated random effects (CREs).

References

Keane, M. P. (1992), A Note on Identification in the Multinomial Probit Model, *Journal of Business and Economic Statistics*, **vol. 10**(2): pp. 193–200.

Mincer, J. (1963), Market Prices, Opportunity Costs, and Income Effects, in C. Christ (Editor), *Measurement in Economics*, pp. 67–82, Stanford University Press, Stanford.

Moffitt, R. (1984), Profiles of Fertility, Labour Supply and Wages of Married Women: A Complete Life-Cycle Model, *Review of Economic Studies*, **vol. 51**(2): pp. 263–78.

Walker, J. L., Ben-Akiva, M. and Bolduc, D. (2007), Identification of Parameters in Normal Error Component Logit-Mixture (NECLM) Models, *Journal of Applied Econometrics*, **vol. 22**(6): pp. 1095–1125.