Dynamic labor force participation of married women in Sweden

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Abstract: This paper analyzes the inter-temporal labor force participation behavior of married women in Sweden. A dynamic probit model is applied, controlling for endogenous initial condition and unobserved heterogeneity, using longitudinal data to allow for a rich dynamic structure. Significant unobserved heterogeneity is found, along with serial correlation in the error components, and negative state dependence. The findings may indicate serial persistence due to persistent individual heterogeneity.

Keywords: Inter-temporal labor force participation, state dependence, heterogeneity.
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1 Introduction

Individuals who have experienced unemployment are more likely to experience same event in the future. Heckman (1981) shows two explanation of this serial persistence. The first one is "true state dependence" in which current participation depends on past participation. And the second is "spurious state dependence" in which an individual component determines current participation irrespective of past participation. However, these two sources of persistence in individual participation decisions have very different implications, for example, in evaluating the effect of economic policies that aim to alleviate short-term unemployment (e.g., Phelps 1972), or the effect of training programs on the future employment of trainees (e.g., Card and Sullivan 1988).

Hyslop (1999) interprets these serial persistence from the standpoint of the job-search uncertainty, and estimated these effects (he calls "State dependence", "unobserved heterogeneity", "serially correlated transitory error" respectively) empirically. He proposes a very general probit model with correlated random effects, auto correlated error terms and state dependence and compare the results obtained adopting different levels of generality in the specifications. Hyslop (1999), using U.S. panel data (PSID), shows that "state dependence" and "unobserved heterogeneity" have strong effect for the married women's participation decision. Hyslop also shows that both state dependence and unobserved heterogeneity play an important role in shaping participation decisions and improves substantially the predictive performance of the model. The analysis rejects the exogeneity of fertility to participation decision in static model; however, exogeneity hypothesis is not rejected when the dynamics are modeled.

The objective of this study is to examine the dynamic discrete choice labor supply model that allows unobserved heterogeneity, first order state dependence and serial correlation in the error components. In particular, the study examines the relationships between participation decisions and both the fertility decision and women's non-labor income. The study is essentially a replication of what Hyslop (1999) did with US data on Swedish data.

We follow an alternative approach proposed by Heckman and Singer (1984) and assume that the probability distribution of unobserved heterogeneity can be approximated by a discrete distribution with a finite number of support points.. For models with general correlated disturbances, we use simulation based estimation methods (MSL) proposed by Lerman and Manski (1981), McFadden (1989), and Pakes and Pollard (1989), among others.

The results show that there is a negative fertility effect on participation propensities. Similar to Hyslop (1999), substantial unobserved heterogeneity is found in the participation decision. However, contrary to Hyslop (1999), negative state dependence and positive serial correlation in the transitory errors is found in women's participation decision.

The paper is organised as follows; Section 2 compares the data set used in the analysis with the U.S. data used by Hyslop (1999). Section 3 presents the model and empirical specification while the empirical and simulation results are discussed in Section 4. Section 5 summarizes and draws conclusions.

2 Data

An important feature of the data is the persistence in women's participation decision.[1] Table 1a presents the observed frequency distribution of the numbers of years worked and the associated participation sequences. It appears that there is significant persistency in the observed annual participation decision. For instance, if individual participation outcomes are independent draw from a binomial distribution with fixed probability of 0.84 (the average participation rate during the ten years), then about 17 percent of the sample would be expected to work each year, and almost no one (0.000000011) would not work at all. But in fact 59% work every year, while 5% do not work at all. However, this observed persistence in annual participation can be the result of women's observable characteristics, unobserved heterogeneity or true state dependence.

Table-1a>>>

Table 1b and Table I (in the appendix) compare the women's observable characteristics between the sample used here and the sample used by Hyslop (1999) for U.S. data.[2] In Table 1b for Swedish data, women who always work are better educated (36% women have

[1] The data used in the analysis are drawn from the Swedish Longitudinal Individual Data (LINDA). LINDA, a joint endeavor between the Department of Economics at Uppsala University, The National Social Insurance Board (RFV), Statistics Sweden (the main administrator), and the Ministries of Finance and Labor, is a register based data set consisting of a large panel of individuals, and their household members. The sampling procedure ensures that each annual cross section is representative for the population that year. The sample consists of 236,740 married couples, aged 20 to 60 in 1992-2001.

[2] The data used by Hyslop (1999) are from the 1986 panel study of income dynamics (PSID) and pertain to the seven calendar years 1979-85, corresponding to waves 12-19 of the PSID and the sample consists of 1812 continuously married couples, aged between 18 and 60 in 1980. Sample characteristics are included in the Appendix (Hyslop Table I).

University education) than those who never work (9% women have University education). In Table I for US data, women who always work are also better educated (average years of education is 13.26) than those who never work (average years of education is 11.86).

Table-1b>>>

In Table 1b, women who always work have fewer dependent children and their husband's earnings are considerably higher than those who never work. On the other hand, in Table I, women who always work have fewer dependent children but their husband's earnings are lower than those who never work.

Swedish women who experience a single transition from work are older and have fewer infant children aged 0-2. However Swedish women who experience a single transition to work or who experience multiple transitions are younger than average, and have considerably more dependent children. Their husband's earnings are slightly bellow average. The U.S. women who experiences a single transition to work are younger than average while their husband's earnings is higher than average. The U.S. women who experiences multiple transitions are also younger than average but their husband's earnings is lower than average. The differences in the total number of dependent children between the first four columns and the last two for both countries (especially Sweden) correspond with age differences. The presence of dependent children, together perhaps with lower than average husband's earnings, may increase the probability of frequent employment transitions, especially in Sweden which has more widely available childcare than in the U.S.

In order to see the effect of observable characteristics on participation decisions, we analyzed the following variables:

Employment status: There are two different labor market states. An individual is defined as a participant if they report both positive annual hours worked and annual earnings[3].

Age: Married couples aged 20 to 60 in 1992 are included in the sample.

Education: Educational attainment is included since there may be different participation behavior among different educational groups. Three dummy variables for educational attainment are used: one for women who have at most finished Grundskola degree (9 years education); one for women who have Gymnasium degree (more than 9 but less than 12 years of education); and one for women who have education beyond Gymnasium (high school).

Fertility variables: Number of children aged 0-2, 3-5 and 6-7 are defined as fertility variables.

Place of birth: In the sample it is observed that Swedish born women (93%, who work all ten years) work more than the foreign born women (85%, who never work). A dummy

[3] To avoid part-time earnings and earnings from short unemployment, the individuals with earnings lower than a threshold level are considered as non participant.

variable for place of birth is included to see if there is any difference in the participation pattern between Swedish born and foreign born individuals. This dummy variable indicates the immigration status of the individual, where 1 refers to native born and 0 otherwise.

Husband's earning: Husband's earning is used as a proxy for non-labor income. The time average ($\bar{y}_{i.}$) of husband's earnings is used as permanent income (y_{mp}); while the deviations from the time average ($\bar{y}_{i.}$) is transitory income (y_{mt}). Annual earnings are expressed in constant (2001) SEK[4], computed as nominal earnings deflated by the consumer price index.

Future birth: An indicator variable for whether a birth occurs next period is also included.

3 The Empirical model

The empirical model used here is, similar to that used by Hyslop (1999). The model is a simple dynamic programming model of search behavior under uncertainty, in which search-costs associated with labor market entry and labor market opportunities differ according to the individual's participation state.

[4] 1 US Dollar = 10.7962 Swedish Kroner (2000-06-01).

The model can defined as -

$$h_{it} = 1(\gamma h_{it-1} + \beta X_{it} + u_{it} > 0) \qquad (i = 1,...,N; t = 0,1,....,T) \tag{1}$$

$$u_{it} = \alpha_i + \varepsilon_{it}$$

where h_{it} is the observable indicator of participation; and X_{it} is a vector of explanatory variables, including time dummies, age, years of education, number of children, husband's annual earnings. *True* state dependence is captured by the parameter γ. β is a set of associated parameters to be estimated. It is assumed that the error term, u_{it}, is composed of two terms: First, α_i captures time invariant unobserved human capital and taste factors which may be correlated with observed fertility and/or income; Second, ε_{it} represents error which is independent of X_{it}.

Along with Hyslop (1999), we estimate dynamic participation decision of married women using (1) linear probability models and (2) probit models.

3.1 Linear probability models

Let consider first linear participation model in level specification

$$h_{it} = \gamma h_{it-1} + X_{it}^{'}\beta + \alpha_i + \varepsilon_{it} \qquad (i = 1,...; N; t = 0,1,...,T)\,. \tag{2}$$

If ε_{it} is not serially correlated, then equation (2) can be consistently estimated using Δh_{it-1} or previous lag as instruments for h_{it-1}.

The equation (2) in first difference can be written as:

$$\Delta h_{it} = \gamma \Delta h_{it-1} + \Delta X_{it}^{'}\beta + \Delta\varepsilon_{it}\,. \tag{3}$$

If ε_{it} is not serially correlated, then equation (3) can be consistently estimated using h_{it-2} or previous lags and non-contemporaneous realizations of the covariates as instrument for Δh_{it-1}.

Even if ε_{it} is serially correlated, it can be consistently estimated by two-step procedure using h_{it-2} as instrument for Δh_{it-1} However if ε_{it} follows an AR(1) process: $\varepsilon_{it} = \rho\varepsilon_{it-1} + v_{it}$, where -1< ρ <1, $v_{it} \sim (0, \sigma^2)$, we can eliminate the serial correlation in the errors as :

$$h_{it} = (\rho + \gamma)h_{it-1} - \rho\gamma h_{it-2} + X_{it}^{'}\beta - X_{it-1}\rho\beta + (1-\rho)\alpha_i + v_{it}\,. \tag{4}$$

Then equation (4) can be consistently estimated by instrumenting for h_{it-1} and h_{it-2} using Δh_{it-1} and Δh_{it-2}. Alternatively, first-difference of (4) gives the equation:

$$\Delta h_{it} = (\rho + \gamma)\Delta h_{it-1} - \rho\gamma\Delta h_{it-2} + \Delta X_{it}^{'}\beta - \Delta X_{it-1}\rho\beta + \Delta v_{it}\,. \tag{5}$$

In this case, h_{it-2} is a valid instrument for Δh_{it-1}[5].

3.2 Non-linear models

$$h_{it} = 1(\gamma h_{it-1} + \beta X_{it} + \alpha_i + \varepsilon_{it} > 0) \tag{6}$$

$u_{it} = \alpha_i + \varepsilon_{it}$ and $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$ $\quad\quad (i = 1,...; N; t = 1,...,T)$

where h_{it} is the indicator variable for participation and X_{it} is a vector of explanatory variables, including time dummies, age, years of education, number of children, husband's annual earnings. The subscript i indexes individuals and the subscripts t indexes time

[5] For more details see, Hyslop (1999).

periods. The parameter γ represents true state dependence whereby an individual's propensity to participate is changed because of past participation. α_i represents for all unobserved determinants (such as taste for work, intelligence, ability, motivation or general attitude of individuals) of participation that are time invariant for an individual i. And finally ε_{it} represents the idiosyncratic error term.

The equation (6) can be estimated by random effect probit model using MLE. The standard (uncorrelated) random effect model assumes that α_i is uncorrelated with X_{it}. But if the number of children and/or income is correlated with unobserved tastes, as expected in this paper, then α_i will be correlated with X_{it}. Hence we consider the correlated random effects model (CRE) which is based on the following relationship between α_i and the observed characteristics[6]:

$$\alpha_i = \sum_{s=1}^{T} (\delta_{1s}(\#Kids0-2)_{is} + \delta_{2s}(\#Kids3-5)_{is} + \delta_{3s}(\#Kids6-17)_{is})$$
$$+\sum_{s=1}^{T} \delta_{4s} y_{mis} + \eta_i$$

Thus the model (6) can be written as:

$$h_{it} = 1(\gamma h_{it-1} + (\beta + \delta_{1t}) X_{it} + \sum_{s \neq t} \delta_s X_{is} + \eta_i + \varepsilon_{it} > 0) \qquad (7)$$

$$v_{it} = \eta_i + \varepsilon_{it} \qquad (i = 1,...;N; t = 1,...,T)$$

where $\eta_{it} \sim iidN(0, \sigma_\eta^2)$ and independent of X_{it} and ε_{it} for all i, t.

[6] There is substantial literature concerned with this issue. See for example Mundlak (1978), Chamberlain (1984).

The initial condition in dynamic probit model with unobserved effects complicates estimation considerably. Estimation requires an assumption about the relationship between the initial observations, h_{i0}, and η_i .We consider the approach to the initial conditions problem proposed by Heckman (1981b). The model specifies a linearized reduced form equation for the initial period as:

$$h_{i0} = 1\left(\beta_0 z_{i0}^{'} + \eta_0 + \varepsilon_{i0} > 0\right) \tag{8}$$

where $\eta_0 \sim iidN(0, \sigma_{\eta 0}^2)$ and independent of z_{i0}. and ε_{i0} . z_{i0} includes the variables for initial period (X_{i0}) and other exogenous variables. It is also assumed that the error term ε_{i0} satisfies the same distributional assumptions as ε_{it} for t ≥ 1. For normalization we assume $\sigma_\varepsilon^2 = 1$.

For a random sample of individuals the likelihood to be maximized is then given by

$$L = \prod_{i=1}^{N} \int_{\eta} \left\{ \Phi\left[\left(\beta_0 z_{i0}^{'} + \eta_0\right)\left(2h_{i0} - 1\right)\right]\right\} \left\{ \prod_{t=1}^{T} \Phi\left[\left(\gamma h_{it-1} + \left(\beta + \delta_{1t}\right) X_{it} + \sum_{s \neq t} \delta_s X_{is} + \eta_i \right)\left(2h_{it} - 1\right)\right]\right\} dF\left(\eta\right) \tag{9}$$

where F is the distribution function of η (consisting of η_0 and η_i). However, as η is not observed, we have to integrate out this term from the above likelihood to obtain the unconditional likelihood function. To do this, we need to specify a distribution for η . If η is taken to be normally distributed, the integral over η can be evaluated using Gaussian—Hermite quadrature (Butler and Moffitt, 1982). In this paper, we follow an alternative approach proposed by Heckman and Singer (1984), and assume that the probability distribution of η can be approximated by a discrete distribution with a finite number (*J*) of support points. In this specification the distribution of η . is taken to have mass points $\eta^{(j)}$ (j=1,2,...,J) with corresponding probabilities π_j satisfying $0 \le \pi_j \le 1$. $\forall$ j and $\sum_{j=1}^{J} \pi_j = 1$. To be specific, we assume that there are *J* types of individuals and that each individual is endowed with a set of unobserved characteristics, $\eta^{(j)}$ (j=1,2,...,J). We report estimates based on this models where *J=3*.

The likelihood is then:

$$L = \prod_{i=1}^{N} \left\{ \sum_{j=1}^{J} \pi_j \left\{ \Phi\left[\left(\beta_0 z_{i0}^{'} + \eta_0 \right) \left(2h_{i0} - 1 \right) \right] \right\} \left\{ \prod_{t=1}^{T} \Phi\left[\left(\gamma h_{it-1} + \left(\beta + \delta_{1t} \right) X_{it} + \sum_{s \neq `t} \delta_s X_{is} + \eta_i \right) \left(2h_{it} - 1 \right) \right] \right\} \right\} \tag{10}$$

This specification, controlling for endogenous initial condition, also allow arbitrary correlation between unobserved effect (η_0) of initial period and unobserved effects (η_i) of other periods with the probability distribution of initial and other period support points.

Autocorrelation in the ε_{it}, perhaps reflecting correlation between transitory shocks, which is also complicates estimation considerably. For the models with autocorrelation $\varepsilon_{it} = \rho \varepsilon_{it-1} + v_{it}$, $v_{it} \sim N(0, \sigma_v^2)$; the Heckman estimator requires the evaluation of T-dimensional integrals of Normal densities. Simulation estimators provide a feasible way to address this problem. A Maximum Simulated Likelihood (MSL) estimator (see for example Gourieroux and Monfort, 1996, and Cameron and Trivedi, 2005), based on the GHK algorithm of Geweke, Hajivassiliou and Keane (see for example Keane, 1994) can be used. The above model and estimator are discussed in Lee (1997) in more details. Following Lee (1997) first we generate $u_1, u_2, ..., u_T$ independent uniform [0, 1] random variables. Then with given initial condition the truncated random variables $w_1, w_2, ..., w_T$ for GHK simulator can be generated recursively from the following steps, from t=1….,T:

(1) Calculate $$w_t = -(2h_{it} - 1)\Phi^{-1}\left[u_t \Phi\left((2h_{it} - 1)\left(\gamma h_{it-1} + (\beta + \delta_{1t}) X_{it} + \sum_{s \neq t} \delta_s X_{is} + \eta_i + \rho\varepsilon_{it-1}\right)\right)\right].$$

(2) Update the disturbances process $\varepsilon_t = \rho\varepsilon_{it-1} + w_{it}$

For each i, with R independently generated vectors from random draws the simulated likelihood is

$$L = \prod_{i=1}^{N}\left[\frac{1}{R}\sum_{r=1}^{R} \left\{\sum_{j=1}^{J} w_j \left\{\Phi\left[\left(\beta_0 z_{i0}' + \eta_0\right)(2h_{i0} - 1)\right]\right\}\left\{\prod_{t=1}^{T}\Phi\left[\left(\gamma h_{it-1} + (\beta + \delta_{1t}) X_{it} + \sum_{s \neq t}\delta_s X_{is} + \eta_i + \rho\varepsilon_{i,t-1}^{r}\right)(2h_{it} - 1)\right]\right\}\right\}\right] \tag{11}$$

4 Results

This section reports and compares the results with the results of Hyslop (1999) for various linear probability models and probit models. The results for all specifications are reported based on 10% (random draw) sub-sample. [7]

4.1 Linear Probability Models

Various dynamic linear probability specifications corresponding to equation (2) and (3) have been estimated both in levels and in first difference specification, just as Hyslop (1999) did. Table 2 shows the results for seven years data. In row 1, the GLS estimate of lagged dependent variable for first difference is -0.31 which is downwards biased due to negative correlation between Δh_{it-1} and the error due to first differencing. While the estimate obtained from level specification is 0.73 which is upwards biased because of unobserved heterogeneity. These findings are very close to Hyslop's GLS findings for lagged dependent variables. The estimates for first difference and level specifications in Hyslop (1999) are -0.35 and 0.67 respectively (See appendix row 1 Table II).

Row (2) shows the results using out-of-period realizations of the covariates as instruments for the lagged dependent variable. If the regressors are exogenous with respect to the transitory error component, these instruments are valid instruments and enable consistent estimates of the effects of lagged dependent variable. Estimated coefficients in first difference and level specification are: -0.10 and 0.35 respectively. These coefficients are close to zero than the GLS estimates.

If it is assumed that there is no serial correlation in the transitory errors then lagged values of h would be valid instruments for Δh_{it-1}, and lagged values of Δh would be valid instruments for h_{it-1}. In row 3, h_{it-2} is added to the vector of instruments for Δh_{it-1}, and Δh_{it-1} to the vector of instruments for h_{it-1}. The estimates of the lagged dependent variable coefficients obtained from the first difference and level specification are now 0.22 and 0.34 respectively. The F-statistics indicate that these instruments have substantial explanatory power. In row 4, the regressors have been dropped form the instrument sets. The coefficients of lagged dependent variable are 0.32 to 0.26. Row (5) shows the specifications based on Arellano and Bond (1991), which include all valid lagged participation effects in the instrument sets. The estimated coefficients for first-differences and levels are very close, -0.24 and -0.27, respectively. Finally row (6) presents the specification which relaxes the assumption that the transitory errors are uncorrelated, and allows the errors to follow a stationary AR(1) process. Two-step GMM estimation shows that the coefficients of lagged dependent variable in both first difference and level specification decreased dramatically to -0.05 and -0.006 respectively. On the other hand, the estimates of the AR(1) serial correlation parameter are positive and quite similar: 0,32and 0.28 respectively. Interestingly, the results of GMM contrast sharply with Hyslop(1999). In Hyslop(1999), the effects of lagged dependent variable are positive, while AR(1) coefficients are negative. We will check these contrasts by another specification.

Table-2>>>

Table 3 shows the estimated regressor coefficients from the specifications presented in rows (4)-(6) of Table 2. Like Hyslop's findings (See appendix Table III), the results show that pre-school children have substantially stronger effects on participation outcomes than school-aged children. The results also show that permanent non-labor income effect (y_{mp}) is positive and significant.

Table-3>>>

4.2 Static probit models

Table 4 shows the results for the static probit specifications focusing on demographic and other characteristics of married women in Sweden. Here, the model is estimated for the sample over the ten year period (1992-2001). Column 1 contains the results of simple probit model where each of the fertility variables has significantly negative effect on women's participation decisions. The younger children have stronger effects than older. An additional child aged 0-2 reduces the probability of participation by 18 percent (marginal effect). The permanent non-labor income effect is significantly positive which may reflect the predominant dual income family structure in Sweden.

Table -4>>>

Column 2 contains the results of random effects probit model estimated by MLE using Gaussian quadrature. The result indicates that 77 percent of the latent error variance is due to unobserved heterogeneity. Compared to simple probit model, the estimated effects of young children aged 0-2 increase by 53 percent while that of children aged 6-17 increases by 62 percent. The random effect probit model is re-estimated considering two different types of distribution of unobserved heterogeneity. In column 3 the heterogeneity is assumed to be normally distributed whereas in column 4 it is assumed that the heterogeneity have a common discrete distribution with a finite number of mass points (Heckman and Singer approach). The estimates of these models are broadly similar.

The estimated support points and accompanying probabilities for the model in column 4 indicate unobserved heterogeneity in individuals' preferences. The first estimated support point (θ_1 = -3.15) and the corresponding probability (π_1 = 0.761) indicate a relatively strong preference for work by 76% of the sample (compared to the sample information that 58% actually work all 10 years of the study period). The second estimated-support point (θ_2 = -4.88) and the corresponding probability (π_2 = 0.156) indicates flexible preference for work by 16%. The third estimated support point (θ_3 = -6.86) and the corresponding probability (π_3 = 0.083) indicates low preference for work by 8% (compared to the sample information that 5% don't work at all during the study period).

It has been assumed that the fertility and/or income variables are independent of unobserved heterogeneity. If these assumptions are incorrect, the resulting coefficient estimates will be biased and inconsistent. For this reason the correlated random effects (CRE) specification for α_i, given in equation (7) is estimated in column 5. A likelihood ratio test (not reported) of simple versus correlated random effects models gives no support for rejecting the simple model (LR statistic = 14.97). Moreover, separate Wald–statistics for the correlation between unobserved heterogeneity and three fertility variables provide evidence in favor of exogeneity hypothesis in each case. These findings sharply contradict Hyslop (1999) finding in static case, who rejects the hypothesis that fertility decisions are exogenous to women's participation decisions.

4.3 Dynamic probit models

Table 5 shows the results of inter-temporal participation decisions of married women. A latent class (model is used in the dynamic probit model with unobserved individual specific effect. Column 1 contain the results for the specification which allows first order autoregressive error AR(1).The results show that the addition of a transitory component of error has significant effect on the model and the estimated coefficient is 0.81. The percentage of the women of strong preference for work is now increased to 13%.

Column 2 contains the results for the specification which allows first order state dependence SD(1). This specification allows arbitrary correlation between the initial and other periods with the same probability of initial and other periods support points. The results show a large first order state dependence effect and the coefficient is 1.28.

Column 3 shows the results for the random effects specifications with a first order autoregressive error component AR(1) and first order state dependence SD(1). The model is estimated using simulated maximum likelihood (MSL) estimation method and based on two support points.[7] For simulation I use standard approach to random draws from the specified distribution. The results show that including state dependence has a little effect on the distribution of unobserved heterogeneity and serial correlation parameter in the model. The AR(1) coefficient is now 0.86.

4.4 Simulated responses to "fertility" *and to changes in* "non-labor" *Income*

Figure 1 shows simulated responses to a birth in year 1 for the simple probit model, random effects MSL probit model, AR(1) probit model, and dynamic probit with first order state dependence model. The effect of an additional child aged 0-2 is -0.18 in simple probit, -0.21 in RE MSL, -0.19 in AR (1), and -0.16 in dynamic probit. The difference between simple probit and RE-MSL shows the bias due to unobserved heterogeneity. However, the distance between RE-MSL and dynamic probit shows the bias that arises from not controlling for state dependence. The simulated responses decline initially as the child ages, and are nearly indistinguishable when the age is 3. The simulation patterns explain that the women leave the labor force to have children and return as the children age beyond infancy. The return of Swedish women to work is quicker than the US women (See Hyslop 1999). This indicates that Sweden has more widely available childcare system than the U.S.

[7] The model is also estimated with three support points and found that the model is fitted well with two support points (for this and other results concerning this issue, see Hansen and Lofstrom 2001, Cameron and Heckman 2001, Stevens 1999, Ham and Lalonde 1996, Eberwein, Ham and Lalonde 1997). This issue is also discussed in Heckman and Singer.

Figure 2 shows the simulated effects of ten percent increase in permanent non-labor income. Ten percent increase in permanent non-labor income increases women's participation in the first year by 0.08 in simple-probit, 0.16 in RE-MSL, and 0.10 in dynamic probit. The figure suggests that there is a positive income effect of husbands' earnings on wives' participation decision.

Figure 3 shows the dynamic probit model responses to a birth during first year for middle educated (Gymnasium) and highly educated (University) women. The results show that the effect of one birth during first year for middle educated women is stronger than those of highly educated. Figure 4 shows broadly similar responses of immigrant and native born women. Figure 5 presents the dynamic probit model responses of 10 percent increase in permanent non-labor income for middle educated (Gymnasium) and highly educated (University) women. The response of dynamic probit model for middle educated women is stronger than those of highly educated. Figure 6 shows quite similar responses of immigrant and native born women.

5 Summary and Conclusions

The purpose of this study is to analyze the inter-temporal labor force participation behavior of married women in Sweden, using a ten year sample from Longitudinal Individual Data (LINDA). We estimated linear probability models and dynamic probit models with a variety of specifications. Both linear probability and probit results suggest that the inter-temporal participation decisions are characterized by a substantial amount of unobserved heterogeneity. In the specification which allows first order state dependence and serial correlation in the transitory errors components, it is found that almost no true state dependence in individual propensities to women participation. However the estimated first order AR(1) component has a large and significant effect in both linear probability model and dynamic probit model. The findings indicate serial persistence on participation decisions due to persistent individual heterogeneity

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Table 1a: Distribution of Number of Years Worked

Number of years worked	Full sample (1)	Employed all 10 years (2)	Employed 0 years (3)	Single transition from work (4)	Single transition to work (5)	Multiple transitions (6)
Zero	4.67	-	100	-	-	-
One	1.49	-	-	10.48	4.17	2.42
Two	1.56	-	-	7.06	4.80	3.37
Three	1.74	-	-	6.68	5.53	3.92
Four	2.16	-	-	6.53	5.63	5.87
Five	2.41	-	-	7.06	4.56	7.27
Six	3.46	-	-	8.73	7.47	10.43
Seven	4.36	-	-	10.86	10.62	12.68
Eight	6.97	-	-	15.03	16.83	20.93
Nine	12.45	-	-	27.56	40.40	33.13
Ten	58.73	100	-	-	-	-

Column percentages.

Table 1b: Sample Characteristics

	Full sample (1)	Employed all 10 years (2)	Employed 0 years (3)	Single transition from work (4)	Single transition to work (5)	Multiple transitions (6)
$Age_{(1992)}$	42.92 (8.15)	45.03 (7.12)	45.73 (7.84)	46.04 (8.02)	37.98 (7.25)	37.94 (8.05)
Education[(a)] (Primary)	0.18 (0.38)	0.16 (0.37)	0.44 (0.50)	0.29 (0.45)	0.16 (0.37)	0.16 (0.36)
Education[(a)] (High-school)	0.50 (0.50)	0.48 (0.50)	0.47 (0.50)	0.51 (0.50)	0.54 (0.50)	0.56 (0.50)
Education[(a)] (Universitet)	0.32 (0.47)	0.36 (0.48)	0.09 (0.28)	0.20 (0.40)	0.29 (0.46)	0.29 (0.45)
Place of birth (Born in Sweden=1)	0.92 (0.27)	0.93 (0.26)	0.85 (0.36)	0.89 (0.31)	0.91 (0.29)	0.91 (0.29)
No. of children aged 0-2 years	0.13 (0.37)	0.05 (0.23)	0.09 (0.32)	0.06 (0.28)	0.25 (0.50)	0.31 (0.53)
No. of children aged 3-5 years	0.20 (0.45)	0.10 (0.33)	0.14 (0.39)	0.10 (0.34)	0.40 (0.59)	0.40 (0.58)
No. of children aged 6-17 years	0.95 (1.01)	0.89 (0.96)	0.82 (1.04)	0.67 (0.90)	1.38 (1.11)	1.04 (1.05)
Husband's Earnings (SEK 100,000)	2.67 (1.73)	2.78 (1.78)	2.23 (1.63)	2.64 (1.90)	2.54 (1.51)	2.52 (1.60)
Participation	0.84 (0.37)	1.00	0.00	0.60 (0.49)	0.69 (0.46)	0.70 (0.46)
Sample size	236,740	139,030	11,070	13,170	20,620	52,850

Note: Standard errors in parentheses. Sample selection criteria: continuously married couples, aged 20-60 in 1992 with positive husband's annual earnings and hours worked each year.

(a) Three dummy variables for educational attainment are used: One for women who have at most finished Grundskola degree (9 years education); One for women who have Gymnasium degree (more than 9 but less than 12 years of education); and one for women who have education beyond Gymnasium (high school).

Table 2: Linear Probability Models of Married Women's Participation

	First Difference Specification				Levels Specification			
	Instruments	γ	ρ	Test statistic	Instruments	γ	ρ	Test statistic
(1)	-	-0,314 (0.002)	-	-	-	0,725 (0.005)	-	-
(2)	$\Delta X_{is}, \forall s$	-0,099 (0.013)	-	232.40[a] (0.00)	$X_{is}, \forall s$	0,353 (0.036)	-	102.29[a] (0.00)
(3)	$\Delta X_{is}, \forall s$ h_{it-2}	0,221 (0.006)	-	322.08[a] (0.00)	$X_{is}, \forall s$ Δh_{it-1}	0,336 (0.015)	-	121.37[a] (0.00)
(4)	h_{it-2}	0,326 (0.007)	-	-	Δh_{it-1}	0,264 (0.012)	-	-
(5)	$h_{it-s}, \forall s > 1$	-0,246 (0.003)	-	2535.68 [b] (0.00)	$\Delta h_{it-s}, \forall s > 0$	-0,270 (0.009)	-	3409.39 [b] (0.00)
(6)	h_{it-2}	-0,049 (0.014)	0,317 (0.020)	3.48[c] (0.00)	$\Delta h_{it-1}, \Delta h_{it-2}$	-0,006 (0.061)	0,282 (0.071)	

Note: Standard errors in parentheses except F Statistics with p values. All specifications include time dummies, age, age-squared , educational status, number of kids aged 0-2, 3-5, and 6-17, permanent non labor income, transitory non labor income, place of birth, and a variable for a birth next year

a) F test statistics for the explanatory power of the instruments

b) Sargan over identification statistics

Table 3: Linear Probability Models of Married Women's Participation

	First Difference Specification			Levels Specification		
	(1)	(2)	(3)	(4)	(5)	(6)
Permanent non-labor income (y_{mp})	-	-	-	0,011 (0.006)	-	-
Transitory income (y_{mt})	-0,001 (0.001)	-0,001 (0.001)	-0,001 (0.008)	-0,005 (0.002)	-0,009 (0.003)	-0,005 (0.004)
No. Children aged 0-2 years	-0,033 (0.005)	-0,015 (0.005)	-0,014 (0.008)	-0,127 (0.009)	-0,160 (0.014)	-0,080 (0.022)
No. Children aged 3-5 years	-0,060 (0.004)	-0,012 (0.004)	-0,047 (0.005)	-0,018 (0.007)	-0,004 (0.011)	-0,004 (0.013)
No. Children aged 6-17 years	-0,024 (0.003)	-0,003 (0.003)	-0,025 (0.003)	-0,014 (0.004)	0,019 (0.008)	-0,004 (0.007)
Birth_{t+1}	0,089 (0.004)	0,073 (0.005)	0,064 (0.007)	0,029 (0.011)	-0,007 (0.013)	0,014 (0.072)
Lagged dependent (h_{t-1})	0,326 (0.007)	-0,246 (0.003)	-0,049 (0.014)	0,264 (0.012)	-0,270 (0.009)	-0,006 (0.061)
AR(1) Coefficient (ρ)	-	-	0,317 (0.020)	-	-	0,282 (0.061)
Instruments	h_{it-2}	$h_{it-s}, \forall s > 1$	h_{it-2}	Δh_{it-1}	$h_{it-s}, \forall s > 0$	Δh_{it-1} Δh_{it-2}

Note. Estimated standard errors are in parenthesis. All specifications include time dummies, age, age-squared , educational status, number of kids aged 0-2, 3-5, and 6-17, permanent non labor income, transitory non labor income, place of birth, and a variable for a birth next year

Table 4: Static Probit Models of Married Women's Participation Outcomes

	Simple-Probit Effect (1)	Random-effect Probit (2)	Random-effect (MSL) (3)	Random-effect (Heckman and Singer) (4)	Correlated Random-effect (MSL) (5)
Permanent non-labor income (y_{mp})	0.062 (0.008)	0.123 (0.025)	0.06 (0.006)	0.042 (0.009)	0.160 (0.008)
Transitory income (y_{mt})	-0.005 (0.009)	-0.029 (0.016)	-0.029 (0.008)	-0.016 (0.015)	-0.019 (0.009)
No. of children aged 0-2 years(#kid0-2)	-0.779 (0.028)	-1.197 (0.044)	-1.169 (0.02)	-1.079 (0.038)	-1.110 (0.024)
No. of children aged 3-5 years(#kid3-5)	-0.220 (0.018)	-0.309 (0.034)	-0.285 (0.016)	-0.264 (0.034)	-0.210 (0.019)
No. of children aged 6-17 years(#kid6-17)	-0.127 (0.012)	-0.207 (0.022)	-0.183 (0.009)	-0.151 (0.015)	-0.120 (0.015)
Var(η_i)[(a)]	-	0.774 (0.008)	0.650 (0.050)	-	0.660 (0.021)
Log-likelihood	10100.41	6359.59	6381.36	6294.80	6352.14
First support point (θ_1)	-	-	-	-3.15 (0.01)	-
Second support point (θ_2)	-	-	-	-4.88 (0.01)	-
Third support point (θ_3)	-	-	-	-6.86 (0.01)	-
Probability (π_1)	-	-	-	0.761	-
Probability (π_2)	-	-	-	0.16	-
Probability (π_3)	-	-	-	0.08	-
Wald statistic for H_0:CRE=0					
Transitory income (y_{mt})	-	-	-	-	18.52 (0.00)
No. of children aged 0-2 years(#kid0-2)	-	-	-	-	0.26 (0.61)
No. of children aged 3-5 years(#kid3-5)	-	-	-	-	0.19 (0.66)
No. of children aged 6-17 years(#kid6-17)	-	-	-	-	0.01 (0.91)

Notes: Estimated standard errors in parentheses. . All specifications include time dummies, age, age-squared , educational status, number of kids aged 0-2, 3-5, and 6-17, permanent non labor income, transitory non labor income, place of birth, and a variable for a birth next year.
Var (η_i) is expressed as a fraction of the total error variance.

Table 5: Dynamic Probit Models (Heckman and Singer approach) of Married Women's Participation Outcomes

	Random effect with AR(1) () (1)	Random effect with SD(1) (endogenous initial condition) (2)	Random effect with AR(1)+ SD(1) (endogenous initial condition) (3)
Permanent non-labor income (y_{mp})	0.057 (0.131)	0.040 (0.016)	0.080 (0.009)
Transitory income (y_{mt})	-0.009 (0.062)	-0.021 (0.024)	-0.004 (0.011)
No. of children aged 0-2 years(#kid0-2)	-1.139 (0.085)	-0.799 (0.064)	-1.144 (0.049)
No. of children aged 3-5 years(#kid3-5)	-0.444 (0.191)	-0.208 (0.051)	-0.439 (0.038)
No. of children aged 6-17 years(#kid6-17)	-0.183 (0.140)	-0.115 (0.031)	-0.142 (0.012)
Lagged dependent (h_{t-1})	-	1.280 (0.042)	-0.040 (0.008)
AR(1) Coeff.(ρ)	0.812 (0.018)	-	0.855 (0.013)
First support-point (θ_1)	-5.176 (1.912)	0.451 (0.007)	-5.36 (0.210)
Second support- point (θ_2)	-7.596 (1.980)	-0.673 (0.005)	-9.65 (0.281)
Third support- point (θ_3)	-11.678 (2.340)	-2.224 (0.006)	-
First support- point for initial-period (θ_{11})	-	-3.007 (1.059)	-2.46 (0.167)
Second support- point for initial period (θ_{22})	-	-4.279 (1.063)	-5.06 (0.208)
Third support- point for initial period (θ_{33})	-	-5.950 (1.071)	-
Probability (π_1)	0.83	0.74	0.90
Probability (π_2)	0.13	0.19	0.10
Probability (π_3)	0.04	0.07	-

Notes: Estimated standard errors in parentheses. All specifications include time dummies, age, age-squared , educational status, number of kids aged 0-2, 3-5, and 6-17, permanent non labor income, transitory non labor income, place of birth, and a variable for a birth next year

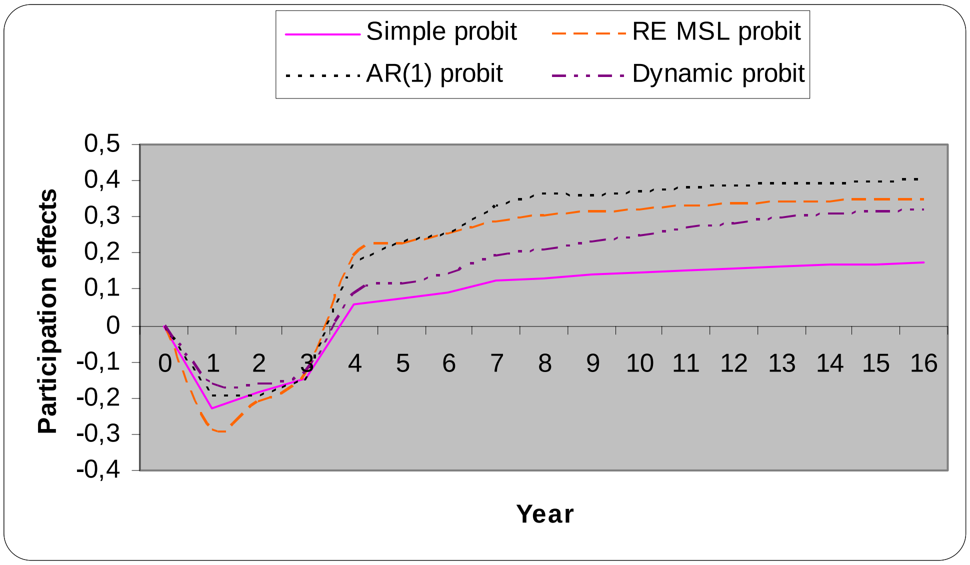

Figure1: Response to a birth in year 1, various models.

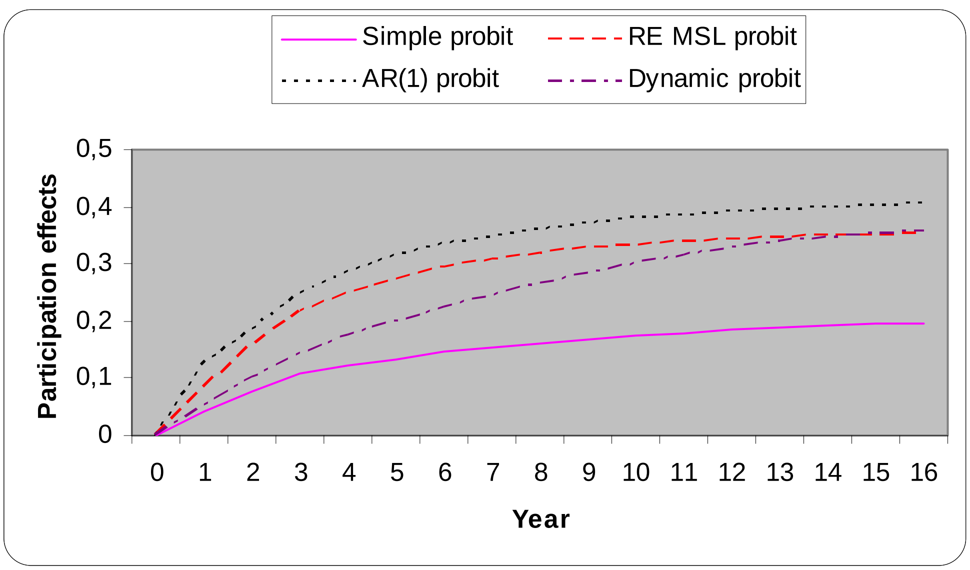

Figure2: Response to a 10% increase in permanent income in year 1, various models.

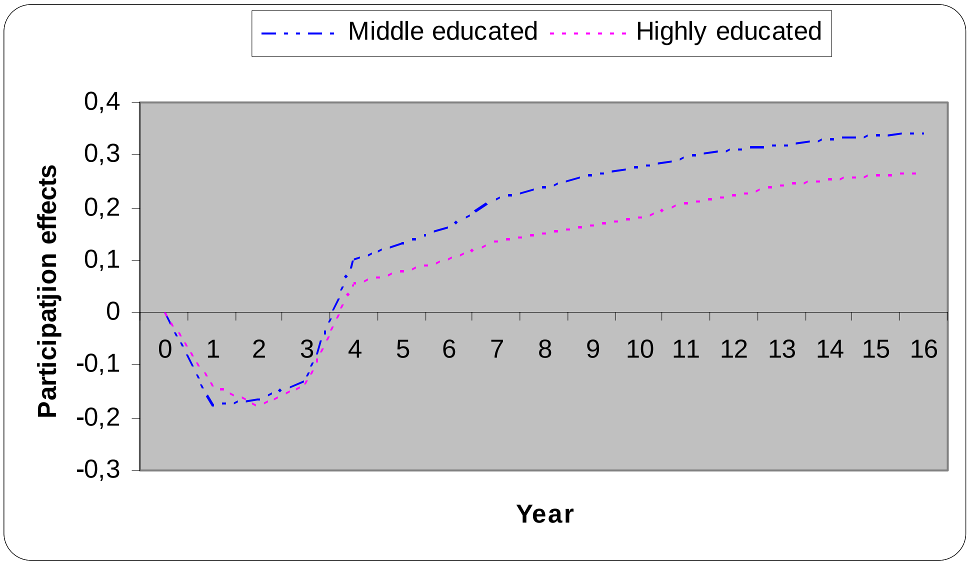

Figure 3: Dynamic probit response to a birth in year 1, by education level.

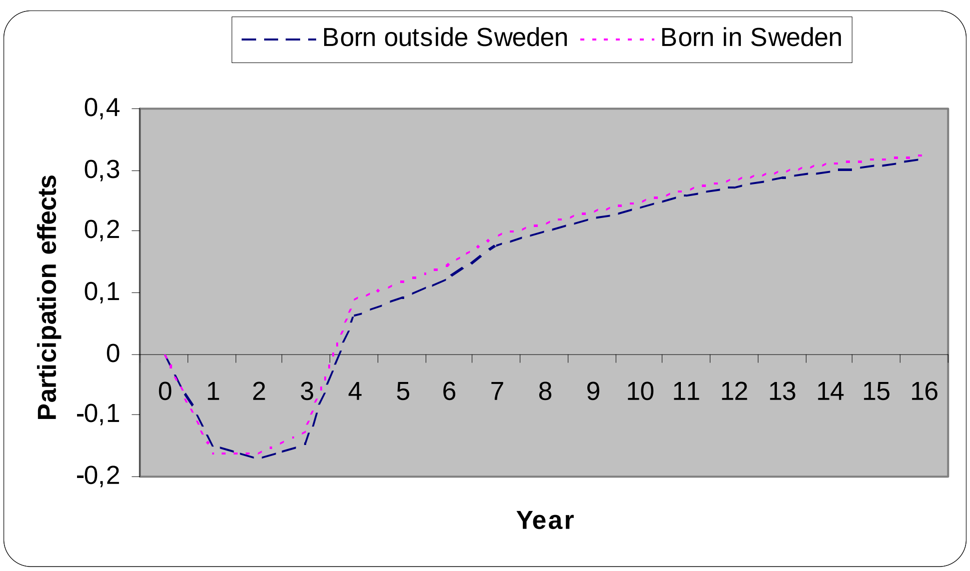

Figure 4: Dynamic probit response to a birth in year 1, by immigration-status.

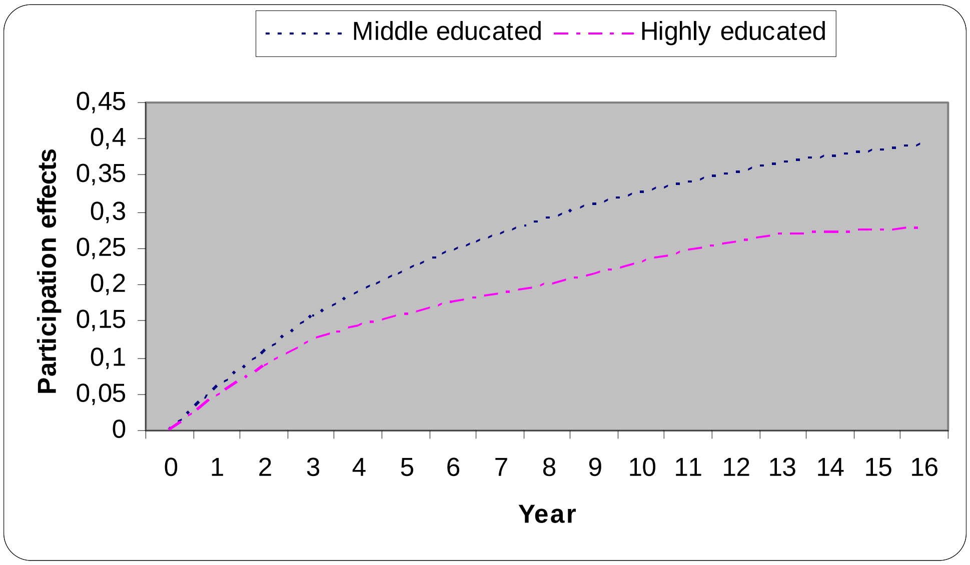

Figure 5: Dynamic probit response to a 10% increase in permanent income in year 1, by education level.

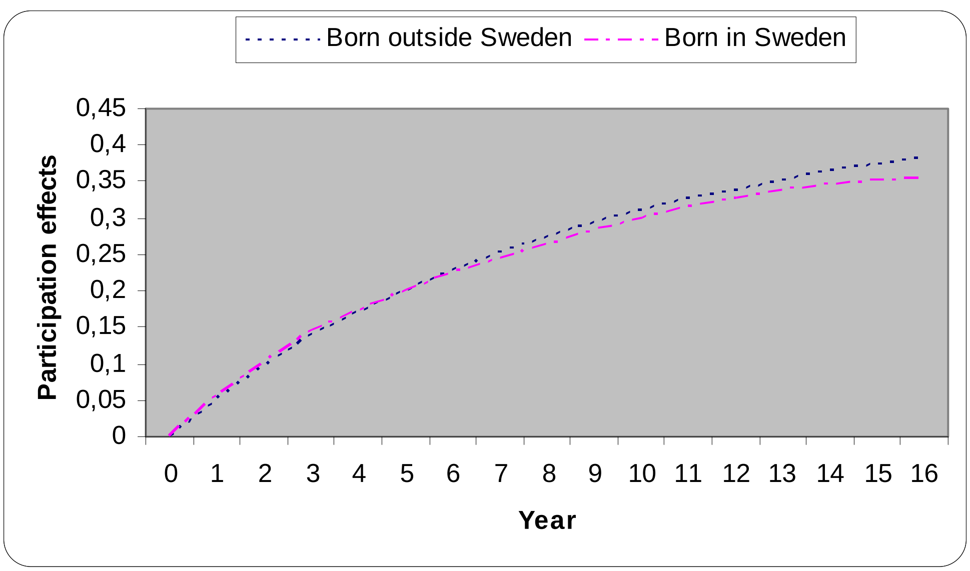

Figure 6: Dynamic probit response to a10% increase in permanent income in year 1, by immigration-status.

Appendix: The following tables are taken from Hyslop (1999) for US data

TABLE I

SAMPLE CHARACTERISTICS

	Full Sample (1)	Employed 7 Years (2)	Employed 0 Years (3)	Single Transition from Work (4)	Single Transition to Work (5)	Multiple Transitions (6)
Age	34.34	34.52	39.66	34.35	33.12	32.08
(1980)	(.23)	(.31)	(.81)	(.89)	(.67)	(.44)
Education[a]	12.90	13.26	11.86	12.85	12.90	12.67
	(.05)	(.08)	(.17)	(.21)	(.16)	(.11)
Race (1 = Black)	0.22	0.25	0.24	0.16	0.15	0.20
	(.01)	(.01)	(.03)	(.03)	(.03)	(.02)
No. Children[b]	0.25	0.20	0.23	0.33	0.25	0.32
aged 0–2 years	(.01)	(.01)	(.02)	(.03)	(.02)	(.02)
No. Children[b]	0.30	0.24	0.26	0.28	0.41	0.40
aged 3–5 years	(.01)	(.01)	(.03)	(.03)	(.03)	(.02)
No. Children[b]	1.00	0.96	0.97	0.60	1.32	1.08
aged 6–17 years	(.02)	(.03)	(.07)	(.08)	(.07)	(.05)
Husband's Earnings[b]	29.59	27.90	35.17	31.46	33.64	28.22
(1987 $1000)	(.47)	(.64)	(1.93)	(1.56)	(1.97)	(.72)
Participation[b]	0.70	1	0	0.46	0.55	0.57
	(.01)			(.02)	(.02)	(.01)
No. years worked[c]						
zero	10.6	—	100	—	—	—
one	6.1	—	—	24.7	15.3	11.1
two	5.4	—	—	19.2	14.8	10.4
three	5.7	—	—	14.4	12.5	14.1
four	6.7	—	—	9.6	12.5	20.0
five	8.8	—	—	13.0	19.3	24.9
six	8.6	—	—	19.2	25.6	19.5
seven	48.2	100	—	—	—	—
Sample size	1812	873	192	146	176	425

Notes: Standard errors in parentheses. Sample selection criteria: continuously married couples, aged 18–60 in 1980, with positive husband's annual earnings and hours worked each year.

[a]Years of Education are imputed from the following categorical scheme: 1 = '0–5 grades' (2.5 years); 2 = '6–8' (7 years); 3 = '9–11' (10 years); 4 = '12' (12 years); 5 = '12 plus non-academic training' (13 years); 6 = 'some college' (14 years); 7 = 'college degree, not advanced' (16 years); 8 = 'college advanced degree' (18 years). Education is measured as the highest level reported in the 1980–86 surveys.

[b]Sample Averages: child variables based on 8 observations; participation and male earnings based on 7 observations.

[c]Column percentages.

TABLE II

LINEAR PROBABILITY MODELS OF MARRIED WOMEN'S PARTICIPATION

	First Difference Specification				Levels Specification			
	Instruments	γ	ρ	Test Statistic	Instruments	γ	ρ	Test Statistic
(1)	—	−0.348	—	—	—	0.668	—	—
		(.02)				(.01)		
(2)	$\Delta X_{is}, \forall s$	−0.181	—	1.50[a]	$X_{is}, \forall s$	0.483	—	1.23[a]
		(.05)		(.06)		(.05)		(.25)
(3)	$\Delta X_{is}, \forall s$	0.257	—	14.34[a]	$X_{is}, \forall s$	0.337	—	13.41[a]
	h_{it-2}	(.03)		(.00)	Δh_{it-1}	(.02)		(.00)
(4)	h_{it-2}	0.274	—	—	Δh_{it-1}	0.306	—	—
		(.03)				(.03)		
(5)	$h_{it-s}, \forall s > 1$	0.338	—	26.96[b]	$\Delta h_{it-s}, \forall s > 0$	0.399	—	29.36[b]
		(.03)		(.00)		(.03)		(.00)
(6)	h_{it-2}	0.647	−0.194	10.73[c]	Δh_{it-1}	0.563	−0.166	11.15[c]
		(.09)	(.04)	(.06)	Δh_{it-2}	(.13)	(.10)	(.05)

Notes: All specifications include unrestricted time effects, a quadratic in age, race, years of education, permanent and transitory nonlabor income, current realizations of the number of children aged 0–2, 3–5, and 6–17, lagged realizations of the number of children aged 0–2, and a dummy variable for a birth next year. Arbitrary cross-equation correlation and cross-sectional heteroscedasticity-corrected estimated standard errors are in parentheses, except p-values for test statistics. The model is:

$$h_{it} = \gamma h_{it-1} + X_{it}'\beta + \alpha_i + \varepsilon_{it}$$

Specifications in rows (1)–(5) assume ε_{it} is serially uncorrelated; specifications in row (6) assume $\varepsilon_{it} = \rho\varepsilon_{it-1} + v_{it}$. The estimates in row (6) are based on 2-step minimum distance estimation, using unrestricted first stage coefficient estimates.

[a] First-stage F statistic for the explanatory power of the instruments, conditional on the included exogenous variables; averaged over the period equations.

[b] Sargan over-identification statistic, with 3 degrees of freedom.

[c] Second-stage goodness-of-fit statistic, with 5 degrees of freedom.

TABLE III

LINEAR PROBABILITY MODELS OF MARRIED WOMEN'S PARTICIPATION

	First-Differences			Levels		
	(1)	(2)	(3)	(4)	(5)	(6)
y_{mp}	—	—	—	−0.076	−0.068	−0.064
				(.01)	(.01)	(.01)
y_{mt}	−0.034	−0.026	−0.030	−0.021	−0.024	−0.023
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
$\#\text{Kids0–2}_{t-1}$	−0.044	−0.050	−0.028	−0.048	−0.045	−0.034
	(.01)	(.01)	(.02)	(.01)	(.01)	(.02)
$\#\text{Kids0–2}_t$	−0.034	−0.034	−0.047	−0.077	−0.070	−0.055
	(.02)	(.02)	(.02)	(.01)	(.01)	(.01)
$\#\text{Kids3–5}_t$	−0.031	−0.040	−0.024	−0.062	−0.053	−0.022
	(.02)	(.02)	(.02)	(.01)	(.01)	(.01)
$\#\text{Kids6–17}_t$	−0.010	−0.008	−0.027	−0.010	0.010	−0.005
	(.01)	(.01)	(.01)	(.01)	(.01)	(.004)
Birth_{t+1}	0.038	0.045	0.030	0.004	0.010	0.003
	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
h_{t-1}	0.274	0.338	0.647	0.306	0.399	0.563
	(.03)	(.03)	(.09)	(.03)	(.03)	(.13)
ρ	—	—	−0.194	—	—	−0.166
			(.04)			(.10)
Instruments	h_{it-2}	h_{it-s} $\forall s > 1$	h_{it-2}	Δh_{it-1}	Δh_{it-s} $\forall s > 0$	Δh_{it-1} Δh_{it-2}

Notes: All specifications also include unrestricted time effects, a quadratic in age, race, and years of education. Arbitrary cross-equation correlation and cross-sectional heteroscedasticity-corrected estimated standard errors are in parentheses. The model is:

$$h_{it} = \gamma h_{it-1} + X_{it}'\beta + \alpha_i + \varepsilon_{it}.$$

Columns (1), (2), (4), and (5) assume ε_{it} is serially uncorrelated.
Columns (3) and (6) assume $\varepsilon_{it} = \rho\varepsilon_{it-1} + v_{it}$.