Dynamic Labour Force Participation of Married Women and Endogenous Work Experience

Zvi Eckstein, Kenneth I. Wolpin

The Review of Economic Studies, Volume 56, Issue 3 (Jul., 1989).

Stable URL:
http://links.jstor.org/sici?sici=0034-6527%28198907%2956%3A3%3C%3ADLFPOM%3E2.0.CO%3B2-0

Your use of the JSTOR archive indicates your acceptance of JSTOR's Terms and Conditions of Use, available at http://www.jstor.org/about/terms.html. JSTOR's Terms and Conditions of Use provides, in part, that unless you have obtained prior permission, you may not download an entire issue of a journal or multiple copies of articles, and you may use content in the JSTOR archive only for your personal, non-commercial use.

Each copy of any part of a JSTOR transmission must contain the same copyright notice that appears on the screen or printed page of such transmission.

The Review of Economic Studies is published by The Review of Economic Studies Ltd.. Please contact the publisher for further permissions regarding the use of this work. Publisher contact information may be obtained at http://www.jstor.org/journals/resl.html.

The Review of Economic Studies
©1989 The Review of Economic Studies Ltd.

JSTOR and the JSTOR logo are trademarks of JSTOR, and are Registered in the U.S. Patent and Trademark Office. For more information on JSTOR contact jstor-info@umich.edu.

©2002 JSTOR

http://www.jstor.org/
Sun Nov 24 05:16:41 2002

Review of Economic Studies (1989) 56, 375-390 0034-6527/89/00250375$02.00
© 1989 The Review of Economic Studies Limited

Dynamic Labour Force Participation of Married Women and Endogenous Work Experience

ZVI ECKSTEIN
Tel-Aviv University

and

KENNETH I. WOLPIN
University of Minnesota

First version received February 1987; final version accepted December 1988 (eds.)

This paper presents and estimates a dynamic model of married women's labour force participation and fertility in which the effect of work experience on wages is explicitly taken into account. Because current participation alters future potential earnings, the investment return to work will be an important factor in the current work decision in any forward-looking behavioural model. The model is estimated using the National Longitudinal Surveys mature women's cohort. We use the estimates of our model to predict changes in the lifecycle patterns of employment due to changes in schooling, fertility, husband's income, and the magnitude of the experience effect on wages. We find that although work experience increases the disutility of further work, the effect is overwhelmed by the positive effect of experience on wages, leading to persistence in the employment patterns of these women. In addition we find that an increase in young children and in husband's income substantially reduces participation while increased schooling has a powerful positive impact on participation.

This paper presents an estimable structural dynamic model of married women's labour force participation and fertility in which wages are stochastic and work experience or cumulative participation is endogeneous. The model is structural in the sense that the parameters which are estimated are contained in the fundamental relationships governing behaviour, namely the utility function and the constraints. The model is contained in the class of models which describe the life-cycle capital accumulation process with endogeneous labour supply such as Weiss (1972) and Heckman (1976). It is closest in spirit to that of Weiss and Gronau (1981).[1] The basic feature of their model and ours is that labour market participation affects future wages, which then affects future participation. The investment return to current work will necessarily be taken into account in any forward-looking optimizing model. As Weiss and Gronau note, estimates of labour supply models have ignored the inherent behavioural dynamics associated with a positive wage-experience profile. There is no adequate empirical treatment of the human capital investment dimension of the labour force participation decision in the literature.

Heckman and Willis (1977) have studied a sequential discrete choice model of the labour force participation of married women in a reduced-form framework. Their work

1. See Weiss (1986) for a recent survey of the literature.

stresses the importance of unobserved population heterogeneity in accounting for persistence in observed labour force participation behaviour for which they find strong empirical support. However, as they discuss at length, their method does not allow for the existence of state dependence, i.e. prior employment status does not affect either the current shadow wage or the current market wage, or the introduction of time-varying variables such as age or the number and age distribution of children. Further, they provide informal evidence that true state dependence or omitted time-varying variables is important in the data. The method we develop and apply in this paper is capable of accommodating time-varying variables, state dependence, and unobserved heterogeneity. It involves solving the dynamic programming problem faced by the individual and embedding that solution is a maximum likelihood procedure (Wolpin, 1984, 1987).[2]

Another way to view this paper is as providing a firmer theoretical base for the recent literature on general dynamic discrete choice models as discussed by Heckman (1981). We specify the explicit dynamic finite horizon stochastic optimization problem that underlies the decision rules which are the starting point for the analysis by Heckman. Although we focus on labour force participation behaviour, the method is general enough to encompass models of fertility, schooling, job search, and job matching (see Eckstein and Wolpin (1986)).

Much of the recent life-cycle labour supply literature has attempted to integrate the participation and hours of work decisions. Empirical implementation of such life-cycle models is based on MaCurdy's (1978) insight that marginal-utility-of-wealth-constant demand functions can be estimated in a fixed-effect framework.[3] Although this is a major simplification, as MaCurdy has noted, only a subset of the parameters necessary to describe complete life-cycle labour supply behaviour can be estimated in this way. To fully characterize behaviour requires a complete solution of the life-cycle model, i.e. a solution for the evolution of the marginal utility of wealth in terms of the fundamental parameters. In addition, serious complications arise with this method when either the utility function is not intertemporally separable or when wages are a function of past actual labour supply, i.e. experience rather than age.[4]

Our model embodies intertemporal substitution in leisure over the life-cycle both through preferences and opportunities. These correspond loosely to the notion of timing and persistence discussed by Clark and Summers (1982), who argue that the relative importance of the two has an important bearing on the debate about the effect of government policy on aggregate performance. If leisure is intertemporally highly substitutable in utility, then inducements to participate currently will reduce future participation, while if work experience augments future wages, inducements to participate currently will increase future participation. We provide direct estimates of the timing and persistence components of the participation decision.

The model is estimated using data from the National Longitudinal Surveys mature women's cohort. We restrict attention to women who were between 39 and 44 years old

2. Alternative methods of estimating dynamic discrete choice models have recently been suggested by Miller (1984), Pakes (1986) and Rust (1987).

3. See also Heckman and MaCurdy (1980), MaCurdy (1981), MaCurdy (1983), and Browning, Deaton and Irish (1985).

4. The only paper of which we are aware to have incorporated endogenous experience is that by Sedlacek and Shaw (1984). They use generalized method of moments estimation in a continuous-hours labour supply model. However, such methods are not applicable when there are corner solutions and so are not useful to study female labour supply. The other empirical papers previously mentioned assume wages to depend on either rather than prior work experience. Hotz, Kydland and Sedlacek (1988) incorporate non-separability of leisure also using method of moments estimation.

in 1967, and who were therefore beyond the childbearing stage. The estimation considers only post-fertility employment decisions. In this way, we do not have to solve the model for both the optimal fertility and labour supply decisions during the fertile periods of the life cycle. We follow this cohort of women for as many consecutive years in which it was possible to tell whether or not they were employed in the market. Our results show that work experience increases the disutility of further work. However, this effect is overwhelmed by the positive effect of experience on wages, leading to persistence in employment. In addition, we find that an increase in young children and in husband's income substantiallly reduce participation. Schooling is also shown to increase the disutility of work, consistent with the notion that it increases productivity in the home. Nevertheless, increased schooling has a powerful positive impact on participation because of its substantial impact on market earnings.

The rest of the paper is organized as follows. Section 1 presents the model. The next section discusses issues of estimation and identification. The data are discussed in Section 3 and the results and interpretations are presented in Section 4. The final section presents concluding remarks.

1. THE MODEL

In this section we present a dynamic model of married female labour force participation and fertility. The household is assumed to maximize the present value of utility over a known finite horizon by choosing whether or not the wife will work (p_t), and whether or not to have an additional child (n_t) in each discrete period. The fertility decision is restricted to a known sub-period corresponding to the fertile period of the woman. The objective of the household, then, is to maximize

$$E_t\left[\sum_{k=0}^{T-t}\delta^j U(p_{t+k}, N_{t+k,j} x_{t+k}, K_{t+k-1}, S)\right] \tag{1}$$

with respect to p_t and n_t for periods $t=1,\ldots,\tau$ and for p_t only for $t=\tau+1,\ldots,T$. The variables are defined as follows: p_t is a dichotomous variable equal to unity if the woman does any market work during the period t and equal to zero otherwise; K_{t-1} is the number of prior periods the woman has worked; x_t is consumption during period t of a composite good; N_{ti} is a vector representing the number of children at time t of different ages i; S is the level of schooling; δ is the subjective discount factor; τ is the length of the fertile period; and T is the length of the decision horizon. The household's budget constraint in each period is

$$y_t^w p_t + y_t^H = x_t + \sum_{j=1}^{J} c_j N_{tj} + bp_t, \tag{2}$$

where y_t^H is husband's earnings, y_t^w the wife's earnings, c_j the goods cost per child of age j, and b a fixed cost of work. Husband's labour supply is taken as exogeneous to the decision about the woman's labour force participation.

The wife's earnings are stochastic and given by the standard Mincer earnings function

$$\ln y_t^w = \beta_1 + \beta_2 K_{t-1} + \beta_3 K_{t-1}^2 + \beta_4 S + \varepsilon_t, \tag{3}$$

where S and K_{t-1} are as previously defined. The random component of wages, ε_t, reflects changes in earnings that are independent of the household decision process.[5] It is assumed to have zero mean and finite variance and to be serially uncorrelated.

5. As with the mean wage, we could allow the variance of the wage distribution to depend on prior work decisions.

The number of children in age group j evolves according to

$$N_{tj} = N_{t-1,j} + n_{tj} - d_{tj}, \tag{4}$$

where $n_{tj} = 1$ if a child enters the age group at t and is otherwise zero, and $d_{tj} = 1$ if a child leaves the age group at t and is otherwise zero. Similarly, work experience evolves according to

$$K_t = K_{t-1} + p_t. \tag{5}$$

The initial values for N_{tj}, K_t, and p_t are zero. The terminal period T can either be considered as the end of life or as an exogenous retirement date, say, given by the husband's retirement date.

The assumption that the individual neither saves nor borrows is extreme. However, it should be noted that if the contemporaneous utility function given in (1) is linear and additive in consumption, then the problem reduces to that of wealth maximization modified by the psychic value of work and children. Indeed, if the monetary net costs and benefits of children and of work, as given in (2), are not observed, but treated as parameters, they are indistinguishable from their respective psychic values except by functional form. Pure wealth maximization is a special case.[6] We adopt the following functional form for period-specific utility, which, however, is not separable in consumption,

$$U_t = \alpha_1 p_t + x_t + \alpha_2 p_t x_t + \alpha_3 p_t K_{t-1} + \textstyle\sum_{j=1}^{J} \alpha_{4j} N_{tj} p_t + \alpha_5 p_t S + f(N_{ti}). \tag{6}$$

We do not adopt a specific functional form for the way children enter the utility function, i.e. we leave $f(N_{ti})$ unspecified, because we estimate the model only for the non-fertile period. Notice that the utility function is not assumed to be intertemporally separable ($\alpha_3 \neq 0$); $\alpha_3 < 0$ would reflect diminishing marginal utility of non-market time over the life cycle, while $\alpha_3 > 0$ could be interpreted as habit persistence.

Given the previous discussion, a test of wealth maximization is a test of whether α_2 is zero. Of course, if α_2 is not zero, the individual would be better off without the capital market constraint. This does not imply that if we find α_2 equal to zero that the capital market assumption is correct, because α_2 might not be zero in a model with perfect capital markets. It is useful to keep in mind the relevant trade-offs. To our knowledge, the only method available to estimate dynamic labour supply models which allow for non-participation and which incorporate endogeneous work experience and intertemporal non-separability is the full solution method. There are no shortcuts available. To accommodate state dependence in labour market participation, a characteristic of any life-cycle labour supply model in which wages depend on experience, we have assumed away intertemporal consumption decisions. Others have done the opposite by assuming wages depend on age rather than experience.

The dynamic programming solution to the optimization problem is obtained by a proces of backwards recursion. We limit attention in what follows to the post-childbearing period. Letting $V_t(K_{t-1}, \varepsilon_t, \Omega_t)$ be the maximum of expected discounted lifetime utility given K_{t-1} periods of experience (prior periods of employment), a wage draw of ε_t, and all other relevant components of the state space, Ω_t, including schooling S, the age distribution of children, N_{tj}, and the forecast (expected value) of husband's income $\bar{y}_t^H$,

$$V_t(K_{t-1}, \varepsilon_t, \Omega_t) = \max [V_t^1(K_{t-1}, \varepsilon_t, \Omega_t), V_t^0(K_{t-1}, \varepsilon_t, \Omega_t)] \tag{7}$$

6. In Eckstein and Wolpin (1986) we show how this model is nested in a more general class of discrete time structural models of labour force dynamics which can accomodate not only labour force participation but also job search and job matching.

where $V_t^1(\cdot)$ and $V_t^0(\cdot)$ are expected discounted lifetime utilities if the woman works ($p_t=1$) or does not work ($p_t=0$) respectively.[7] At T, the value functions are:

$$\begin{aligned} V_T^1(K_{T-1}, \varepsilon_T, \Omega_T) &= \alpha_1+(1+\alpha_2)(\exp\{\beta_1+\beta_2 K_{T-1}+\beta_3 K_{T-1}^2+\beta_4 S+\varepsilon_T\}+\bar{y}_T^H \\ &\quad -\textstyle\sum_{j=1}^J c_j N_{Tj}-b)+\alpha_3 K_{T-1}+\sum_{j=1}^J \alpha_{4j} N_{Tj}+\alpha_5 S+f(N_{Ti}) \qquad (8) \\ V_T^0(K_{T-1}, \Omega_T) &= \bar{y}_T^H-\textstyle\sum_{j=1}^J c_j N_{Tj}+f(N_{Ti}). \end{aligned}$$

The woman works if $V_T^1(\cdot)$ is greater than $V_T^0(\cdot)$. The explicit decision rule governing the participation decision at T is

$$\begin{aligned} p_T=1 \quad \text{iff } \varepsilon_T &\geqq \ln[-\alpha_1-\alpha_2(\bar{y}_T^H-\textstyle\sum_{j=1}^J c_j N_{Tj})+b(1+\alpha_2) \\ &\quad -\alpha_3 K_{T-1}-\textstyle\sum_{j=1}^J \alpha_{4j} N_{Tj}-\alpha_5 S] \\ &\quad -(\beta_1+\beta_2 K_{T-1}+\beta_3 K_{T-1}^2+\beta_4 S) \\ &= \varepsilon_T^*(K_{T-1}, \Omega_T) \qquad (9) \\ p_T=0 \quad &\text{otherwise.} \end{aligned}$$

The function $\varepsilon_T^*(K_{T-1}, \Omega_T)$ defines, for given Ω_t, T critical value of ε that depend on the T possible values of K_{T-1}. The solution at T is of the reservation price form; an ε_T draw higher than ε_T^* will induce the woman to work while a lower draw will not be accepted. It is clear from (9) that the effect of prior work experience on the reservation ε depends both on the experience-wage relationship and the effect of experience on the disutility of market participation. Assuming, as has been repeatedly documented, that wages increase with experience, only if α_3 is sufficiently negative will the reservation ε increase with experience.

For any t, $\tau<t\leqq T-1$, the analogous value functions are (where we drop Ω_t for convenience)

$$\begin{aligned} V_t^1(K_{t-1}, \varepsilon_t) &= \alpha_1+(1+\alpha_2)(\exp\{\beta_1+\beta_2 K_{t-1}+\beta_3 K_{t-1}^2+\beta_4 S+\varepsilon_t\}+\bar{y}_T^H-\textstyle\sum_{j=1}^J c_j N_{tj}-b) \\ &\quad +\alpha_3 K_{t-1}+\textstyle\sum_{j=1}^J \alpha_{4j} N_{tj}+\alpha_5 S+f(N_{ti}) \\ &\quad +\delta E V_{t+1}(K_t=K_{t-1}+1) \qquad (10) \\ V_t^0 &= \bar{y}_T^H-\textstyle\sum_{j=1}^J c_j N_{tj}+f(N_{ti})+\delta E V_{t+1}(K_t=K_{t-1}) \end{aligned}$$

where $EV_{t+1}(K_t)$ is given by the expected value of (7) and δ is the discount factor.

Because of the i.i.d. assumption about ε_t, the expected value operator in (10) is not time subscripted, i.e. $E_{t-j}V_t=EV_t$ for all $j\geqq 0$. The decision rule at t is

$$\begin{aligned} p_t=1 \quad \text{iff } \varepsilon_t &\geqq \ln[-\alpha_1-\alpha_2(\bar{y}_T^H-\textstyle\sum_{j=1}^J c_j N_{tj})+b(1+\alpha_2) \\ &\quad -\alpha_3 K_{t-1}-\textstyle\sum_{j=1}^J \alpha_{4j} N_{tj}-\alpha_5 S \\ &\quad +\delta(EV_{t+1}(K_{t-1})-EV_{t+1}(K_{t-1}+1))] \\ &\quad -(\beta_1+\beta_2 K_{t-1}+\beta_3 K_{t-1}^2+\beta_4 S) \\ &= \varepsilon_t^*(K_{t-1}) \qquad (11) \\ p_t=0 \quad &\text{otherwise.} \end{aligned}$$

7. We adopt the assumption that husband's earnings, though stochastic, is realized only after the woman's participation decision is made, which combined with the form of the utility function (6) implies that only expected earnings matters in the decision.

Given a distributional assumption for ε_t, it is possible to numerically solve for the set of $\varepsilon_t^*(K_{t-1})$'s by backwards recursion. Using (9) to obtain $\varepsilon_T^*(K_{T-1})$ we calculate $EV_T(K_{T-1})$ which then is used to calculate $V_{T-1}^1(K_{T-2})$ and $V_{T-1}^0(K_{T-2})$, which in turn yields $\varepsilon_{T-1}^*(K_{T-2})$ and the process is repeated.

The propensity to work over the life cycle is determined by the path and properties of the ε_t^*'s. It can be demonstrated by induction that (a) the propensity to work declines with age for given experience, i.e. $\varepsilon_t^*(K) < \varepsilon_{t+1}^*(K)$, and (b) unless α_3 is sufficiently negative the propensity to work increases with experience for any age, i.e. $\varepsilon_t^*(K) > \varepsilon_t^*(K+1)$. The declining propensity to work with age arises because the experience return to working in terms of higher future wages declines as one approaches the end of life. The increasing propensity to work at any age with greater experience arises simply because the wage rises monotonically with experience. This characteristic is offset to the extent that the marginal disutility of work increases with experience ($\alpha_3 < 0$). The experience effect is magnified in a dynamic model because the propensity to work in the future as viewed from the current period, and thus the likelihood of benefiting from the investment component of participation, is increased by current experience.[8]

2. ESTIMATION AND IDENTIFICATION

Given a simple of homogeneous individuals, it is clear that the reservation wage at any age cannot be greater than the smallest wage observed in the sample at that age; otherwise, that woman would not have worked. Thus, the age profile of reservation wages will be strongly influenced by wage outliers. To reduce that influence, it is assumed, not unreasonably, that wages are measured with error.[9] In particular, let

$$\ln y_t^w = \beta_1 + \beta_2 K_{t-1} + \beta_3 K_{t-1}^2 + \beta_4 S + \varepsilon_t + u_t, \tag{12}$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$, $u_t \sim N(0, \sigma_u^2)$, $E(\varepsilon_t u_t) = E(\varepsilon_{t-j} u_{t-k}) = E(\varepsilon_t \varepsilon_{t-j}) = E(u_t u_{t-j}) = 0$ for all $j \neq 0$, k.[10]

The joint likelihood function for labour force participation and earnings for a sample of I women, each observed for T_i periods, is given by

$$L = \prod_{i=1}^{I} \prod_{t=1}^{T_i} \left[\Phi\left(\frac{\varepsilon_t^*}{\sigma_\varepsilon}\right)\right]^{1-p_t} \left[\left(1 - \Phi\left(\frac{\varepsilon_t^* - \rho \dfrac{\sigma_\varepsilon}{\sigma_\eta}\eta_t}{\sigma_\varepsilon\sqrt{1-\rho^2}}\right)\right)\frac{1}{\sigma_\eta}\phi\left(\frac{\eta_t}{\sigma_\eta}\right)\right]^{p_t} \tag{13}$$

where ϕ is the standard normal density, Φ is the standard normal cumulative, $\eta_t = \varepsilon_t + u_t$, $\rho = \sigma_\varepsilon/\sigma_\eta$ and $\sigma_\eta = \sqrt{\sigma_\varepsilon^2 + \sigma_u^2} \cdot 1 - \rho^2$ is the fraction of the wage variance attributable to measurement error and ε_t^* is defined as in the previous section.[11]

It is important to recognize that the entire content of the theory is contained in the representation of the reservation values of ε, the ε_t^*'s. The ε_t^*'s are functions of the

8. Solving the model during the fertile period for both fertility and participation is conceptionally straightforward, but computationally more burdensome. Eckstein and Wolpin (1986) discuss the procedure when there is more than one discrete decision.

9. An alternative to measurement error would be to make the reservation wage stochastic by introducing an additional stochastic element into the optimization problem. For example, a preference parameter could be assumed random over time or husband's income might be assumed to be better forecasted by the household than by the researcher. However, measurement error in the wage is simpler because it does not require modifying the solution to the optimization problem.

10. Allowing u and ε to be correlated is a minor complication. Allowing ε to be serially correlated creates major complications both in solving the dynamic programme and in estimation.

11. The second component of the likelihood function uses the fact that the joint normal distribution of ε_t and η_t can be written as the product of a conditional normal and a marginal normal.

fundamental parameters of the model, the preference parameters of equation (6), the budget constraint parameters of equation (2) and the earnings function parameters of equation (3). In the more standard astructural approach to labour force participation, the ε_t^*'s would be a linear-in-parameters function of contemporaneous obserable variables such as husband's earnings and children.[12] The likelihood function of alternative models of the employment decision, e.g. job search models or the astructural labour force participation approach, would be identical to (13), except for the determination of the ε_t^*'s. All such models are thus nested in a common unrestricted model in which these ε_t^*'s are free to vary over the life cycle independently of one another.

Initial conditions

As long as there is no serial dependence in unobservables, experience and the age distribution of children can be treated as predetermined; conditioning on either of them even though they reflect prior decisions does not lead to inconsistent parameter estimates. However, if there is any unobserved (to the researcher) permanence in the decision process, then conditioning on prior choices will lead to biased and inconsistent parameter estimates. Suppose that a preference parameter in equation (6) is individual-specific and uncorrelated with other random variables; for example, individuals may differ in their taste for children. Several estimation strategies have been suggested in this case. With the usual caveat concerning "consistency" in short panels, it is possible to estimate a separate taste parameter for each individual, i.e. fixed effects (Heckman (1981)). A random effects discrete mixture approach as discussed in Heckman and Singer (1984) is also feasible and will produce consistent parameter estimates if the entire history is available. Alternatively, if the entire history is not available, the current marginal distribution of the state variable can be calculated by solving the dynamic programming problem back to the initial period and then integrating over all possibilities in the future up to the first period of the data. All of these approaches increase the computational burden.

Identification

Ignoring the optimization problem first, it is clear from (13) that in the unrestricted model all of the ε_t^*'s, the wage parameters $(\beta_1, \beta_2, \beta_3, \beta_4)$, σ_ε, and σ_η are identified from data on participation and wages. The logarithmic form of the wage function is not necessary for identification. Identification of the parameters of the dynamic participation model can be established by considering the form of the ε_t^*'s. It is clear from (9) that using data in period T, the following parameters are identified; α_2, α_3, α_5, $\alpha_1+b(1+\alpha_2)$, and $\alpha_2 c_j-\alpha_{4j}$ $(j=1,\ldots,J)$. Because of the recursive nature of the solution as shown by (11), using data from other periods will still not permit α_1 to be distinguished from b, or c_j to be distinguished from α_{4j}. In what follows, we assume $b=0$ and $c_j=0$ for all j, but the reader should keep in mind that the utility parameters α_1 and α_{4j} cannot really be distinguished from their corresponding budget parameters.

3. THE DATA

The data are from the mature women's cohort of the National Longitudinal Survey of Labor Market Experience. The original sample consisted of approximately 5000 women

12. The general approach to estimating labour supply models in this way is due to Heckman (1974).

between the ages of 30 and 44 in 1967. These women had been interviewed 11 times between 1967 and 1982. The sample used in our analysis consists of white women age 39 to 44 in 1967, who were married at most once and whose spouse was present at each interview between 1967 and 1982, and for whom at least four consecutive years of data on labour force participation beginning in 1966 could be derived. Unfortunately, it is difficult to determine whether a woman engaged in any market work (at least one week) during each calender year even if there is no missing information in the data. This is due to the fact that in the years following a non-interview year, employment data were not collected back to the previous interview date, but only for the last 12 months. Using primarily information on weeks worked in the 12 months prior to the interview and survey week employment data, we constructed a continuous annual employment profile for each woman beginning in 1966 for as long a period as possible up to 1981. The employment series was terminated for any woman at any year in which we would not be certain as to her employment status even if subsequent years' employment could be determined. The distribution of women by years of data is shown in Table I. The 318 women comprising the sample are not evenly distributed over the number of years that they have consecutive participation data. Almost one-fifth of the sample has all 16 years of data and almost three-fifths have over ten years of data. Almost all of the rest of the women have the minimum of four years used as the sample selection criterion.

TABLE I

Distribution of observations by number of years of employment data

Number of years	4	5	6	7	8	9	10	11	12	13	14	15	16
Number of observations	104	8	6	0	12	1	2	105	4	1	0	13	62
Cumulative proportion of observations	0·33	0·35	0·37	0·37	0·41	0·41	0·42	0·75	0·76	0·76	0·76	0·81	1·00

The participation data from this sample are likely to be biased towards greater employment than in the entire population of women with the same characteristics. It is simply easier to determine whether a woman did market work in any week of a given calendar year than to determine whether she did no maket work in every week. In all, we have 3020 annual observations for the 318 women. Of those, there were 1587 work periods, 53% and 1433 non-work periods. In addition, 26% of the women worked in each period for which we have data, 42% did not work in any period, and 31% had some periods of work and some of no work.

The other variables used in the analysis were calculated in the following manner. To calculate husband's expected (real) earnings, a logarithmic husband's earnings regression was run which contained a linear and a quadratic term in husband's age, an individual-specific constant, and a schooling-age interaction. It is assumed that each household uses this equation in forecasting future husband's earnings. Work experience is based on a question in the 1982 survey which asked for the total number of years since age 18 in which the woman worked at least two weeks during the year. The number of years of work experience between 1966 and 1981 is calculated by working backward from the 1982 data under the assumption that the woman did no market work in the years in which actual participation could not be discerned. Table II presents descriptive statistics for these variables.

Wages are available in 406 periods or only about 25% of all employment periods. The real hourly wage rate is obtained by dividing real annual earnings by annual hours worked. In solving the dynamic programme, actual hours worked are ignored; each woman's hourly wage rate is multiplied by 2000 hours to obtain potential annual earnings.[13] In esssence, each woman is assumed to be deciding about full-time work and the wage rate is assumed to be independent of hours worked. The missing observations arise either because there are some years without interviews or because earnings and/or hours worked are unreported.[14] The (ln) real hourly wage rate regression on these data yield the following coefficients and standard errors: $\beta_1 = -0{\cdot}61$ (0·13), $\beta_2 = 0{\cdot}037$ (0·012), $\beta_3 = -0{\cdot}0005$ (0·0036), $\beta_4 = 0{\cdot}08$ (0·01). These results, the concavity of the experience profile and the positive schooling effect, are consistent with many other studies. It should be noted, however, that these estimates are not selectivity corrected and that the standard correction may not be consistent with the structural model.

As a parsimonious means of describing the pattern of participation, Table III presents a probit which includes the variables in Table II as regressors. Women with more experience, who are younger, with lower husband's earnings, with fewer young children,

TABLE II

Descriptive statistics

	Mean	Standard deviation
Years of work experience	12·5	9·7
Age	46·4	4·3
Husband's expected earnings	8950	4725
Schooling	11·0	2·7
Number of children less than six	0·091	0·35
Number of children six to 17	1·17	1·5
Hourly wage (dollars)	2·27	1·39

TABLE III

Employment probit

	Coefficient	Standard error	Partial derivative evaluated at means
Experience	0·133	0·010	0·052
Experience squared	−0·002	0·0003	−0·0007
Age	−0·004	0·007	−0·002
Husband's earnings (0·01)	−0·102	0·0007	0·004
Number of children less than six years of age	−0·635	0·103	−0·25
Number of children six to 17 years of age	0·010	0·020	0·004
Schooling	0·118	0·012	0·047
Constant	−1·27	0·354	—
Log likelihood	−1445·4		

13. Thus in equation (2) we write y_t^w = hourly wage × 2000. In addition we estimate the hourly wage function rather than the earnings function, so the β_1 we report differs from the representation in (3) by ln 2000.

14. The likelihood function given by equation (11) must be modified slightly to account for observations of participants with unobserved wages. Those individuals each will contribute a term $1-\Phi(\varepsilon_t^*/\sigma_\varepsilon)$ to the sample likelihood.

with more older children, and with higher schooling are more likely to work. The experience and age participation relationships in particular are consistent with the nodel of the previous section. These results are consistent with the findings across many other data sets.

4. RESULTS

The maximum likelihood estimates and asymptotic standard errors are presented in the first column of Table IV.[15] The sign of the parameters conform to priors. Participation reduces utility ($\alpha_1 < 0$) and the marginal utility of children is lower when the woman participates ($\alpha_4 < 0$), particularly for young children. Also, the value of goods consumption is reduced when the woman participates ($\alpha_2 < 0$) and the disutility of work increases with schooling ($\alpha_0 < 0$), i.e. schooling enhances home production. In addition, the disutility of work increases with the amount of prior work ($a_3 < 0$), rather than there being habit persistence. The hourly wage rate increases with experience at a decreasing rate and increases with schooling. It turns out that the proportion of the wage variance due to measurement error is very high, approximately 85%. Standard errors are generally small. A two standard deviation change in all but two cases would not reverse the signs

TABLE IV

Maximum likelihood estimates

Parameters	Full sample	Restricted sample (fixed effects)
α_1	−1357	—
	(213)	
α_2	−0·047	−0·017
	(0·008)	(0·0013)
α_3	−11·5	−31·9
	(7·14)	(15·3)
α_{41}	−353	−271
	(82·0)	(27·7)
α_{42}	−15·6	−39·9
	(9·17)	(3·65)
α_5	−95·6	—
	(14·5)	
β_1	−0·280	0·200
	(0·135)	(0·112)
β_2	0·024	0·018
	(0·005)	(0·0064)
β_3	−0·0002	−0·0003
	(0·00005)	(0·00004)
β_4	0·050	0·015
	(0·007)	(0·0011)
σ_ϵ	0·194	0·033
	(0·041)	(0·003)
ρ	0·380	0·060
	(0·018)	(0·007)
$\ln L$	−1741·6	−532·95

Note. Asymptotic standard errors in parentheses.

15. The discount factor was set at 0·952, i.e. an annual rate of time preference of 0·05. Also to save on computation, the horizon is fixed at age 60, the last period about which a decision to work or not is assumed to be made. As noted, one can think of this as an exogenous retirement age.

of the parameters.[16] In this regard, an asymptotic t-test would not reject the hypothesis that $\alpha_3 = 0$ at the five percent significance level. Restricting α_3 to be zero would reduce the effect of experience on wages. Similarly, assuming away any wage-experience relationship, although clearly not justified by the results, would force α_3 alone to account for the persistence in participation, and thus to be positive rather than negative. With respect to the wage function parameters, in comparison to those estimates shown previously, jointly estimating the dynamic labour force participation and wage functions leads to a less-steep experience profile and a lower return to schooling. The direction of the movement in these parameters is reinforced by the estimated utility parameters α_3 and α_5 in terms of the effect of experience and schooling on labour force participation. The behavioural interpretations of these parameter values are presented below in simulations which demonstrate the impact of changes in the values of the parameters and in the exogenous forcing variables on the profile of employment probabilities. First, however, we provide tests of goodness of fit.

Several goodness of fit tests are performed. Table V compares the predicted employment proportions to actual proportions. As indicated in the first column of Table V, the actual experience-employment profile is steeply rising. The predicted profile parallels the actual in this characteristic. Thus, the increased wage offsets the increased disutility of work associated with more work experience. A chi-square test does not reject the null hypothesis that predicted and actual proportions are the same at the five percent level. Tabel V also cross-tabulates actual and predicted employment proportions by experience and age. The proportion of women who work increases with experience within each age

TABLE V

Actual and predicted participation rates by years of work experience and age

			Age								
	All ages		39–42		43–46		47–50		51–58		χ^2
Experience	A	P	A	P	A	P	A	P	A	P	(row)
0	0·098 (224)	0·139	0·1321	0·1401	0·1236	0·1520	0·0164	0·1158	0·1429	0·1120	5·88
1–5	0·244 (713)	0·226	0·3057	0·2343	0·2893	0·2425	0·1047	0·1998	0·2941	0·2135	17·18*
6–10	0·385 (634)	0·430	0·4934	0·4965	0·3644	0·4295	0·3298	0·3953	0·3623	0·3832	4·33
11–15	0·729 (398)	0·636	0·7312	0·7190	0·7248	0·6414	0·5714	0·5752	0·8861	0·5861	13·71*
16–20	0·742 (325)	0·754	0·7246	0·8040	0·7182	0·7665	0·6338	0·7267	0·8933	0·7154	5·04
21–25	0·754 (333)	0·820	0·8315	0·8294	0·7248	0·8228	0·6282	0·8014	0·8596	0·8255	4·24
26+	0·929 (393)	0·885	0·8000	0·8810	0·9192	0·8726	0·9053	0·8794	0·9565	0·8942	1·23
χ^2 (column)	7·53		4·12 (628)		8·69 (1061)		19·73* (761)		19·12* (570)		

Note. A = Actual, P = Predicted, * signifies the actual and predicted to be statistically different, $\chi^2 = \sum (n_p - n_a)^2/n_p$, n_p = number predicted, n_a = number actual $\chi^2_6(0{\cdot}05) = 12{\cdot}59$, $\chi^2_3(0{\cdot}05) = 7{\cdot}82$. Sample sizes are in parentheses.

16. Estimation was performed using the GQOPT package. A search routine NMSIMP was first used to reach the neighborhood of the optimum and then a gradient routine GRADX was used. Derivatives of the likelihood function are all numerically calculated because the dynamic programme solution can only be obtained numerically. Standard errors are obtained directly from GRADX.

group. The pattern is more complex within experience groups. Except for the largest experience class, the pattern is for the proportion of working women to decline from ages 30 to 50 and then to rise. The chi-square statistics reveal that the model does not accurately capture the experience profile for the older groups, but does accurately capture the age profile for all experience classes but two.

An alternative explanation for persistence in employment is unobserved heterogeneity, e.g. some women may dislike work less intensely than others. We, therefore, estimated a fixed-effects model allowing α_1 to differ for each woman for whom an individual-specific parameter was estimable, i.e. for each woman who switched employment status. The parameter estimates are shown in the second column of Table IV for the restricted sample of 98 women.[17] Compared to the full sample results, the fixed-effect estimates are qualitatively identical. The positive wage-experience relationship is slightly diminished and the effect of experience on the disutility of work somewhat increased. Most importantly, however, persistence due to state dependence remains when unobserved heterogeneity is introduced. (We present the non-fixed-effect estimates for the restricted sample in Appendix A.)

Although the employment probit in the previous section shown in Table II is not nested in the structural model (nor vice versa), it is informative to compare their relative within-sample predictive content. The probit can be viewed as a simple linear approximation to the ε_t^*'s generated by the dynamic programming model. The reduced form parameters of the probit are unspecified functions of the structural parameters of the optimization model. The structural model estimates six employment related parameters (the α's) while the probit estimates seven. A χ^2 test using the probit applied to Table V (All Ages) yields a value of 27·1 which is much greater than shown in Table V for the structural model. In a loose sense the structural model fits the observed experience-participation profile better than the probit with one less parameter. Indeed, in order to obtain the structural non-linearities present in the ε_t^*'s of the model, an incredibly large number of parameters would need to be estimated in any approximation to the ε_t^*'s. Therefore, the dynamic model provides a much more parsimonious representation of the data.

Simulations

The probability of working by age and experience for a woman of fairly representative characteristics is shown in Table VI based on the estimated parameters of the full sample shown in Table IV.[18] As is consistent with the observed experience profile of participation rates, working probabilities increase with experience at each age quite rapidly. For given experience, the probability of working declines with age as the finite horizon is approached. Using the table it is possible to trace out the employment probability profile over the life cycle for different experience profiles. Thus, a woman with five years of work experience at age 39 who does no market work thereafter will almost halve the probability of working by age 59. If she works five years out of each ten, her working probability will rise by 28% by age 59 while if she works in every subsequent year, her probability of working

17. α_5 is not estimable because schooling does not change over time for any of the women in the reduced sample. An alternative would have been to introduce a fixed-effect into the wage function to capture permanent differences in participation patterns. We did not pursue this strategy because it would have required two wage observations for each individual and the wage data, as noted, has such an extremely high proportion of missing observations.

18. We chose to do the simulations based on the full sample because of the larger sample size. However, the main result would not be altered significantly using the restricted sample.

TABLE VI

Predicted probability of working by age and experience

	Age		
Experience	39	49	59
0	0·138	0·113	0·094
5	0·398	0·280	0·207
10	0·648	0·497	0·356
15	0·781	0·673	0·510
20	0·849	0·783	0·642
25	—	0·846	0·741
30	—	0·879	0·808
35	—	—	0·851
40	—	—	0·876

Note. Schooling is 12 years, husband's earnings is 10,000 each year, and there are no children in the household at age 39.

will rise 86%. For a woman with 20 years of experience at age 39, the age effect essentially cancels the experience effects even if she continues to work, so that by age 59 her probability of working will be almost the same.

Tables VII(a)-(d) simulate the effects of changing household characteristics on the expected numbers of additional years of work from age 39 to age 60. To summarize briefly, increasing husband's earnings (Table VII(a)) substantially reduces anticipated

TABLE VII(a)

Expected number of years worked from age 39 to age 59 for given experience at age 39 by husband's earnings

	Husband's earnings				
Experience	5000	10,000	15,000	25,000	50,000
0	1·825	1·013	0·677	0·170	0·002
5	4·640	1·782	1·085	0·507	0·011
10	8·102	3·661	1·725	0·898	0·054
15	10·930	5·910	2·961	1·172	0·176
20	12·747	7·807	4·317	1·553	0·398

Note. Schooling is 12 years, and there are no children in the household at age 39.

TABLE VII(b)

Expected number of years worked from age 39 to age 59 for given experience at age 39 by schooling level

	Schooling		
Experience	8 years	12 years	16 years
0	0·742	1·013	1·907
5	1·118	1·781	5·247
10	1·725	3·661	9·205
15	2·801	5·910	12·280
20	3·936	7·807	14·185

Note. Husband's earnings is 10,000 per year, and there are no children in the household at age 39.

TABLE VII(c)

Expected number of years worked from age 39 to age 59 for given experience at age 39 by age and number of children at age 39

	Children's age(s)			
Experience	None	4	16	4 and 16
0	1·013	0·909	1·005	0·907
5	1·781	1·914	1·746	1·180
10	3·661	2·231	3·605	2·180
15	5·910	4·150	5·860	4·067
20	7·807	6·153	7·769	6·064

Note. Schooling is 12 years and husband's earnings is 10,000 per year.

TABLE VII(d)

Expected number of years worked from age 39 to age 59 for given experience at age 39 by the wage-experience slope (β_2)

	Wage-experience slope (β_2)			
Experience	0	0·01193	0·02385	0·04770
0	0·897	0·936	1·034	21·0
5	0·837	1·052	5·965	21·0
10	0·770	1·179	16·726	21·0
15	0·698	1·393	20·414	21·0
20	0·624	1·805	20·956	21·0

Note. Schooling is 12 years and husband's earnings is 10,000 per year, there are no children in the household at age 39, and $\beta_3 = 0$.

employment; increasing husband's earnings from 5000 to 10,000 dollars about halves the expected number of future employment years at most current levels of experience. Schooling has offsetting effects. It increases wages and increases the disutility of work. On balance, increased schooling substantially increases the expected years of work (Table VII(b)). The presence of a young child at age 39 substantially reduces future work while the presence of an older child has a minor effect (Table VII(c)). Changing the wage-experience profile has a powerful effect on work (Table VII(d)). Because experience increases the disutility of work, a flat wage-experience profile would actually lead to a negative experience-work profile. Leisure seems to be mildy substitutable over time. Halving the slope of the log wage-experience profile implies that for a woman with ten years of experience at age 39, the expected additional number of years of work to age 60 will fall from 16·7 to 1·2. Doubling the coefficient implies that all women will work in every year subsequent to age 39 independent of work experience at age 39.

CONCLUDING REMARKS

In this paper we have estimated a structural dynamic model of married women's labour force participation and used the estimates to predict changes in the life cycle pattern of employment due to changes in schooling, fertility, and the wage-generating process. The model was shown to fit the observed data adequately. An important feature of the data is persistence, in that women who participate at one age are more likely to participate at future ages. By estimating a structural model we are able to distinguish between the effect of work experience on wages and on the disutility of employment. It turns out that, in fact, the disutility of work increases with experience which by itself, would lead to negative state dependence. It is the large positive estimated experience effect on wages which, thus, leads to the positive state dependence observed in the data. Persistence due to state dependence was also shown to be robust to the introduction of unobserved heterogeneity in preferences for work. Schooling, which enters both the utility function and the wage function, behaves in the same way as does experience, increasing the disutility of work but increasing the wage sufficiently to yield a positive schooling-participation profile. In addition, we find that an increase in young children and in husband's earnings both reduce participation substantially. However, increases in the level of schooling has the largest (positive) impact on participation. For example, at ten years of experience and at age 39, the elasticity of the expected number of additional years worked with respect to schooling is 4·6. This is suggestive of the potential importance of schooling as a determinant of the increased labour force participation of women over time. Stronger conclusions would require considering the interaction of both schooling and labour force participation as choice variables.

APPENDIX A

Maximum likelihood estimates for the restricted sample (non-fixed-effects)

α_1	−2578	β_1	0·276
	(5·02)		(0·030)
α_2	−0·015	β_2	0·010
	(0·002)		(0·026)
α_3	4·52	β_3	−0·0002
	(80·7)		(0·0001)
α_{41}	−330	β_4	0·011
	(0·443)		(0·038)
α_{42}	−27·4	σ_ϵ	0·105
	(0·147)		(0·26)
α_5	−10·1	ρ	0·185
	(112)		(0·014)
$\ln L$	−721·48		

Note. Asymptotic standard errors in parentheses.

Acknowledgement. This paper was prepared under a contract with the Employment and Training Administration, U.S. Department of Labor, under the authority of the Comprehensive Employment and Training Act. Researchers undertaking such projects under government sponsorship are encouraged to express their own judgments. Interpretations or viewpoints contained in this paper do not necessarily represent the official position or policy of the Department of Labor. Funding was also received under NSF grant SES-8502214 and is gratefully acknowledged. Yoram Weiss provided useful comments as did several anonymous referees. Tung-hao Lee and Hwei-Lin Chuang provided most able research assistance.

REFERENCES

BELLMAN, R. E. (1957), *Dynamic Programming* (Princeton, NJ: Princeton University Press).

BROWNING, M., DEATON, A. and IRISH, M. (1985), "A Profitable Approach to Labor Supply and Commodity Demands over the Life Cycle", *Econometrica*, **53**, 503–543.

CLARK, K. B. and SUMMERS, L. H. (1982), "Labour Force Participation: Timing and Persistence", *Review of Economic Studies*, **49**, 825–844.

ECKSTEIN, Z. and WOLPIN, K. I. (1986), "On the Estimation of Labor Force Participation, Job Search, and Job Matching Models Using Panel Data", in Weiss, Y. and Fishelson, G. (eds.), *The Theory and Measurement of Unemployment* (London: Macmillan).

HECKMAN, J. J. (1974), "Shadow Prices, Market Wages, and Labor Supply", *Econometrica*, **42**, 679–694.

HECKMAN, J. J. (1976), "A Life Cycle Model of Earnings, Learnings and Consumption", *Journal of Political Economy*, **84**, 511-544.

HECKMAN, J. J. (1981), "Statistical Models for Discrete Panel Data", in Manski, C. and McFadden, D. (eds.), *Structural Analysis of Discrete Data with Econometric Applications* (Cambridge: The MIT Press).

HECKMAN, J. J. and MACURDY, T. E. (1980), "A Life Cycle Model of Female Labour Supply", *Review of Economic Studies*, **47**, 47-74.

HECKMAN J. J. and SINGER, B. (1984), "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data", *Econometrica*, **52**, 271-320.

HECKMAN, J. J. and WILLIS, R. J. (1977), "A Beta Logistic Model for the Analysis of Sequential Labor Force Participation of Married Women", *Journal of Political Economy*, **85**, 27-58.

HOTZ, V. J., KYDLAND, F. E. and SEDLACEK, G. L. (1988), "Intertemporal Preferences and Labor Supply", *Econometrica*, **56**, 411-432.

MACURDY, T. E. (1978), "Two Essays on the Life Cycle" (unpublished Ph.D. dissertation, University of Chicago).

MACURDY, T. E. (1981), "An Empirical Model of Labor Supply in a Life Cycle Setting", *Journal of Political Economy*, **89**, 1059-1085.

MACURDY, T. E. (1983), "A Simple Scheme for Estimating an Intertemporal Model of Labor Supply and Consumption in the Presence of Taxes and Uncertainty", *International Economic Review*, **24**, 265-289.

MILLER, R. A. (1984), "Job Matching and Occupational Choice", *Journal of Political Economy*, **92**, 1086-1120.

PAKES, A. (1986), "Patents as Options: Some Estimates of the Value of Holding European Patent Stocks", *Econometrica*, **54**, 755-784.

RUST, J. (1987), "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher", *Econometrica*, **55**, 999-1034.

SEDLACEK, G. and SHAW, K. L. (1984), "An Empirical Model of Life-Cycle Labor Supply and Human Capital Accumulation" (Mimeo, Carnegie-Mellon University).

WEISS, Y. (1972), "On the Optimal Lifetime Pattern of Labour Supply", *Economic Journal*, **82**, 1295-1315.

WEISS, Y. (1986), "The Determination of Life Cycle Earnings: A Survey", in Ashenfelter, O. and Layard, R. (eds.), *Handbook of Labor Economics, Volume* 1 (Amsterdam: North-Holland).

WEISS, Y. and GRONAU, R. (1981), "Expected Interruptions in Labour Force Participation and Sex-Related Differences in Earnings Growth", *Review of Economic Studies*, **48**, 607-619.

WOLPIN, K. I. (1984), "An Estimable Dynamic Stochastic Model of Fertility and Child Mortality", *Journal of Political Economy*, **92**, 852-874.

WOLPIN, K. I. (1987), "Estimating a Structural Search Model: The Transition from School to Work", *Econometrica*, **55**, 801-818.