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ABSTRACT

Children and Women's Participation Dynamics: Transitory and Long-Term Effects*

Children affect the after-birth labor force participation of women in two ways. Directly, the time spent in child-care reduces the labor market effort. The time spent out of the labor market while on maternity leave alters women's participation experience and, thus, indirectly affects subsequent participation behavior. This paper proposes a model that disentangles the direct and indirect effect of children on women's labor force participation, and evaluates their relative importance. Participation decisions on a three-state space - employed full-time, employed part-time, not employed - are represented by a multivariate probit model with a general correlation structure. The model allows for a high degree of flexibility in modeling the dependence of sequential decisions. The estimation is performed using Markov chain Monte Carlo methods. It is shown that the indirect effect, through time out of the labor market, is more important. The discrepancy is sharper for full-time employment and grows with the length of the interruption.

JEL Classification: C11, C15, J13, J22

Keywords: female labor supply, multivariate probit model, Gibbs sampler

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1 Introduction

The effects of family structure on women’s labor force participation have often been studied in labor economics. Many empirical studies¹ found that the number of children and the children’s age distribution are important factors affecting the number of hours of work and labor force participation decisions. Findings suggest that the presence of children has a strong negative effect on mother’s labor supply. Although many different interpretations are possible we can classify them into two broad channels. The *direct* effect captures the reduced probability of working part time or full time for women with children. This direct effect could be easily interpreted in a model framework such as Becker (1985) that predicts that mother’s market effort diminishes as the child-care time increases. The *indirect* effect operates through the effect of time out from the labor market, which is correlated with family structure. This indirect effect could easily be interpreted in a model framework in which wages and participation depend on experience and job seniority. Interruptions affect these factors and will subsequently have an effect on labor market outcomes (e.g. Blau and Ferber, 1991).

This paper investigates the intertemporal labor force participation of married women and analyzes the effect of family structure on the likelihood of part time and full time employment. We are particularly interested in separating the direct and indirect effect of children on mother’s labor force participation.

Participation decisions are represented by a multivariate probit model with a general correlation structure. This model allows for a high degree of flexibility in modeling the dependence of decisions, both across choices and over time. It also avoids strong assumption about preferences². Most importantly, this approach allows us to disentangle the direct and indirect effect.

Lately, two state models of labor force participation have been estimated using maximum simulated likelihood (Hyslop, 1999). Due to the difficulty in estimation, three-state models have been rarely used in empirical studies. To our knowledge three-state models of dependent sequential decisions have not yet been estimated. In this paper we use a Bayesian Markov Chain Monte Carlo (MCMC) method, introduced by Chib and Greenberg (1998), to estimate the multivariate probit model. This method avoids the convergence problems that hamper the maximum likelihood estimation. The remainder

¹See for instance Hotz and Miller (1988), Heckman and Willis (1975), or Moffit (1984).

²In contrast, the multinomial logit or probit model assumes that individual’s preferences are defined over entire labor market histories (e.g. Chintagunta, 1992).

of the paper is structured as follows. Section 2 briefly discusses our data followed by an outline of our methodology in section 3. In section 4 we discuss our findings. Section 5 concludes.

2 Data

We use data from the German Socio Economic Panel (GSOEP) for the years 1994 to 1998, restricting ourselves to a balanced panel of all women between the ages of 25 and 65 who are either married or living in consensual union³. This results in 2,576 individuals or 12,880 person-year observations. Tables 1 and 2 contain some of the mean characteristics of the sample. Approximately half the married women between the age of 25 and 65 work and when they work they are about twice as likely to work full time than part time. In general younger women and women with a higher education work more often. When we compare women without children and women with a young child we observe a virtual collapse of the incidence of working full time, but we do not find any noticeable drop with regards to working part time for either medium educated young women or highly educated older women. In general, the reduced incidence of working part time is much less dramatic than what we observe for full time. Women with older children are even more likely to be working part time than women without children. Overall, total employment rates for women without children are always higher. A rough sketch of the dynamics is captured in the five transition matrices in figure 1, indicating movements between labor states from one wave to the next and from the start to the end of the sample⁴.

³For a good discussion on the GSOEP data in general see for instance the paper by Wagner, Burkhauser and Behringer (1993).

⁴Shorrocks (1978) defines $\frac{(n - \text{trace}(P))}{(n-1)}$ as a measure of mobility, where n is the number of states and P is the transition probability matrix. This measure is naturally bounded between 0 (immobility) and 1 (perfect mobility). For comparison, Boeri and Flinn (1999) find a measure of 0.2 for occupational mobility in Italy during the mid to late nineties, when looking at quarterly transitions and classifying nine occupation categories.

3 Methodology

Models of multiple individual decisions fall in one of the following three categories: different decisions are made by the same individual at a given time, the same decision is made sequentially, or several different decisions are repeated over time. The main difficulty in estimating such models is accounting for the statistical dependence between different or sequential decisions made by the same person. It is widely accepted that this dependence has three main sources: unobserved heterogeneity, state dependence, and autocorrelated disturbances. For different decisions at a given point in time, the only possible source of correlation is the unobserved heterogeneity - the existence of one or more unobserved individual characteristics relevant to all underlying objective functions. In the economic literature the preferred approach has been the use of random effects. Individual random effects are typically assumed to have a multivariate normal distribution, such that the correlation coefficients embody the desired dependence of different decisions. The models are estimated using simulated maximum likelihood, as random effects must be integrated out. These models have been used in conjoint analysis in the marketing literature⁵.

If one decision is repeatedly observed, all three sources of correlation can play a role. State dependence basically assumes that at any given time, the decision depends in a specified way on the current value of the state variable (for example, in the search model framework, search costs, the value of time spent in alternative activities, or the arrival rate of new wage offers may depend on the labor market state currently occupied). Unobserved heterogeneity works the same way as in the case of different decisions. Finally the correlation matrix can be parametrized to allow the stochastic elements driving the process to be serially correlated⁶.

If several different decisions are observed over time the number of dependencies increases but there is no substantial difference in the way they can be modeled. The estimation by maximum likelihood becomes increasingly difficult, as higher level multiple integrals have to be evaluated within each step of the maximization routine. The solution generally involves the use of random effects to model the dependence across sequential decisions. The

⁵Conlon, Dellaert and van Soest (2000) use simulated maximum likelihood to estimate the model, while Liechty, J., V. Ramaswamy, S. H. Cohen (1999) use a MCMC approach.

⁶Hyslop (1999) develops a two-state model of labor force participation with state dependence random effects and serial correlation. The estimation is performed using simulated maximum likelihood.

main drawback of this approach is that it imposes a constant correlation between sequential decisions. When the multivariate logit model is used to model contemporary decisions, it imposes the additional restriction that the random utilities corresponding to each choice are independent.

The multivariate probit model we use in this paper allows for a general correlation structure, both across choices and over time. In this respect it is the most general framework we are aware of. As the estimated model is not structural, it is less important to break down dependence into state dependence and unobserved heterogeneity. However, in this framework, the effect of past status on the present decision can be estimated using simple conditional probabilities. This approach is more general than the usual method of using lagged dependent variables in the present decision. It does not suppress the dependence beyond the immediate past status and allows for a more general dependence than the simple linear relationship between the past status and the expected value of the current latent dependent variable.

To study labor market dynamics of German women, we employ a three-state labor force participation model where we distinguish between full time employment, part time employment and non employment. We use a simple random utility model to represent individual labor market experiences in this three-dimensional state space. In this setting individuals choose, every time period, among three alternative states: full time, part time or not employed. Each state is associated with a latent variable, which can be thought of as the utility of being in the respective state. Every time period, individuals draw realizations of the three latent variables from a known joint distribution.

Let the three latent variables be Z_{it}^{ft} , Z_{it}^{pt} , and Z_{it}^{nw} , corresponding to the three states - full time, part time and not employed, respectively.

$$\begin{aligned} Z_{it}^{ft} &= X_i \beta_t^{ft} + u_{it}^{ft} \\ Z_{it}^{pt} &= X_i \beta_t^{pt} + u_{it}^{pt} \\ Z_{it}^{nw} &= X_i \beta_t^{nw} + u_{it}^{nw} \end{aligned}$$

The subscript i indicates individuals and subscript t indicates time periods. The superscripts ft , pt and nw indicate the respective states. u_{it}^{ft} , u_{it}^{pt} , and u_{it}^{nw} have a joint multivariate normal distribution. The dimension of the distribution is $3T$, where T is the number of waves in the panel. Let $u_{it} = \begin{bmatrix} u_{it}^{ft} \\ u_{it}^{pt} \\ u_{it}^{nw} \end{bmatrix}$. $E[u_{it}] = 0$, u_{it} are independent over i 's and it has a correlation structure over t given by a general $3T \times 3T$ correlation matrix. The number of free elements in the correlation matrix is $3T(3T - 1)/2$.

The state choice is represented by a set of binary variables defined in the following way:

$$\begin{aligned}
y_{it}^{ft} &= 1 \text{ if } Z_{it}^{ft} > 0, Z_{it}^{pt} < 0, \text{ and } Z_{it}^{nw} < 0 \\
y_{it}^{pt} &= 1 \text{ if } Z_{it}^{pt} > 0, Z_{it}^{ft} < 0, \text{ and } Z_{it}^{nw} < 0 \\
y_{it}^{nw} &= 1 \text{ if } Z_{it}^{nw} > 0, Z_{it}^{ft} < 0, \text{ and } Z_{it}^{pt} < 0
\end{aligned}$$

Let

$$\begin{aligned}
y_{it} &= [y_{it}^{ft} | y_{it}^{pt} | y_{it}^{nw}] \\
y_i &= [y_{i1} | y_{i2} | \dots | y_{iT}] \\
y &= [y_1 | y_2 | \dots | y_n] \\
Z_{it} &= [Z_{it}^{ft} | Z_{it}^{pt} | Z_{it}^{nw}] \\
Z_i &= [Z_{i1} | Z_{i2} | \dots | Z_{iT}] \\
Z &= [Z_1 | Z_2 | \dots | Z_n]
\end{aligned}$$

This structure closely resembles that of a multivariate probit model. The difference consists of additional truncation imposed on contemporary latent variables by the fact that only one choice can be made at any given time. The major difference between our model and that of Chib and Greenberg (1998) is that the vector y is restricted to a subset of all possible combinations of values. Any time period, an individual can be in one, and only one, state. This means that, in any time period, only three combinations of values are feasible out of a total of eight⁷. This induces an additional truncation for the joint distribution of Z_i . Not only is the distribution of each component restricted by the value of the corresponding discrete dependent variable, but the joint distribution is further truncated to the space of feasible combinations for the components of y_i . This does not affect the estimation, but any predictions made on the basis of the results have to be adjusted to account for this additional truncation.

Our objective is to obtain a series of draws from the joint posterior distribution of the parameters. Using Bayes formula, the joint posterior distribution of the parameters, conditional on data, is

$$\pi(\beta, \sigma | y) \propto \pi(\beta, \sigma) pr(y | \beta, \Sigma) \quad \beta \in R^k, \sigma \in C$$

where $\pi(\beta, \sigma)$ is the prior distribution of β and σ , and $pr(y | \beta, \Sigma) = \prod_i pr(y_i | \beta, \Sigma)$ is the likelihood function. To draw from this posterior density we use the MCMC algorithm introduced by Chib and Greenberg (1998).

⁷To see this point, let Z_{it}^{ft} , Z_{it}^{pt} and Z_{it}^{nw} take on only two possible values, being -1 or 1. This generates $2^3 = 8$ possible combinations of $(Z_{it}^{ft}, Z_{it}^{pt}, Z_{it}^{nw})$. However, only (1,-1,-1), (-1,1,-1) and (-1,-1,1) are feasible.

For each parameter, we report the moments of the posterior distribution, the numerical standard error of the estimated mean (which accounts for dependence of successive draws) and evaluate the convergence of the MCMC algorithm. We estimate six sets of slope coefficients for every labor market state we estimate an initial set for the first wave and a second set for the subsequent waves 2 to 5. We also estimate the 105 free elements of the correlation matrix⁸. Table 3 for employed full time, table 4 for employed part time, and table 5 for not employed report the posterior means, the posterior standard deviation (PSTD), and the numerical standard errors (NSE) for the β s and the scale reduction factors (R). The values of R very close to 1 indicate convergence. The interpretation of the β s is the same as that in a linear regression model with dependent variable Z_{it} . Table 6 reports the posterior means for the correlation coefficients.

After having estimated the parameters of the model we compute the probabilities for all possible labor market histories⁹. The probabilities are evaluated at the posterior means. We use these probabilities to construct life cycle profiles for selected events. These life cycle profiles provide a much clearer understanding and our discussion of the estimation results will be limited to this representation of them. These life cycle profiles are computed for women with 3 different education levels, 5 categories of children, and for 4 different types of spouses. Based on the highest level of general or higher education completed we construct three education indicators. Ranked from high to low there are educ0 (ISCED 5-7), educ1 (ISCED 3), and educ2 (ISCED 0-2). We also specify five children indicators being kids1 (no children), kids2 (one child under 3), kids3 (one child 3 or over, but less than 6), kids4 (one child 6 or over but under 17) and kids5 (one child 17 or over). Finally, we specify four types of spouses: a non working spouse (spouse0), and working spouses earning income from wages at the 25th, 50th and 75th percentile (spouse1, 2 and 3 respectively)

The life cycle profiles for working full time and working part time are displayed in the figures 2 and 3, respectively. We condition on a working

⁸Recall that the symmetric σ -matrix had $3T*(T-1)/2$ free off-diagonal correlations, where T equals the number of periods. In our case T=5. Also note that we do not superimpose a structure on the correlation matrix other than the restriction that all elements lay within the interval [-1,1] and that the is matrix positive definite at all times.

⁹In a five-period three-state model, there are $3^5 = 243$ possible histories. The probability of a complete history is the cumulative distribution function (CDF) of a trivariate normal distribution. To calculate the normal CDFs, we use the GHK smooth recursive simulator (Geweke, 1989; Hajivassiliou, 1990; and Keane, 1994).

spouse earning median income (spouse2) and median household non labor income. We plot these profiles for women across different combinations of education and child categories. In figures 4 and 5 we investigate the effect of spouse participation and income on employment and plot profiles for women in wave 2. Again, we distinguish between different combinations of education and child categories.

4 Findings and discussion

4.1 The effect of children

The probability of working full time (figure 2) is reduced sharply in the presence of a young child (kids2) and to the lowest levels for a woman with a low educational attainment (educ3). In subsequent waves (years) the probability of working full time recovers, but nowhere near the employment levels of similarly educated women without children (kids1).

We seek to disentangle the direct effect of having children from the indirect effect caused by time out from the labor market. Assume a woman has a newborn in wave 1. This child will remain in kid category kids2 until wave 4. In wave 4 and 5 this child will be in the next age category, kids3. Instead of having a newborn in wave 1 assume a child in age category kids3 is 'adopted' in wave 1. In the case of a newborn, participation in waves 4 and 5 captures not only the direct effect of a child in category kids3 but also the indirect effect through time out the labor market following the birth. In contrast, in the 'adoption' case the reduced employment probability -compared to a situation with no children- captures the direct effect of a child in category kids3 *only*. Absent any indirect effect, the employment probabilities in waves 4 and 5 in the case of a newborn should coincide with the employment probabilities in waves 1 and 2, respectively, in the case of 'adoption'. Clearly this is not the case. The employment probabilities in waves 4 and 5 are much lower than those in waves 1 and 2. For highly educated women the indirect effect is the more important.

Next assume a woman does not have a newborn in wave 1, as in the previous case, but instead 'adopts' a child in age category kids3. An analogous comparison can now be made to identify the direct and indirect effect of having a child in category kids4. Both a direct and indirect effect can be observed. However, this time the indirect effect only plays a role for medium and low educated women.

For part time employment probabilities (figure 3) the only observable

deviation from the stable hump shaped life cycle profile are the first two years after having given birth (wave 1 and 2 for ‘kids2’). This suggests that there is only a direct effect during the first two years immediately following a birth. There is no evidence of any indirect effects.

4.2 The effect of time out from the labor market

To investigate the effect of time out of the labor market we compute various conditional probabilities. Figures 6 and 7 display the conditional probability of working full time in wave 5 or the next period, respectively, conditional on having worked full time in wave 1 and for different lengths of subsequent interruptions ranging between 0 and 3 years. We plot these graphs both for a woman with a newborn in wave 2 as well as for a woman without children. These different scenarios are then analyzed for the three different education levels. In each plot we always include the baseline of no time out from the labor market to act as a reference¹⁰.

For women with no children we find that each extra year out of the labor market substantially further reduces the probability of returning to full time employment in wave 5 (figure 6). Only for high educated women (educ0) the decline in the probability of full time employment in wave 5 is less severe when interrupting only in wave 2. The additional effect of each extra year out is not observed in the presence of a young child. We find that conditional on taking *any* time out of the labor market when having a child, it doesn’t really matter if this is one, two, or three years when analyzing the subsequent probability of working full time in wave 5. However, when we compare the profiles for women with and without a newborn in wave 2, and condition on working full time in both wave 1 and 2 (i.e. no interruption), the conditional probability of working full time in wave 5 is only slightly lower for a woman with a child than for a woman without children. This once again suggests that it is time out of the labor market that is driving reduced employment.

When we compare conditional probabilities for women with a high education who worked full time in wave 1 followed by a three year interruption, we find that having a child *increases* the probability of working full time again in the next period, wave 5. This only holds for high educated women (educ0), conditional on taking 3 years off. A possible plausible explanation

¹⁰In the graphs, the ‘f’ and ‘n’ denote full time and not working. The numbers indicate the wave. For example, f5|f1n2n3nokid denotes the probability of working full time in wave 5 (f5) conditional on having worked full time in wave 1 (f1), not having a child in wave 2 (nokid) and having been out of the labor market in waves 2 and 3 (n2n3).

may lie in the German legislation related to maternity and parental leave that guarantees the exact same position and conditions when a woman returns within a single year (providing she did not work for a different employer in the meantime) and offers an employment guarantee with the firm when the mother returns before the child turns 3.

We also compute the conditional probabilities of returning to work full time in the next period, instead of focussing on working full time in period 5 (figure 7). We observe similar patterns as described above.

4.3 The role of spouse types

Finally, we evaluate the role of different spouse types on women's participation. We find that a woman with a working partner earning low wages has higher full time employment probabilities than if she would have had a non working partner (figure 4). This finding is universal across education levels and the presence (or absence) of different children in the household. A possible plausible explanation could be dependence of the household on government transfers. If the husband doesn't work, employment by the woman may greatly diminish or stop the transfers. A salient feature is that highly educated women are less influenced by the behavior of the spouse, except when having a baby. This does not hold for the probability of working part time (figure 5). We find that women respond in the same fashion and in the same proportion, irrespective of their educational attainment. Women with a working spouse earning low wages are least likely to work, although the difference in the case of a non working spouse is negligible. Apart from this, the probability of working part time increases with the spouse's wage.

5 Conclusions

There are several reasons why women with children have lower employment rates. Broadly speaking, they can be viewed to operate along two different channels. The first channel, which we call the direct effect, captures the reduced employment probability when children are present. This channel encompasses, for instance, the reduced hours of market work as a result of the increased hours of care. It also encompasses the often cited lack of (affordable) day care as a reason for reduced employment rates of mothers. The second channel, which we call the indirect effect, captures reduced employment rates that are the result of time out from the labor market. If labor force participation depends on experience and job seniority than interruptions will affect future labor market participation. Our approach enables us to distinguish between this direct and indirect effect. Using a very general and flexible framework we are able to investigate the effect of family structure, education, age and spouse on various conditional employment probabilities. Our estimates show that the indirect effect far outweighs the direct effect when looking at the probability of working full time for women with a young child. The direct effect of having young children is substantial, but rapidly declines as the age of the child increases. For highly educated women it becomes negligible for children aged 6 and up. The direct effects for medium and low educated mothers are stronger and remain substantial even in the presence of older children. We do not find substantial direct or indirect effects of children on the probability of working part time, apart from the first two years immediately following a birth.

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Appendix

Define

$$\begin{aligned} B_{it}^{ft} &= (0, \infty) \times (-\infty, 0] \times (-\infty, 0] \\ B_{it}^{pt} &= (-\infty, 0] \times (0, \infty) \times (-\infty, 0] \\ B_{it}^{nw} &= (-\infty, 0] \times (-\infty, 0] \times (0, \infty) \end{aligned}$$

Every time period, the set of possible values that form Z_{it} is given by

$$B_{it} = B_{it}^{ft} \cup B_{it}^{pt} \cup B_{it}^{nw}$$

For individual i , the set of all feasible values of Z_i is $B_i = B_{i1} \times B_{i2} \times \dots \times B_{iT}$

Using Bayes formula, the joint posterior distribution of the parameters, conditional on data, is

$$\pi(\beta, \sigma | y) \propto \pi(\beta, \sigma) pr(y | \beta, \Sigma) \quad \beta \in R^k, \sigma \in C$$

where $\pi(\beta, \sigma)$ is the prior distribution of β and σ , and $pr(y | \beta, \Sigma) = \prod_i pr(y_i | \beta, \Sigma)$ is the likelihood function. C is a convex solid body in the hypercube $[-1, 1]$ (Rousseeuw and Molenberghs, 1994). The shape of C is given by the following two conditions:

1. Each correlation coefficient lies in the interval $[-1, 1]$.
2. The correlation matrix Σ is positive definite. Since Σ is symmetric, this condition reduces to $\det(\Sigma) > 0$.

The method proposed by Chib and Greenberg (1998) uses the same approach as data augmentation algorithm of Tanner and Wong (1987). Instead of using the posterior distribution in this form, we use the joint posterior of both parameters and latent variables, $\pi(\beta, \sigma, Z_1, \dots, Z_n | y)$.

$$\pi(\beta, \sigma, Z | y) \propto \pi(\beta, \sigma) f(Z | \beta, \Sigma) pr(y | Z, \beta, \sigma)$$

Conditional on Z_i , we have $pr(y_i | Z_i, \beta, \sigma) = I(Z_i \in B_i)$. The posterior distribution becomes

$$\pi(\beta, \sigma, Z | y) \propto \pi(\beta, \sigma) \prod_i f(Z_i | \beta, \Sigma) I(Z_i \in B_i)$$

where

$$f(Z_i|\beta, \Sigma) \propto |\Sigma|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} (Z_i - X_i\beta)' \Sigma^{-1} (Z_i - X_i\beta) \right\} I(\sigma \in C)$$

Regarding the latent variable as a parameter, we sample from the conditional distributions:

- Conditional distribution of Z_i

$$[Z_i|y_i, \beta, \Sigma] \propto \phi_T(Z_i|X_i\beta, \Sigma) \prod_i \{I(z_{it} > 0) I(y_{it} = 1) + I(z_{it} \leq 0) I(y_{it} = 0)\}$$

To draw from a truncated normal distribution, we used the method proposed by Geweke (1991), which consists of running a Gibbs sub-chain with T steps within the main Gibbs sampler cycle.

- Conditional Distribution of β

We assume prior independence between β and σ . The prior distribution of β is a k -variate normal distribution $\pi(\beta) = \phi_k(\beta|\beta_0, B_0^{-1})$. Conditional distribution is

$$[\beta|Z, \Sigma] \sim N_k(\beta|\hat{\beta}, B^{-1})$$

where

$$\hat{\beta} = B^{-1} \left(B_0\beta_0 + \sum_{i=1}^n X_i'\Sigma^{-1}Z_i \right)$$

and

$$B = B_0 + \sum_{i=1}^n X_i'\Sigma^{-1}X_i$$

- Conditional Distribution of σ

$$\begin{aligned} \pi(\sigma|Z, \beta) &\propto \pi(\sigma) f(Z|\beta, \Sigma) \\ f(Z|\beta, \Sigma) &\propto |\Sigma|^{-\frac{n}{2}} \exp \left\{ -\frac{1}{2} \text{tr} (Z^* - \Delta)' \Sigma^{-1} (Z^* - \Delta) \right\} I(\sigma \in C) \end{aligned}$$

where $Z^* = (Z_1, \dots, Z_n)$ and $\Delta = (X_1\beta, \dots, X_n\beta)$. Prior distribution of σ is a normal distribution truncated at C

$$\pi(\sigma) \propto \phi_p(\sigma|\sigma_0, G_0^{-1}) \quad \sigma \in C$$

where p is the number of free parameters in the correlation matrix. To draw from this distribution we use a MH step within the Gibbs sampler.

Convergence of the chain is assessed using the method proposed by Gelman and Rubin (1992) with the modified correction factor proposed by Brooks and Gelman (1998). One preliminary run of 15000 iterations, with OLS coefficients as starting values, was used to construct starting values for three independent chains. The starting values were extreme values chosen from the posterior distribution of the coefficients. The three independent chains, each with 15000 iterations and the initial run, were used to compute the scale reduction factor. We also evaluated the convergence criterion proposed by Geweke(1992) based on a single chain, which uses spectral density estimates of the series. Both criteria indicated that the chain converges fast to the stationary distribution.

We follow Chib and Greenberg (1998) in setting the parameters of the algorithm. The prior distribution of β is multivariate normal with a mean vector of 0 and a variance matrix of 100 times the identity matrix. The prior distribution of the elements of the correlation matrix is multivariate normal with a mean vector of 0 and a variance matrix equal to 10 times the identity matrix. The proposal density used to generate candidate values in the MH step is $q(\phi|\sigma_i^k) = s * g(\phi - \sigma_i^k)$ where g is the standard normal distribution and s is the step size. We use a step size $s = 1/\sqrt{N}$.

Wave	Age	Med. Educ	Low Educ	Log monthly non-wage HH Inc.	Log monthly spouse's income from work	Fraction with working spouse	No. of kids [0,3)	No. of kids [3,6)	No. of kids [6,17)	No. of kids [17,∞)	Fraction working FT	Fraction working PT	Fraction not working
W1 (1994)	mean	.57	.25	5.70	5.95	.75	.08	.14	.61	.41	.37	.16	.47
	stdev	10.16		2.37	3.44		.3	.37	.87	.73			
	min	25		0	0		0	0	0	0			
	max	61		11.96	10.09		2	2	5	5			
W2 (1995)	mean	.57	.25	5.80	5.86	.74	.07	.13	.61	.41	.35	.17	.48
	stdev	10.16		2.35	3.50		.27	.38	.87	.69			
	min	26		0	0		0	0	0	0			
	max	62		11.99	10.06		2	3	5	5			
W 3 (1996)	mean	.57	.25	5.75	5.60	.71	.07	.12	.60	.41	.33	.17	.50
	stdev	10.16		2.45	3.65		.26	.35	.86	.68			
	min	27		0	0		0	0	0	0			
	max	63		12.16	9.39		2	2	4	4			
W4 (1997)	mean	.57	.25	5.76	5.42	.68	.06	.11	.58	.44	.32	.18	.50
	stdev	10.16		2.52	3.74		.24	.34	.84	.69			
	min	28		0	0		0	0	0	0			
	max	64		12.20	10.31		2	2	4	5			
W5 (1998)	mean	.57	.25	5.79	5.32	.67	.06	.10	.56	.45	.32	.17	.53
	stdev	10.16		2.58	3.78		.24	.32	.83	.70			
	min	29		0	0		0	0	0	0			
	max	65		12.13	9.39		2	2	5	5			

Table 1. Characteristics of the sample by wave. 'Med. Educ.' indicates medium education (ISCED 3). 'Low Educ.' indicates low education (ISCED 0-2). High education (ISCED 5-7) is omitted.

	Age 25 - 35			Age 35 - 45			Age 45 - 55			Age 55 - 65						
	No. of Obs.	FT	PT	NW	No. of Obs.	FT	PT	NW	No. of Obs.	FT	PT	NW				
High Education																
No children	140	.6357	.1571	.2071	107	.8131	.0935	.0935	198	.6818	.1212	.1970	207	.3333	.0821	.5845
At least one child [0,3)	103	.0583	.0971	.8447	41	.1951	.0976	.7073	-	-	-	-	-	-	-	-
At least one child [3,6)	144	.3264	.1944	.4792	128	.2656	.2109	.5234	1	1.0000	.0000	.0000	-	-	-	-
At least one child [6,17)	238	.5420	.1555	.3025	733	.5648	.1896	.2456	106	.6038	.1509	.2453	2	.0000	.0000	1.0000
At least one child [17,.)	3	.6667	.0000	.3333	326	.7209	.0767	.2025	277	.6751	.1372	.1877	84	.3929	.0357	.5714
Medium Education																
No children	449	.7862	.0535	.1604	273	.6410	.1575	.2015	732	.4713	.2036	.3251	1021	.1939	.0872	.7189
At least one child [0,3)	472	.0339	.0530	.9131	90	.0667	.0333	.9000	3	.3333	.0000	.6667	-	-	-	-
At least one child [3,6)	633	.1090	.1769	.7141	252	.0913	.1865	.7222	15	.0000	.2667	.7333	-	-	-	-
At least one child [6,17)	888	.2962	.1745	.5293	1639	.2837	.2465	.4698	319	.1787	.3354	.4859	12	.3333	.1667	.5000
At least one child [17,.)	5	.8000	.0000	.2000	770	.3974	.2416	.3610	853	.3025	.2532	.4443	313	.1310	.1214	.7476
Low Education																
No children	67	.6716	.1045	.2239	68	.3971	.0882	.5147	320	.3594	.1438	.4969	559	.1181	.0769	.8050
At least one child [0,3)	95	.0947	.0632	.8421	30	.0000	.0000	1.0000	3	.0000	.0000	1.0000	-	-	-	-
At least one child [3,6)	169	.1479	.1124	.7396	72	.1250	.1667	.7083	2	.0000	.0000	1.0000	-	-	-	-
At least one child [6,17)	321	.1495	.1745	.6760	537	.2533	.1825	.5642	213	.2207	.1268	.6526	29	.0690	.2414	.6897
At least one child [17,.)	4	.5000	.0000	.5000	423	.3452	.1631	.4917	613	.2316	.1827	.5856	433	.1132	.1848	.7021

Table 2. Mean incidence of full time work, part time work and non employment by education and family structure. Waves 1-5 combined.
Low, medium and high education correspond to ISCED 0-2, ISCED 3, and ISCED 5-7, respectively.

LF Status		Wave 2			Total
Wave 1		FT	PT	NW	
	FT	779	50	126	955
	PT	48	288	76	412
	NW	87	95	1027	1209
Total		914	433	1229	2576

LF Status		Wave 3			Total
Wave 2		FT	PT	NW	
	FT	749	41	124	914
	PT	38	311	84	433
	NW	65	87	1077	1229
Total		852	439	1285	2576

LF Status		Wave 4			Total
Wave 3		FT	PT	NW	
	FT	707	53	92	852
	PT	39	314	86	439
	NW	82	86	1117	1285
Total		828	453	1295	2576

LF Status		Wave 5			Total
Wave 4		FT	PT	NW	
	FT	700	37	91	828
	PT	56	325	72	453
	NW	60	66	1169	1295
Total		816	428	1332	2576

LF Status		Wave 5			Total
Wave 1		FT	PT	NW	
	FT	639	70	246	955
	PT	69	216	127	412
	NW	108	142	959	1209
Total		816	428	1332	2576

Figure 1. Wave by wave transition matrices between full time (FT), part time (PT), and non-employment (NW) states.

Full Time β_0	R	mean	NSE	popstd
constant	1.000544	6.4253	0.0236	2.5300
age	1.000479	-0.4199	0.0017	0.1904
age ²	1.000461	1.1140	0.0040	0.4600
age ³	1.000444	-0.1004	0.0003	0.0359
educ1	1.000222	-0.6903	0.0005	0.0785
educ2	1.000361	-0.8505	0.0008	0.0952
nwinc	1.000379	-0.0171	0.0001	0.0121
spwage	1.000770	-0.3521	0.0008	0.0601
sppart	1.000986	2.6586	0.0068	0.4735
kids03	1.001367	-1.6203	0.0023	0.1797
kids36	1.000371	-0.5797	0.0008	0.0909
kids617	1.000479	-0.3463	0.0004	0.0433
kids>17	1.001547	-0.0835	0.0008	0.0440

Full Time β_0	R	mean	NSE	popstd
constant	1.000394	5.9918	0.0153	1.8529
age	1.000562	-0.4075	0.0013	0.1323
age ²	1.000726	1.1308	0.0035	0.3054
age ³	1.000912	-0.1058	0.0003	0.0229
educ1	1.000110	-0.7295	0.0003	0.0524
educ2	1.000170	-0.9361	0.0003	0.0634
nwinc	1.001037	-0.0063	0.0001	0.0068
spwage	1.000454	-0.2882	0.0003	0.0306
sppart	1.000377	2.2040	0.0021	0.2393
kids03	1.001237	-1.3086	0.0011	0.0908
kids36	1.001041	-0.8425	0.0009	0.0603
kids617	1.000699	-0.3963	0.0003	0.0280
kids>17	1.000047	-0.1410	0.0001	0.0286

Table 3. Results from the posterior density draws. Full time parameters. Educ1, educ2, and educ3 correspond to low (ISCED 0-2), medium (ISCED 3) and highly educated (ISCED 5-7), respectively. The variables nwinc, spwage and sppart indicate household non labor income (logs), spouse's income from wages (logs) and a dummy indicator for spouse's participation. The 'kids' variables indicate the number of children in the various age groups.

Part time β_0	R	mean	NSE	popstd
constant	1.000902	-4.1925	0.0373	2.9101
age	1.000807	0.1457	0.0026	0.2167
age ²	1.000706	-0.2068	0.0058	0.5198
age ³	1.000633	0.0057	0.0004	0.0403
educ1	1.000020	0.1964	0.0004	0.0903
educ2	1.000198	0.0539	0.0007	0.1084
nwinc	1.000312	0.0283	0.0001	0.0142
spwage	1.000344	0.1558	0.0006	0.0771
sppart	1.000385	-1.1619	0.0048	0.6167
kids03	1.001303	-0.5874	0.0025	0.1534
kids36	1.000277	0.0308	0.0007	0.0936
kids617	1.000751	0.0444	0.0005	0.0454
kids>17	1.000747	0.0370	0.0006	0.0484

Part time β_1	R	mean	NSE	popstd
constant	1.000143	3.2490	0.0112	1.9300
age	1.000085	-0.3707	0.0006	0.1372
age ²	1.000073	0.9930	0.0013	0.3156
age ³	1.000080	-0.0856	0.0001	0.0235
educ1	1.000277	0.1871	0.0003	0.0536
educ2	1.000032	0.1037	0.0001	0.0648
nwinc	1.000765	0.0108	0.0001	0.0074
spwage	1.000795	0.1912	0.0005	0.0397
sppart	1.000732	-1.4752	0.0037	0.3168
kids03	1.002922	-0.6561	0.0018	0.0875
kids36	1.000631	0.0258	0.0006	0.0537
kids617	1.000372	0.0555	0.0002	0.0276
kids>17	1.000155	0.0186	0.0001	0.0301

Table 4. Results from the posterior density draws. Part time parameters. Educ1, educ2, and educ3 correspond to low (ISCED 0-2), medium (ISCED 3) and highly educated (ISCED 5-7), respectively. The variables nwinc, spwage and sppart indicate household non labor income (logs), spouse's income from wages (logs) and a dummy indicator for spouse's participation. The 'kids' variables indicate the number of children in the various age groups.

Not-working β_0	R	mean	NSE	popstd
constant	1.000805	-4.1852	0.0301	2.4185
age	1.000888	0.2853	0.0024	0.1819
age ²	1.000938	-0.8831	0.0060	0.4390
age ³	1.000972	0.0886	0.0005	0.0342
educ1	1.000203	0.5431	0.0005	0.0782
educ2	1.000250	0.7811	0.0007	0.0925
nwinc	1.000156	-0.0056	0.0001	0.0115
spwage	1.000229	0.2068	0.0004	0.0568
sppart	1.000251	-1.6081	0.0033	0.4496
kids03	1.001568	1.6230	0.0022	0.1280
kids36	1.000694	0.5091	0.0009	0.0789
kids617	1.000167	0.2926	0.0002	0.0398
kids>17	1.000411	0.0605	0.0004	0.0416

Not-working β_1	R	mean	NSE	popstd
constant	1.000547	-7.5203	0.0154	1.7870
age	1.000732	0.5275	0.0014	0.1272
age ²	1.000902	-1.4703	0.0036	0.2926
age ³	1.001073	0.1356	0.0003	0.0218
educ1	1.000608	0.5781	0.0006	0.0533
educ2	1.000429	0.7896	0.0006	0.0631
nwinc	1.001075	-0.0068	0.0001	0.0064
spwage	1.001221	0.1416	0.0005	0.0303
sppart	1.001331	-1.1150	0.0039	0.2385
kids03	1.000751	1.5051	0.0009	0.0760
kids36	1.001634	0.6897	0.0009	0.0506
kids617	1.001866	0.3182	0.0005	0.0267
kids>17	1.000250	0.1144	0.0002	0.0279

Table 5. Results from the posterior density draws. Non-work parameters. Educ1, educ2, and educ3 correspond to low (ISCED 0-2), medium (ISCED 3) and highly educated (ISCED 5-7), respectively. The variables nwinc, spwage and sppart indicate household non labor income (logs), spouse's income from wages (logs) and a dummy indicator for spouse's participation. The 'kids' variables indicate the number of children in the various age groups.

	FT94	FT95	FT96	FT97	FT98	PT94	PT95	PT96	PT97	PT98	NW94	NW95	NW96	NW97	NW98
FT94	1	0.5708	0.5614	0.5111	0.4998	-0.1688	-0.1603	-0.1797	-0.1441	-0.1707	-0.4791	-0.4178	-0.3939	-0.3525	-0.3290
FT95		1	0.5917	0.5421	0.5340	-0.1506	-0.1780	-0.1850	-0.1496	-0.1786	-0.4438	-0.4657	-0.4175	-0.3759	-0.3544
FT96			1	0.5724	0.5604	-0.1348	-0.1491	-0.1788	-0.1308	-0.1557	-0.4474	-0.4475	-0.4748	-0.4188	-0.3963
FT97				1	0.5555	-0.1464	-0.1567	-0.1799	-0.1614	-0.1684	-0.3897	-0.3939	-0.4025	-0.4257	-0.3805
FT98					1	-0.1072	-0.1178	-0.1354	-0.1022	-0.1475	-0.4081	-0.4167	-0.4252	-0.4247	-0.4409
PT94						1	0.4604	0.4378	0.4182	0.3908	-0.2207	-0.2161	-0.2106	-0.2071	-0.2068
PT95							1	0.4918	0.4662	0.4406	-0.1885	-0.2626	-0.2399	-0.2372	-0.2368
PT96								1	0.4890	0.4645	-0.1529	-0.2080	-0.2626	-0.2340	-0.2387
PT97									1	0.4869	-0.1732	-0.2212	-0.2540	-0.3060	-0.2869
PT98										1	-0.1266	-0.1742	-0.2117	-0.2431	-0.2820
NW94											1	0.5709	0.5444	0.5015	0.4783
NW95												1	0.5880	0.5452	0.5247
NW96													1	0.5796	0.5613
NW97														1	0.5840
NW98															1

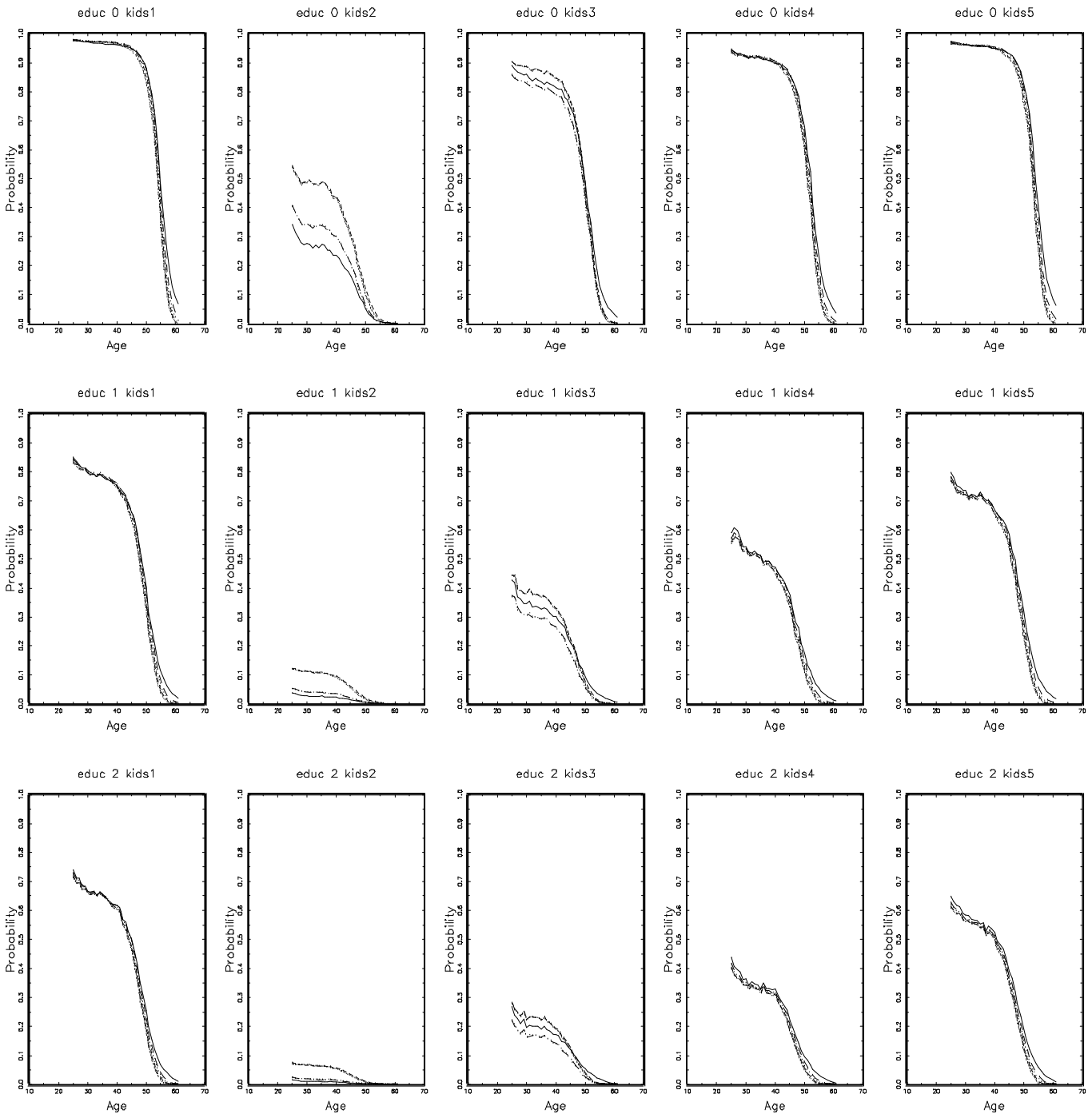
Table 6. Posterior means for the correlation coefficients. Wave 1 - 5 correspond to 1994 - 1998.

PT, FT, and NW indicate full time, part time and non-employment status, respectively.

Education	Age Group	Full Time		Part Time		Not-Working	
		Predicted	Observed	Predicted	Observed	Predicted	Observed
educ0	25-30	0.724	0.492	0.020	0.138	0.256	0.369
educ0	30-35	0.643	0.507	0.032	0.189	0.325	0.303
educ0	35-40	0.727	0.585	0.041	0.160	0.232	0.255
educ0	40-45	0.851	0.716	0.034	0.122	0.114	0.162
educ0	45-50	0.865	0.687	0.031	0.138	0.103	0.174
educ0	50-55	0.706	0.584	0.030	0.149	0.264	0.267
educ0	55+	0.225	0.210	0.016	0.060	0.759	0.730
educ1	25-30	0.364	0.365	0.038	0.115	0.598	0.520
educ1	30-35	0.296	0.317	0.055	0.199	0.649	0.484
educ1	35-40	0.371	0.330	0.075	0.212	0.553	0.458
educ1	40-45	0.448	0.386	0.089	0.291	0.463	0.323
educ1	45-50	0.474	0.359	0.080	0.232	0.446	0.409
educ1	50-55	0.204	0.314	0.047	0.171	0.749	0.514
educ1	55+	0.037	0.145	0.013	0.063	0.950	0.792
educ2	25-30	0.206	0.259	0.030	0.141	0.764	0.600
educ2	30-35	0.152	0.231	0.038	0.172	0.810	0.597
educ2	35-40	0.221	0.314	0.055	0.195	0.725	0.491
educ2	40-45	0.321	0.261	0.065	0.152	0.614	0.586
educ2	45-50	0.288	0.327	0.059	0.156	0.654	0.517
educ2	50-55	0.111	0.205	0.029	0.168	0.861	0.626
educ2	55+	0.017	0.094	0.007	0.113	0.976	0.793

Table 7. Mean fraction of women not working, working full time or working part time, for different age groups and education levels. The category educ0 indicates highly educated (ISCED5-7) educ1 indicates medium educated (ISCED 3) and educ2 indicates low educated (ISCED 0-2).

Figure 2. Life cycle profiles for the probability of working full time. Educ0, educ1, and educ2 represent highly, medium and low educated, respectively. Kids1 indicates no child. Kids2-5 indicate one child in age category [0,3), [3,6), [6,17) or [17,.) , respectively.



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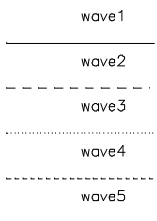
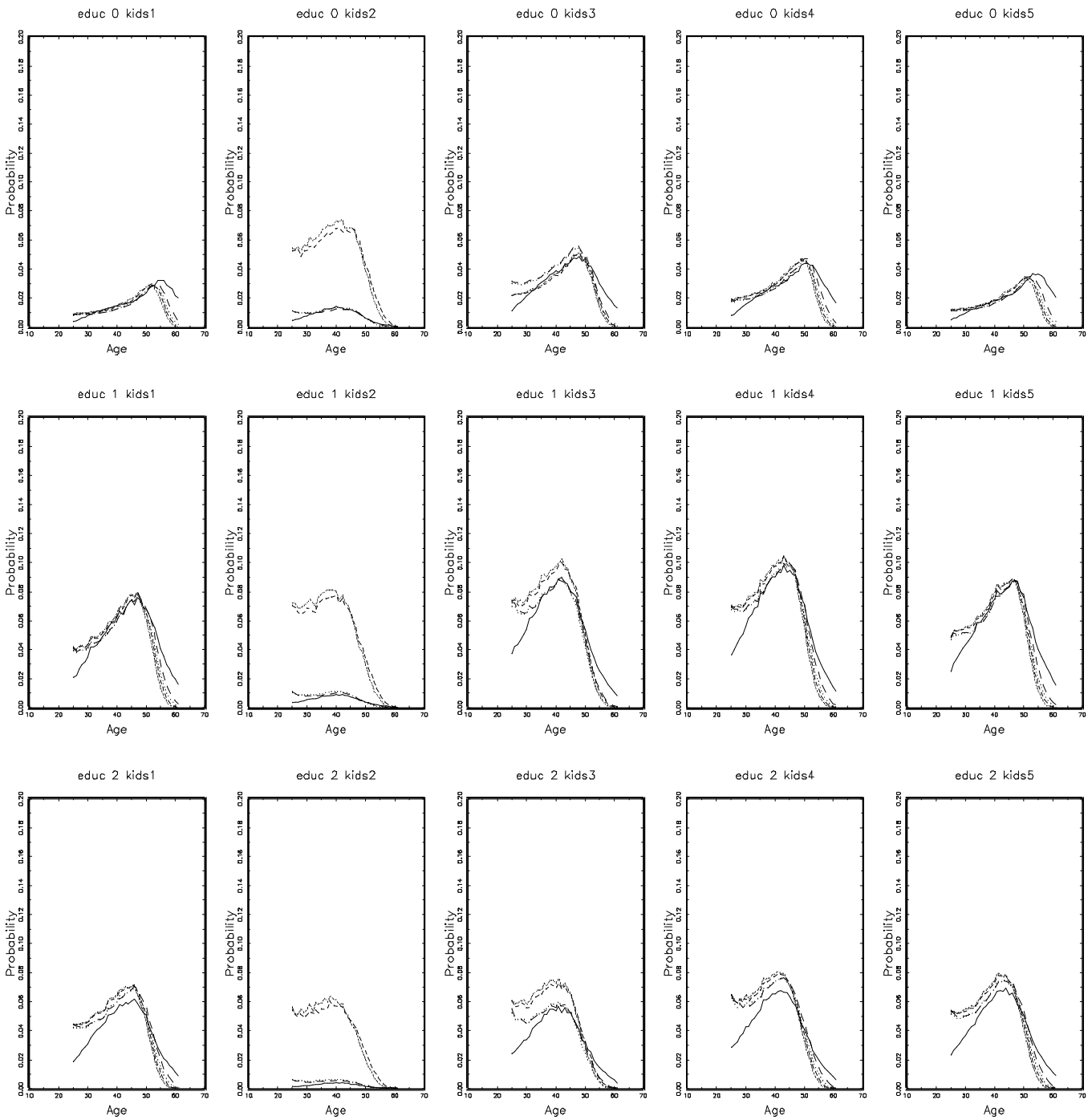


Figure 3. Life cycle profiles for the probability of working part time. Educ0, educ1, and educ2 represent highly, medium and low educated, respectively. Kids1 indicates no child. Kids2-5 indicate one child in age category [0,3), [3,6), [6,17) or [17,.) , respectively.



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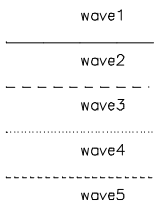


Figure 4. The effect of spouse type on the probability of working full time in wave 2.

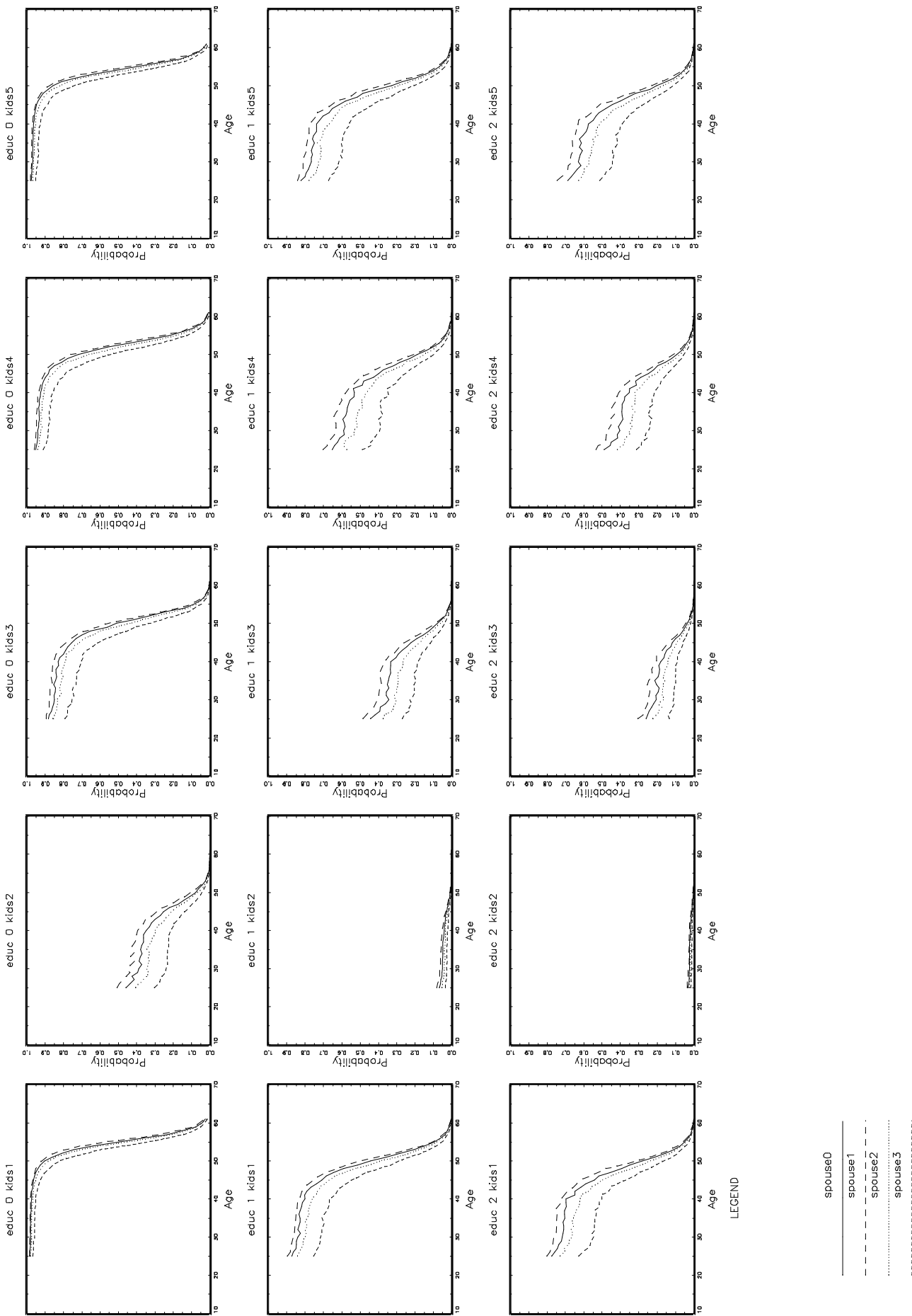
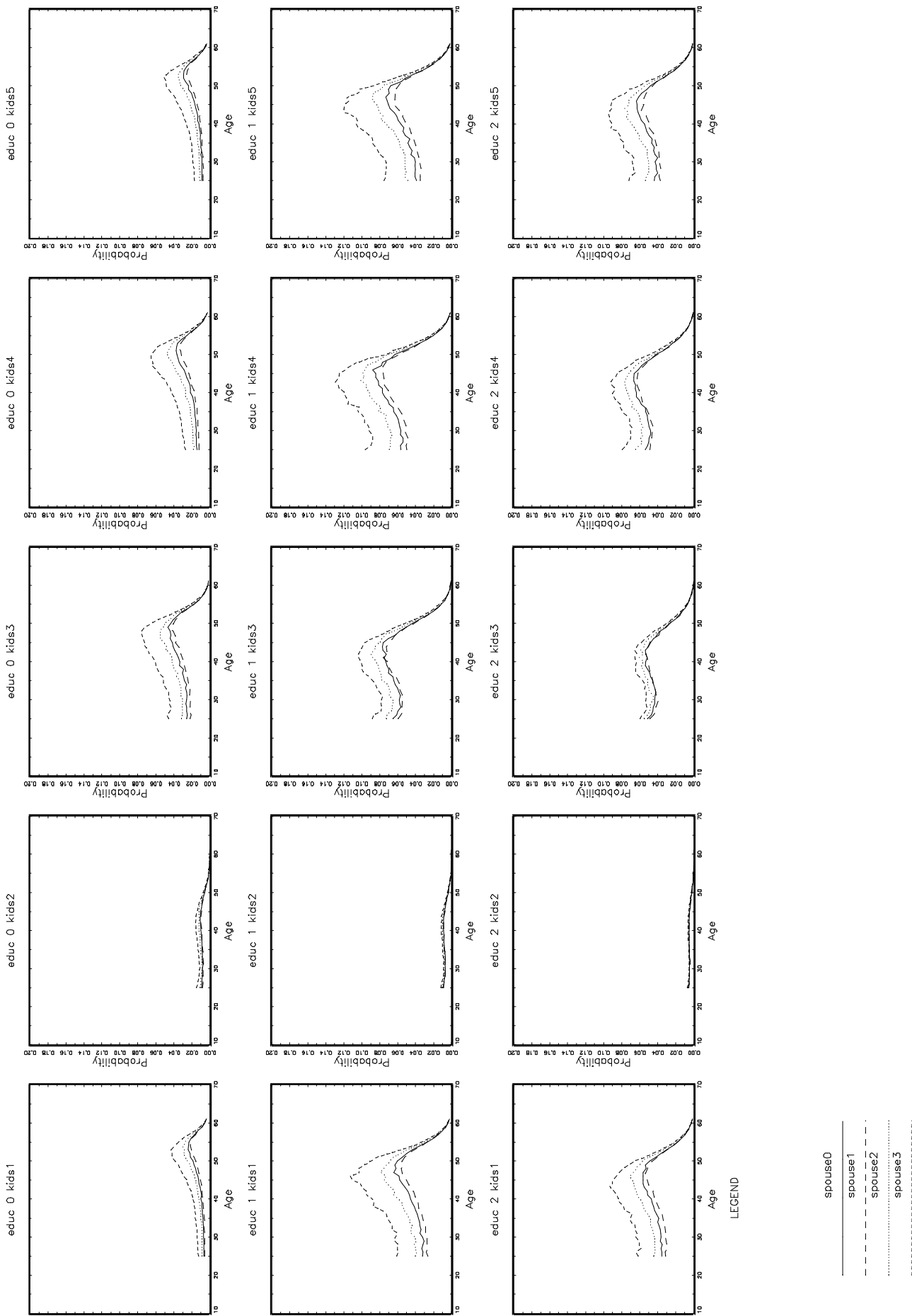


Figure 5. The effect of spouse type on the probability of working part time in wave 2.



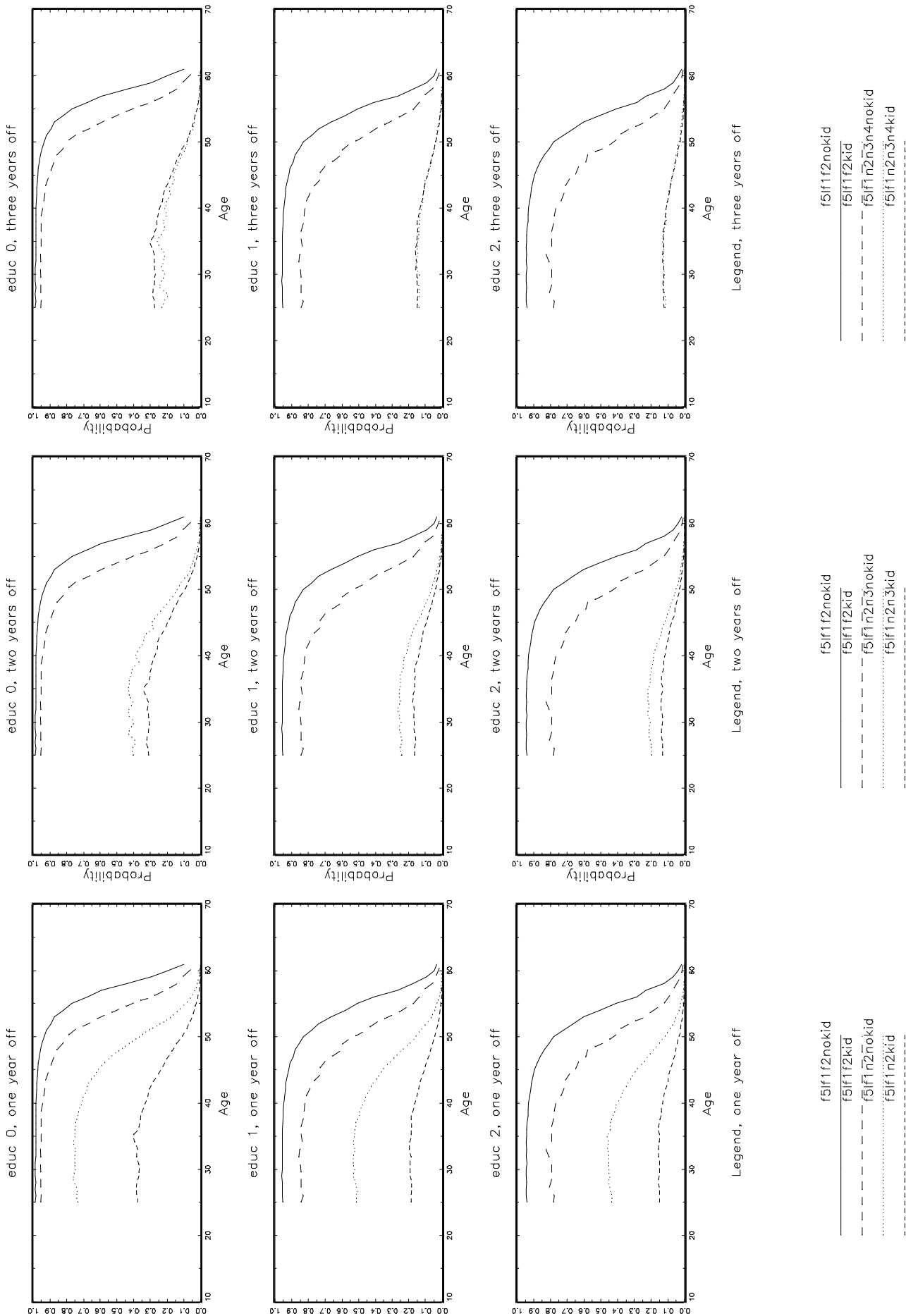


Figure 6. Conditional probabilities of working full time in wave 5, after an interruption.

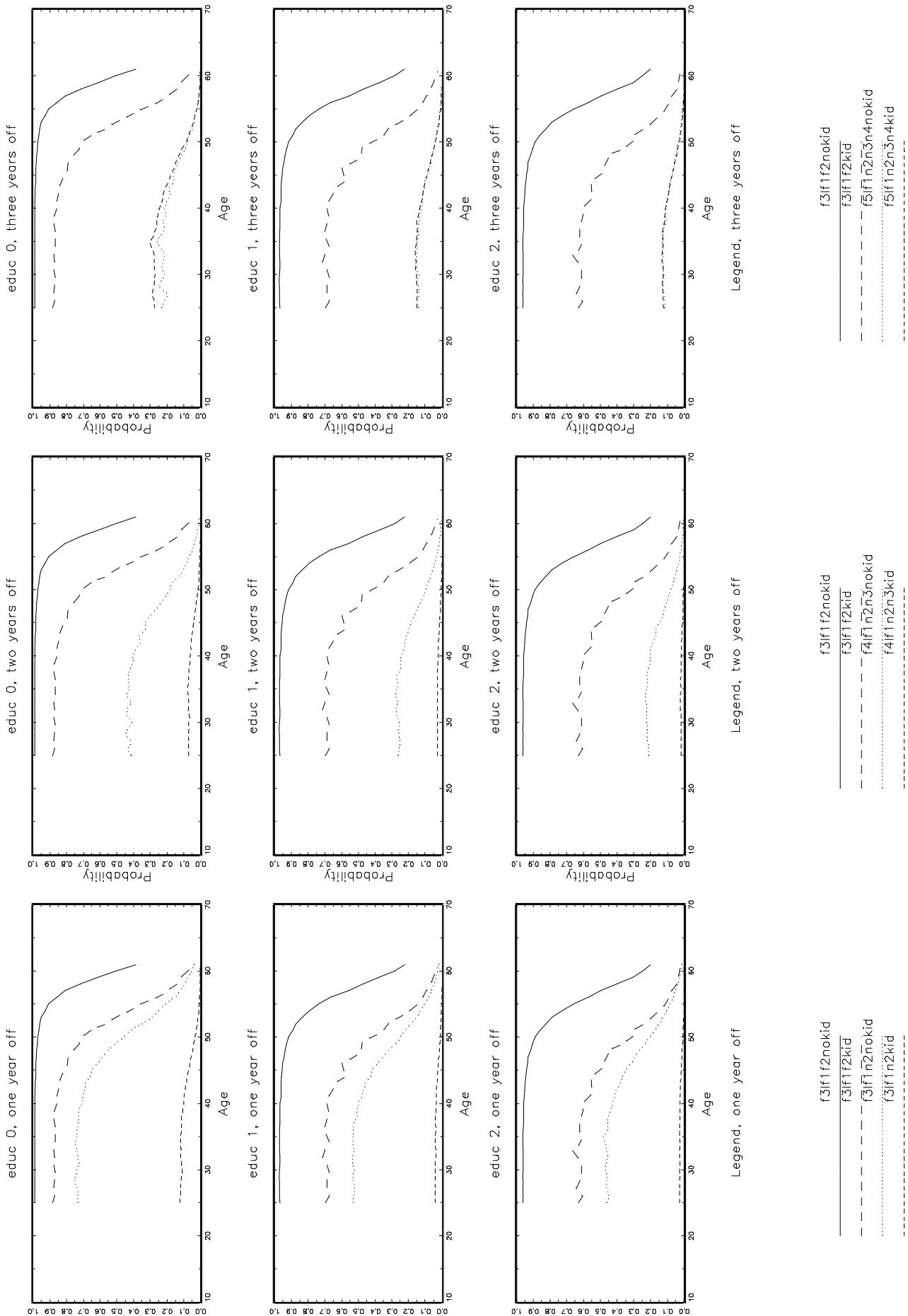


Figure 7. Conditional probabilities of working full time next period, after an interruption.

IZA Discussion Papers

No.	Author(s)	Title	Area	Date
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