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ESSAYS ON LABOR SUPPLY AND POVERTY: A MICROECONOMETRIC APPLICATION

Nizamul Islam

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To my father

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Göteborg, May 2006

Nizamul Islam

Contents

Paper 4 “Poverty dynamics in Ethiopia: state dependence and transitory shocks”

Nizamul Islam and Abebe Shimeles

Abstract

This thesis consists of four papers in applied micro econometrics. The first paper evaluates the discrete choice labor supply Model by Monte Carlo experiment. The 2nd paper investigates the relationships between participation decisions and both the fertility decision and women's non-labor income. The third paper analyses the relationship between hours of work and fertility decision and non wife income. The fourth paper analyses the poverty dynamics in Ethiopia.

The first paper is based on Monte Carlo simulation in order to evaluate the properties of discrete choice labor supply model. The data is generated by a continuous model and a discrete choice model is estimated assuming a translog utility function. The robustness of the results for different number of points in the discrete choice set, as well as for measurement errors in income and hours are compared. The discrete model produces similar results as the 'true' continuous model and apart from large measurement errors in hours these results are robust.

The second 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.

The third paper investigates the dynamic effects of having children on women's hours of work decision. A dynamic Tobit model is applied to longitudinal data to estimate the hours of work of married women in Sweden during 1992-2001. Hours of work are found to be negatively related to fertility. Other characteristics of married women are also found to have an effect on labor supply. Inter- temporal labor supply decisions seemed to be characterized by a substantial amount of unobserved heterogeneity, first order state dependence and serially correlated error components. The findings suggest that the first order state dependence and unobserved heterogeneity are very sensitive to the initial condition.

This paper focuses on the persistency of poverty in rural and urban households in Ethiopia by estimating dynamic probit models. The empirical results find that the risk of poverty increases with the number of household's size. The results also find that the land size is highly correlated (negatively) with the risk of poverty. The most important cash crops (Coffee and Chat) has significant role in the alleviation of poverty in Ethiopia. The effect of true state dependence and transitory shocks in poverty persistency appears to be stronger among urban households than rural households.

Keywords: Labor Supply, State Dependence, Unobserved Heterogeneity, Poverty persistency,

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A Monte Carlo evaluation of discrete choice labour supply models

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This paper is based on a Monte Carlo simulation in order to evaluate the properties of the discrete labour supply model. The data is generated by a continuous model and a discrete choice model is estimated assuming a translog utility function. The robustness of the results for different number of points in the discrete choice set, as well as for measurement errors in income and hours are compared. The discrete model produces similar results as the 'true' continuous model and apart from large measurement errors in hours these results are robust.

I. Introduction

Empirical research in labour supply has experienced an interesting change during the last decade. Inspired by Van Soest (1995) a large number of studies have been based on the discrete choice approach. Compared to the traditional continuous model introduced by Burtles and Hausman (1978) the discrete approach has a number of advantages. First, it is straightforward to deal with non-linear income taxes in a manner that does not impose the Slutsky restriction on the parameters of the model. Secondly, the preference model is fully structural and economic theory is testable. Thirdly, it is easy to analyse the joint decision of the spouses. Fourthly, it is feasible to incorporate preference heterogeneity in the model. Finally, it is straightforward to include as many details as possible regarding the budget set even if this results in non-convexities. For recent applications, see Hoynes (1996); Keane and Moffitt (1998), and Blundell and MaCurdy (2000).

The purpose of this study is to evaluate the properties of the discrete model in a Monte Carlo experiment. It is assumed that the continuous piece wise linear labour supply model is the true process that generates the data. The discrete choice model, assuming a translog utility function, is estimated and the robustness of this model is evaluated. According to the results, the discrete choice model seems flexible enough to encompass the continuous linear model. The estimated welfare effects are similar to the true values. Except for measurement errors in hours, these results are robust.

The plan of this paper is, first, to present the continuous model used for data generation. Next the discrete approach is presented and thereafter the Monte Carlo experiment is explained, finally the results are presented.

II. The Piece-Wise Linear Labour Supply Model

Burtless and Hausman (1978) proposed the piece-wise linear (PWL) approach to estimate the labour supply function in the presence of non-linear taxes. This approach is characterized by a detailed description of the income tax system. It admits randomness in hours of work arising from both variations in individual preferences and in measurement error.

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It also explicitly accounts for endogeneity of the marginal tax rate in estimation.

The PWL approach has recently been criticized for several reasons: First, if preferences are not quasi-concave in some relevant region then the likelihood function is not defined.[1] Second, it assumes that the econometrician have perfect knowledge of the entire budget set that is relevant for the worker in question. Third, the estimates seem to be quite sensitive to measurement errors in the variables see Blomquist (1996) and Ericson and Flood (1997).[2]

In a static labour supply model individual determines hours of work and consumption by maximizing a utility function, $U(C, h)$, subject to the budget constraint, $C = Wh + Y + V - t(I)$, where C is the income after tax, W the gross wage per hour, h hours of market work and Y and V are taxable and non-taxable non-labour income respectively. Income taxes are determined by the tax function $t(I)$, where taxable income $I = Wh + Y - D$ and D is deduction per year.

Given a convex budget set and no measurement errors in hours of work, Hall (1973) noted that the solution to the individual maximization problem would be the same as if the individual faced a linear budget constraint tangent to the actual budget set at observed hours of work. The intercept of this linear budget set is called 'virtual income', and the slope equals the marginal wage. Solving the maximization problem defines the labour supply function,

$$h = f(w', y) \tag{1}$$

where y is the virtual income and w' the marginal wage.

To capture factors that cause heterogeneity in preferences hours of work will also be allowed to be dependent on a vector of measured characteristics, **Z**, and on an unobserved component ν. It will be assumed that $\nu \sim N(0, \sigma_\nu^2)$. The next step is to assume a functional form and a stochastic specification of the conditional supply function. The following linear models will be used:

$$\begin{aligned} f(w'_j, y_j) &= \mu + aw'_j + \beta y_j + \gamma x + \nu \\ j &= 1, \ldots, k \end{aligned} \tag{2}$$

To make the model compatible with observed data an assumption about measurement error, ε is included. Typically an additive error is assumed, $h^* = \hat{h} + \varepsilon$, where h^* denotes measured hours of work, and $\varepsilon \sim N(0, \sigma_\varepsilon^2)$ is considered as a measurement error. Independence between ε and ν is also assumed, $E(\varepsilon, \nu) = 0$.

III. Discrete Choice Model

In the discrete choice model labour supply is treated as a choice of a discrete class of working hours. Van Soest (1995) claimed that non-linear taxes, joint filing, fixed costs of working, unemployment benefits, etc. can easily be incorporated, without affecting model tractability. The study also claimed that a discrete choice model able to allow for a richer stochastic specification than usual: it takes account of the problem of unobserved wage rates of non-workers, and can incorporate random preferences. This is feasible because of simulated maximum likelihood estimation (Gourieroux and Monfort, 1993). Discrete choice model avoids problems of model coherence; the Slutsky constraint can be tested. This model is fully structural in the sense that all policy simulations which can be performed in the continuous model remain feasible.

This study follows Van Soest (1995), and assumes a translog specification of the direct utility function.

$$\begin{aligned} U(C,h) = {} & B_c \log(C) + B_h \log(H-h) + B_{cc}(\log(C))^2 \\ & + B_{hh}(\log(H-h))^2 + 2B_{ch}\log(C)\log(H-h) + \varepsilon \end{aligned} \tag{3}$$

The total endowment of time (H) is set to 4000 hours/year. The individual is assumed to choose among different working states, ranging from 1000 up to 3000 hours/year. Random disturbances (ε) are added to the utilities of all choice opportunities in the same way as in the multinomial logit model, i.e., by assuming an extreme value distribution.

The contribution to the likelihood for an individual becomes

$$(p|\theta_h)_i = \frac{\exp(U_i)}{\sum_i \exp(U_i)} \tag{4}$$

where i indicates individuals' hours. This expression simply denotes the probability that the utility in the observed state is the highest amongst all of the possible hours.

[1] This is the coherency problem discussed in Kapteyn *et al.* (1990).
[2] The differentiable approximation approach, suggested by MaCurdy *et al.* (1990), suggests an alternative to circumvent some of the deficiencies of PWL approach.

IV. The Monte Carlo Experiment

The data used for the analyses comes from a Swedish survey of Household Market and non-market activities, called HUS (see Klevmarken and Olovsson, 1993). This database includes detailed information on a random sample of individuals in Swedish households over several years from 1984. This study is limited to a subsample of married or cohabiting males in 1984. Further, all individuals below 25 or above 65 years of age have been excluded, as well as individuals who have retired, who have been sick more than four weeks in the year, or who are students or self-employed. Observations with missing values on any variable were also excluded. After the selections, 447 individuals remained.

It is assumed that the continuous type model is the true model. Ericson and Flood (1997) is followed where the same data is used. The described data has been used to estimate the parameters in the model (Equation 2). These estimates, along with the following search algorithm, predict hours of work for individuals facing piece-wise linear budget sets. The search algorithm is:

(1) Calculate the marginal wage and virtual income related to the individual at each segment.
(2) Calculate the desired hours of work, h_k, at each segment, using Equation 2.
(3) If h_k falls in the interval of hours of work for any k, this is the desired hours of work. Otherwise h is located at the kink between two segments, where h_k is greater than the upper limit of segment k and h_{k+1}, is less then the lower limit of segment $k+1$.

The simulated hours of work are then obtained by appending an unobserved component and a measurement error to the predicted hours of work. Once the simulated hours of work are available, the discrete choice model can be estimated. In this study, 100 replications are made for each experiment.[3]

It is chosen to evaluate the estimated welfare effect of a 10% increase in gross wage. As a summary statistic, we choose equivalent variation (EV). EV is measured as the amount of money added or subtracted from the individual's disposable income under the initial wage in order to make the individual indifferent between the initial and the alternative wage. This equivalent variation (EV) can be represented as

$$EV = (C^* - C_0)/C_0$$

where C_0 is the disposable income under the initial wage and C^* is the disposable (optimal) income that makes an individual indifferent between the initial and alternative wage.

For the continuous model EV is calculated at the initially estimated parameters, this is considered as the true value of EV. The discrete choice model was estimated 100 times, for each of the generated data sets. Based on these 100 estimates EV was calculated and then the average value was obtained. A comparison of the mean simulated EV and the true value is used in order to assess the quality of the discrete choice model. Next the results are presented and some experiments are evaluated.

V. Results

A comparison of the true EV (calculated from the continuous model) with the mean value of EV from the discrete choice approach is presented in Table 1. The entries in the table denote the percentage deviation from the true value. The first entry in row 1 shows a small underestimation of 4% using 11 working classes. Decreasing the number of points in the discrete choice set has no apparent effect. For six classes there is no bias and for three a negative bias of 4%. These results confirm the findings reported in Van Soest and Das (2000), the results are robust with respect to the number of classes. This is an important result since the choice of classes often is arbitrarily.

The next experiment analyses effects of measurement errors in variables used for the construction of the budget sets. It is assumed that no information

Table 1. Equivalent Variation (EV) due to a 10% wage increase

Experiment	Bias in EV(%)
(1) 11 states	−4
(2) 6 states	0
(3) 3 states	−4
(4) Errors in deductions	−6
(5) Measurement error $\sigma_\varepsilon = 0.5$	10
(6) Measurement error $\sigma_\varepsilon = 0.75$	127
(7) Measurement error $\sigma_\varepsilon = 1.0$	576

Note: The entries denote the percentage difference from the true value.

[3] In this paper unobserved heterogeneity in the estimation is not allowed.

about individual's deduction (D) is available and the researcher uses the base-level deduction (7500 SEK per year) as a proxy for all individuals. The result, reported in row 4 in Table 1, indicates a small negative bias (−6%). This result stands in sharp contrast to the results for the continuous model, reported in Ericson and Flood (1997) and Blomquist (1996). Especially the findings in Blomquist's study indicate that the properties of the continuous model are severely affected by measurement errors in income variables.

The traditional Burtles and Hausman model has two types of errors: random preferences and optimization or measurement error of hours of work. In the discrete choice model random preferences are incorporated, and the GEV I errors could be seen as an alternative specific utility evaluation errors i.e., a form of optimization error. They cannot be seen as measurement errors of hours (desired) worked, however. To investigate whether neglecting measurement error on hours worked could bias the results, new data sets have been generated and the model re-estimated. It is not clear what would be a reasonable size of the measurement error. In the simulation, measurement error with mean zero and standard deviations 0.5, 0.75, and 1.0 (hours (in thousand) per year) were used. Thus, to clarify, the data are generated assuming the presence of measurement errors but estimated without taking this into consideration.

The results are presented in rows 5–7 in Table 1. In accordance with Van Soest *et al*. (2001), it is found that measurement error in hours of work causes serious problem for the discrete choice approach. However, in order to generate a sizeable bias a sizeable variance in the measurement errors are needed. The smallest standard deviation of 0.5 (500 hours) which generates a 10% bias is larger than the standard deviation in the data (315 hours). If the variance in measurement errors is small this does not cause a serious problem but for large measurement errors the problem of bias can be severe. For instance, as reported in row 7, assuming a variance of 1000 hours in the measurement errors produces a bias of 576%.

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Dynamic labor force participation of married women in Sweden

Nizamul Islam[*]

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.
JEL: J22, C23, C25

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1 Introduction

Dynamic discrete choice model has received significant attention in female labor supply research (e.g., Heckman 1981c, Chay and Hyslop 1998, Hyslop 1999). In this model, there is an issue regarding the source of serial persistence on women's participation decision. Heckman (1981) discusses two sources of this serial persistence. The first source is the presence of "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).

In a dynamic search framework, Hyslop (1999) distinguishes the true state dependence from spurious state dependence across married women. 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. The analysis 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.

Following Hyslop (1999), a random effect probit approach which allows for unobserved heterogeneity, first order state dependence and serial correlation in the error term is applied. I formulate a finite mixture model which allows for unobserved heterogeneity in a very flexible way without imposing a parametric structure. The model also allows for endogenous initial condition. For models with general correlated disturbances, I use simulation based estimation methods (MSL) proposed by Lerman and Manski (1981), McFadden (1989), and Pakes and Pollard (1989), among others. I adopt standard approach to simulation estimation to random draws from the specified distribution.

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 results also show that the addition of a transitory component of the error has significant effect on the model. In the specification which allows first order state dependence and serial correlation in the transitory errors components, it is found that the first order state dependence has a little effect on unobserved heterogeneity and serial correlation parameter. However the estimated first order AR(1) component has a large and significant effect on the model.

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,

[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.

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 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.

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[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).

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, the following variables have been analyzed:

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.

[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.

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 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 (2000) 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. The model can defined as -

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

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

where h_{it} is the observable indicator of participation; X_{it} is a vector of observable characteristics, including age, education, places of birth, number of children aged 0-2, 3-5, and 6-17 years; and husband's 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

[4] 1 US Dollar = 8.94698 Swedish Kroner (2000-06-01).

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}.

In the presence of state dependence, expectations of future outcomes may affect current participation decisions. In order to achieve a tractable empirical specification, the following assumptions with respect to the expectation of fertility and non-labor income are needed (Hyslop 1999). First, a robust prediction is surely that expectations effects decline in the future. Thus it is assumed that only expectations of one period ahead of realizations affect the current period participation decisions. Second, there is perfect foresight with respect to lifecycle fertility decisions. Therefore an indicator variable for whether a birth occurs next period is included. Third, a simple stationary stochastic process is adopted for the non labor income process, in which expected future income is taken as permanent income. Thus if transitory income is uncorrelated with tastes, it will only have a direct 'income effect' on participation, while the total effect of permanent income on participation will consist of this direct effect, an 'expectations' effect, and a 'tastes' effect.

3.1 Linear probability models

The linear probability model in level specification for equation (1) can be written as:

(2) $$h_{it} = \gamma h_{it-1} + X_{it}\beta + \alpha_i + \varepsilon_{it} \qquad (\text{ i=1,2,…,N; t=1,2, …,T})$$

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 model in first difference can be written as:

(3) $$\Delta h_{it} = \gamma \Delta h_{it-1} + \Delta X_{it} + \Delta \varepsilon_{it}$$

If ε_{it} is not serially correlated, then equation (3) can be consistently estimated using previous lag h_{it-2} or all past and future covariates as instruments for Δh_{it-1}.

3.2 Non-linear models

A random effect probit specification for individual *i* at time *t* can be defined as follows

(4) $$h_{i0} = 1\left(\beta_0 X_{i0} + u_{i0} > 0\right)$$

(5) $$h_{it} = 1\left(\gamma h_{it-1} + \beta X_{it} + \alpha_i + \varepsilon_{it} > 0\right) \qquad (i = 1,2,\ldots N; \text{ and } t = 1,2,\ldots,T)$$

where h_{it} is the observable indicator of women's participation at time t. X_{it} is a vector of observable characteristics, including age, education, places of birth, number of children aged 0-2, 3-5, and 6-17 years; and husband's earnings. β is a set of associated parameters to be estimated. *True* state dependence is captured by the parameter γ and *spurious* state dependence is captured by both the parameter α_i and ε_{it}. Equation (4) is defined as initial period equation. It is assumed that the initial period error (u_{i0}) is correlated with the other periods errors ($u_{it} = \alpha_i + \varepsilon_{it}$).

Furthermore, if unobserved taste is correlated with fertility and/or income variables, then

(6) $$\alpha_i = \sum_{s=0}^{T}\left(\delta_{1s}\left(\#Kids0-2\right)_{is} + \delta_{2s}\left(\#Kids3-5\right)_{is} + \delta_{3s}\left(\#Kids6-17\right)_{is}\right) + \sum_{s=0}^{T-1}\delta_{4s}y_{mis} + \eta_i$$

with $\eta_i / X_i \sim N(0, \sigma_\eta^2)$.

$\varepsilon_{it} = \rho\varepsilon_{it-1} + v_{it}$,

$v_{it} \sim N(0, \sigma_v^2)$ orthogonal to η_i.

It is assumed that the error term, α_i represents an unobserved individual specific and time invariant effect. Compare to an ordinary probit or logit model, the lagged observed outcome h_{it-1} and the parameter α_i cause some estimation problem. Heckman (1981a) showed that the above model can be estimated by maximum likelihood estimation method under the assumption that the distribution of $\varepsilon_{i1}, \ldots, \varepsilon_{iT}$ is multivariate normal. Lee (1997) argues that Heckman's likelihood formula is correct only for models without lagged latent dependent variables and needs to be revised. However for random component or one factor models, multivariate probability functions involve only single integrals, which can be effectively implemented using Gaussian Quadrature (Butler and Moffitt 1982). But for general correlated disturbances, the likelihood function involves multiple integrals. Thus for correlated disturbances the simulation based estimation (MSL) as proposed by Lerman and Manski (1981), McFadden (1989), and Pakes and Pollard (1989), among others, can be used. In this study simulation based estimation

(MSL) method is used and a standard approach to simulation draw from the specified distribution is applied. Good performance with this method requires a very large number of draws. With a large sample and a large model, this entails a huge amount of computation and thus very time consuming.

In the above model, there is a crucial issue on how to treat the initial observations. The common approach to solve this issue is to assume that either the initial condition is exogenous and can be treated as fixed (e.g., Heckman 1978, 1981a, 1981c) or that the process is in equilibrium at the beginning of the sample period (e.g., Card and Sullivan 1988). The assumption that initial conditions are fixed constants may be justifiable only if the disturbances that generate the process are serially independent and if a genuinely new process is fortuitously observed at the beginning of the sample. If the process has been in operation prior to the time it is sampled, or if the disturbances of the model are serially dependent as in the presence of individual-specific random effects, the initial conditions are not exogenous (Hsiao C. 2003). The assumption that the process is in equilibrium also raises problems in many applications, especially when time varying exogenous variables are driving the stochastic process (Hsiao C. 2003). In order to handle this issue I follow a procedure similar to that suggested by Heckman (1981). For the initial period the individual is observed (t=1), a static binomial probit model is estimated. This procedure approximates the initial conditions for the model. Heckman (1981) reports that this approximation performs well in a binary choice model leading to only a small asymptotic bias.

I formulate a finite mixture model which allows for unobserved heterogeneity in a very flexible way without imposing a parametric structure[5]. The idea of incorporating unobserved heterogeneity originated from Heckman and Singer (1984). They show that the estimation of finite mixture might provide a good discrete approximation even if the underlying distribution is continuous. It is assumed here that the probability distribution of unobserved individual specific effects can be approximated by a discrete distribution with a finite number of support points. Integration is then replaced by summation over the number of support points for the distribution of unobserved heterogeneity. That is, for M types of individuals, each endowed with a set of unobserved characteristics associated with each support point is a probability, π_m, where $\sum_{m=1}^{M} \pi_m = 1$ and $\pi_m \geq 0$. The interpretation of these unobserved heterogeneity parameters are straightforward. A higher value simply implies a higher preference for work. This specification allows for arbitrary correlations between the initial period support point and the other periods support points.

[5] Similar to Hyslop (1999), the model is also estimated by the method of simulated likelihood (MSL) assuming that the heterogeneity distribution is normal

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.[6]

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 -0.36 which is downwards bias due to negative correlation between Δh_{it-1} and the error due to first differencing. While the estimate obtained from level specification is 0.72 which is upwards bias because of unobserved heterogeneity. The results are very close to Hyslop's GLS findings for lagged dependent variables. The estimates for first difference and level specifications in Hyslop's findings are -0.35 and 0.67 respectively (See appendix row 1 Table II).

If the regressors are exogenous with respect to the transitory error component then out of period realizations of the covariates would be valid instrument and enable consistent estimate of lagged dependent variables effect. In row 2, out of period of realizations of

[6] 10% sub sample and full sample produce almost similar result in all specification in the static model. It is mentioned that good performance of simulated maximum likelihood method (MSL) requires a very large number of draws. And with a large sample and a large model, this entails a huge amount of computation and thus very time consuming. Therefore 10% sub sample has been used in the simulated maximum likelihood estimation methods and the results reported here are based on 10% sub-sample in all specification.

the covariates has been used as instruments for the lagged dependent variable. The coefficients in first difference and level specification are: -0.20 and 0.36 respectively. But F statistics indicates that these are weak instruments, and that the results (-0.20 and 0.36) are thus bias towards the least square estimates (Bound, Jaeger, and Baker 1995).

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 0.20 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 estimated lagged dependent variables become closer to each other. The coefficients of lagged dependent variable are 0.35 to 0.26. The estimated coefficient from Arellano and Bond (1991) specification, presented in row 5, is significantly higher than that presented in row 4. The first order state dependence specification is rejected by the over identification test.

Table-2>>>

Table 3 shows the estimated regressor coefficients from the specifications presented in rows 4 and 5 of Table 2. Table 3 also contains the results for the linear model with first order state dependence and AR(1) coefficient (column 4). 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) and the future birth variable is not included. 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. 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 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. 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 (5) 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 also gives no support for rejecting the hypothesis of no-correlation between the unobserved heterogeneity and the three fertility variables. These findings sharply contradict Hyslop (1999), 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 condition 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 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 classes and found that the model is fitted well with two classes (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 objective 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). A dynamic probit model which allows for unobserved heterogeneity, first order state dependence and serial correlation in the error components is estimated. The distribution of individual specific heterogeneity of initial period is assumed to be correlated with other periods. Sensitivity to alternative distributional assumptions is examined using both linear probability regression models and probit models.

Both linear and probit results suggest that there is a negative fertility effect on participation propensities. The empirical findings also suggest that the inter-temporal participation decisions are characterized by a substantial amount of unobserved heterogeneity. The addition of a transitory component of the error has significant effect on the model. In the specification which allows first order state dependence and serial correlation in the transitory errors components, it is found that the first order state dependence has a little effect on unobserved heterogeneity and serial correlation parameter. The estimation results for this model implies that almost no true state dependence in individual propensities to women participation. The state dependence coefficient is -0.04. However the estimated first order AR(1) component has a large and significant effect on the 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			Level-specification		
Instrument	γ	Test statistic	Instrument	γ	Test statistic
(1) -	-0.36 (0.01)	-	-	0.72 (0.01)	-
(2) $\Delta X_{is}, \forall s$	- 0.20 (0.04)	13.11[a] (0.00)	$X_{is}, \forall s$	0.36 (0.04)	17.92[a] (0.00)
(3) $\Delta X_{is}, \forall s$ h_{it-2}	0.20 (0.01)	55.49[a] (0.00)	$X_{is}, \forall s$ Δh_{it-1}	0.34 (0.02)	48.04[a] (0.00)
(4) h_{it-2}	0.35 (0.01)	-	Δh_{it-1}	0.26 (0.01)	-
(5) $h_{it-s}, \forall s > 1$	0.43 (0.02)	97.71[b] (0.00)	–	–	–

(a) First stage F statistic 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		Level-specification	
	(1)	(2)	(3)	(4)
Instruments	h_{it-2}	Δh_{it-s} $\forall s > 0$	Δh_{it-1}	Δh_{it-1}
Permanent non-labor income (y_{mp})	-	-	0.011 (0.006)	0.016 (0.003)
Transitory income (y_{mt})	-0.006 (0.003)	-0.008 (0.003)	-0.004 (0.002)	-0.007 (0.002)
No. of children aged 0-2 years(#kid0-2)	-0.043 (0.014)	-0.040 (0.018)	-0.129 (0.009)	-0.079 (0.009)
No. of children aged 3-5 years(#kid3-5)	-0.060 (0.011)	-0.061 (0.014)	-0.018 (0.007)	-0.035 (0.007)
No. of children aged 6-17 years(#kid6-17)	-0.025 (0.008)	-0.019 (0.009)	-0.015 (0.004)	-0.013 (0.003)
Lagged dependent (h_{t-1})	0. 35 (0. 024)	0.43 (0.018)	0. 263 (0.012)	0. 39 (0.006)
AR(1) Coefficient (ρ)	-	-	-	0.35

Notes: Estimated standard errors in parentheses. All specifications include 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 (latent class) (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)	-	
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 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) Var (η_i) is expressed as a fraction of the total error variance.

Table 5: Dynamic Probit Latent class Models of Married Women's Participation Outcomes

	Random effect with AR(1) (1)	Random effect with SD(1) (correlated initial condition) (2)	Random effect with AR(1)+ SD(1) (correlated 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 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.

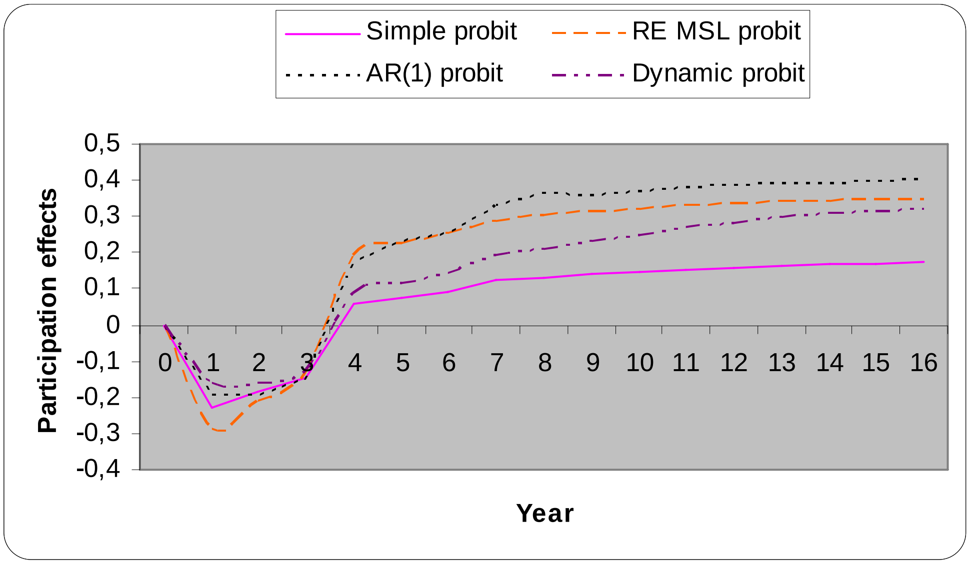

Figure1: Response to a birth in year 1, various models.

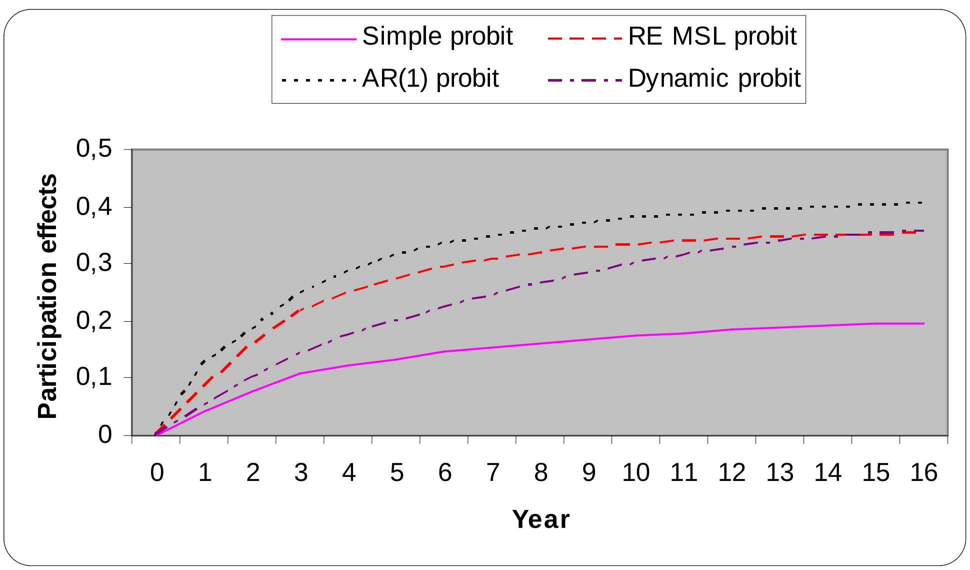

Figure2: Response to a 10% increase in permanent income in year 1, various models.

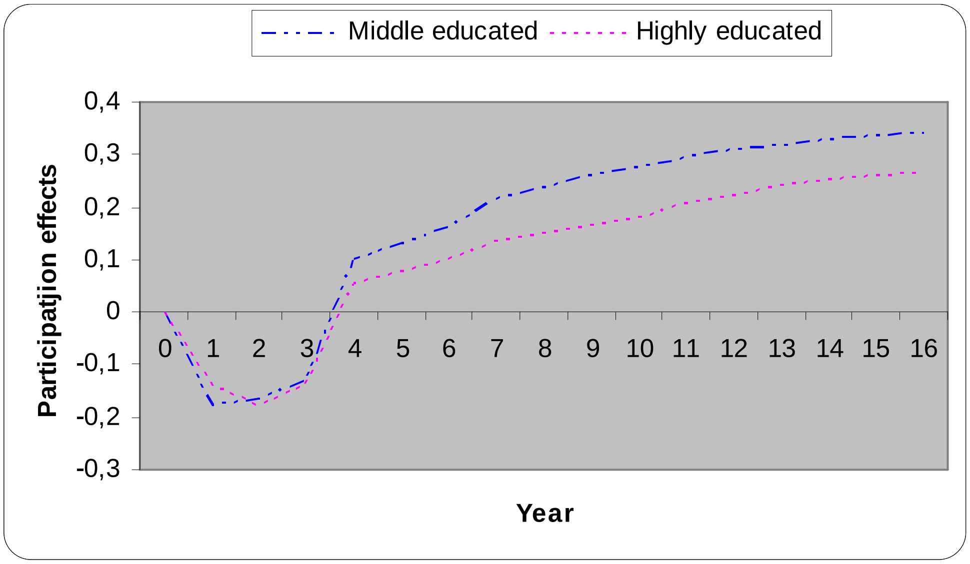

Figure 3: Dynamic probit response to a birth in year 1, by education level.

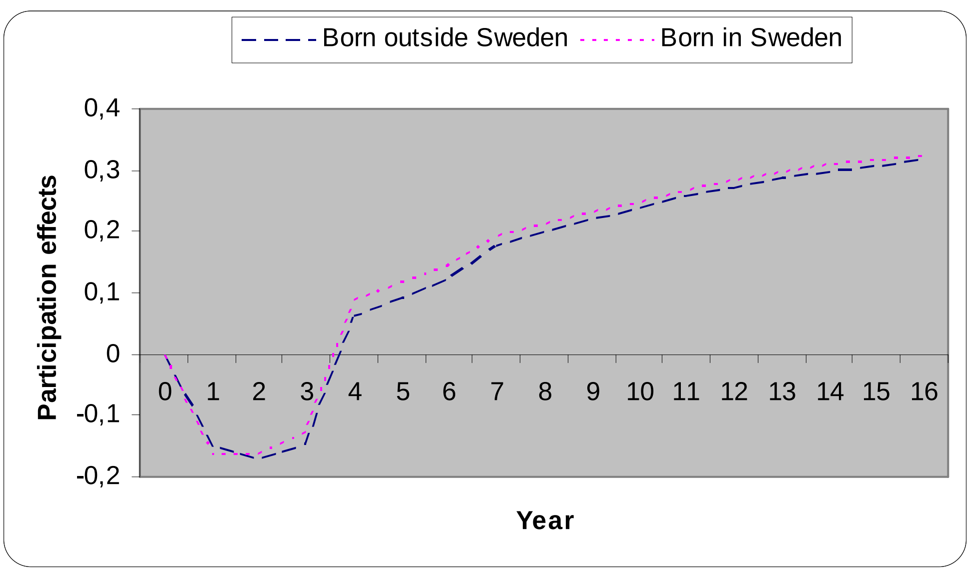

Figure 4: Dynamic probit response to a birth in year 1, by immigration-status.

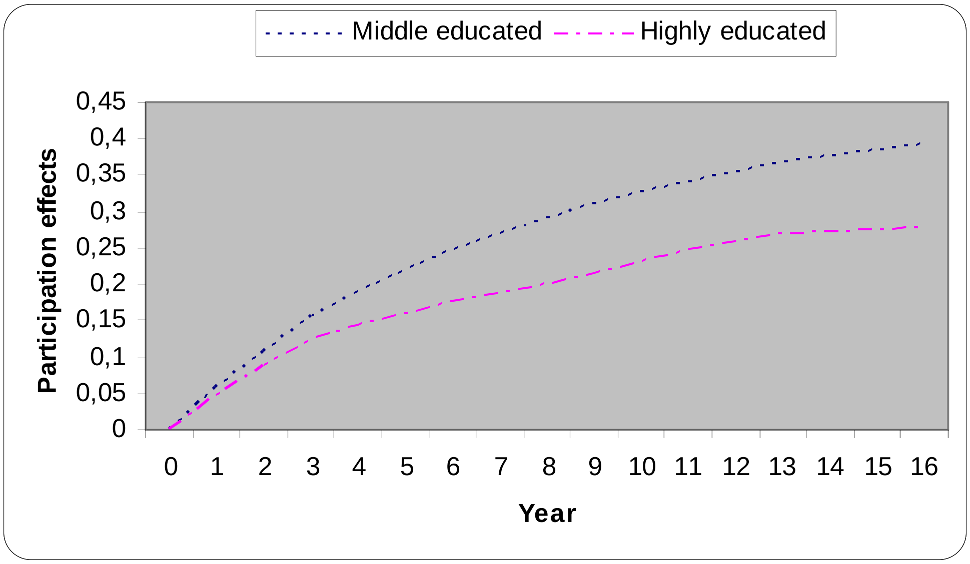

Figure 5: Dynamic probit response to a 10% increase in permanent income in year 1, by education level.

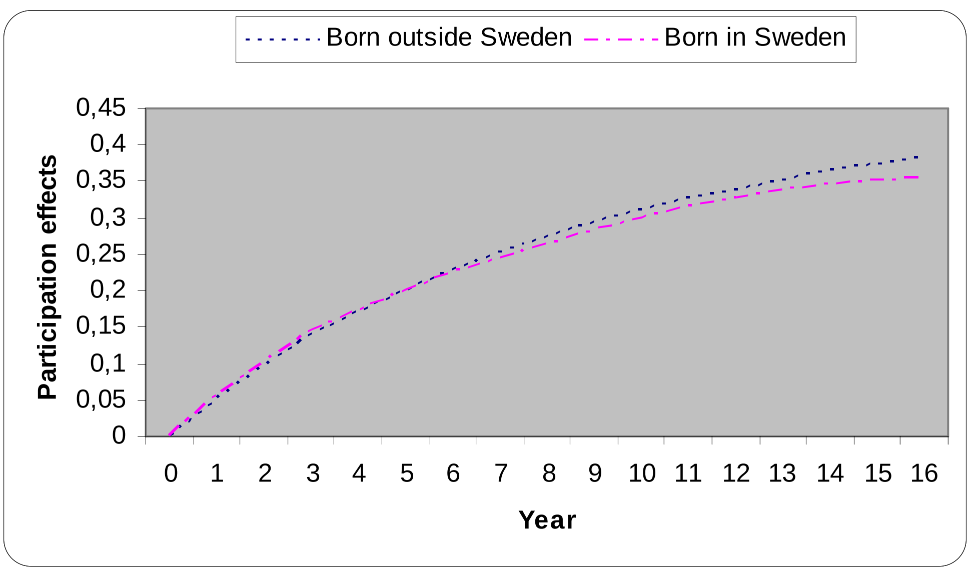

Figure 6: Dynamic probit response to a10% increase in permanent income in year 1, by immigration-status.

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	—	—	—
onè	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 (.02)	—	—	—	0.668 (.01)	—	—
(2)	$\Delta X_{is}, \forall s$	−0.181 (.05)	—	1.50[a] (.06)	$X_{is}, \forall s$	0.483 (.05)	—	1.23[a] (.25)
(3)	$\Delta X_{is}, \forall s$ h_{it-2}	0.257 (.03)	—	14.34[a] (.00)	$X_{is}, \forall s$ Δh_{it-1}	0.337 (.02)	—	13.41[a] (.00)
(4)	h_{it-2}	0.274 (.03)	—	—	Δh_{it-1}	0.306 (.03)	—	—
(5)	$h_{it-s}, \forall s > 1$	0.338 (.03)	—	26.96[b] (.00)	$\Delta h_{it-s}, \forall s > 0$	0.399 (.03)	—	29.36[b] (.00)
(6)	h_{it-2}	0.647 (.09)	−0.194 (.04)	10.73[c] (.06)	Δh_{it-1} Δh_{it-2}	0.563 (.13)	−0.166 (.10)	11.15[c] (.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)
#Kids0–2_{t-1}	-0.044	-0.050	-0.028	-0.048	-0.045	-0.034
	(.01)	(.01)	(.02)	(.01)	(.01)	(.02)
#Kids0–2_t	-0.034	-0.034	-0.047	-0.077	-0.070	-0.055
	(.02)	(.02)	(.02)	(.01)	(.01)	(.01)
#Kids3–5_t	-0.031	-0.040	-0.024	-0.062	-0.053	-0.022
	(.02)	(.02)	(.02)	(.01)	(.01)	(.01)
#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 $\varepsilon_{it} = \rho\varepsilon_{it-1} + v_{it}$.

A Dynamic Tobit Model of Female Labor Supply[#]

Nizamul Islam[♣]

Abstract: A dynamic Tobit model is applied to longitudinal data to estimate the hours of work of married women in Sweden during 1992-2001. Hours of work are found to be negatively related to fertility. Other characteristics of married women are also found to have an effect on labor supply. Inter- temporal labor supply decisions seemed to be characterized by a substantial amount of unobserved heterogeneity, first order state dependence and serially correlated error components. The findings suggest that the first order state dependence and unobserved heterogeneity are very sensitive to the initial condition.

Keywords: Female labor supply, state dependence, heterogeneity, dynamic Tobit.

JEL: J22; C23, C25.

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1 Introduction

The inter-temporal labor supply behavior of married women is a long standing interest in labor supply research (Heckman, 1974; Heckman and MaCurdy, 1980). It has been observed in such research that an individual who has experienced an event in the past is more likely to experience the event again in the future (Blank, 1989; Chay and Hyslop 1998; Hyslop, 1999). Heckman (1981a) calls this inter-temporal dependence "*true* state dependence", as opposed to another kind, *spurious* state dependence, generated by persistent individual heterogeneity. To analyze state dependence and distinguish true from spurious, Heckman (1981a) suggests using a dynamic model with unobserved individual specific effects. Such a model is applied here to estimate the effects of fertility and husband's earnings on labor supply decision (hours of work) of Swedish married women.

Hyslop (1999) analyses a similar model using US data to estimate the effects of the fertility decision and husband's earnings (a proxy for non-labor income) on labor-market participation. He proposes a general probit model with correlated random effects; auto correlated error terms and state dependence, and compares the results for different specifications. Islam (2005) investigates a similar model to Swedish participation data. Like Hyslop, substantial unobserved heterogeneity is found in the participation decision. In contrast to Hyslop, statistically significant positive serial correlation in the transitory errors, as well as negative but small state dependence is found in Islam's analysis.

Following Heckman's (1981a) suggestion but going beyond Hyslop's (1999) and Islam's (2005) analysis of participation, I investigate the inter-temporal labor supply (hours of work) behavior of married women in Sweden. In particular, I am interested to see the dynamic effects of having children on women's hours of work decision. I am also interested to know whether the husband's earnings are sensitive to women's hours of work decision in life cycle consideration.

According to the Heckman and MaCurdy's (1980) labor supply model, the censored model would be relevant if the sample consists of a random sample of individuals, with hours of work reported as 0 if the individual does not work. The techniques used in the estimation of linear panel data models are inappropriate due to censoring nature. The introduction of lagged dependent variables and serial correlation in the error term make the conventional estimation techniques even more difficult to apply in the Tobit model. Moreover, misspecification of the distribution of the unobserved variance yields inconsistent results (Arabmazar and Schmidt, 1982 Goldberger, 1983). Thus the challenging issue is to estimate a Tobit (standard censored regression) models with lagged dependent variables and serially correlated errors. However a random effect specification is applied in the Tobit model which allows for unobserved heterogeneity, first order state dependence and serial correlation in the error components. A finite mixture approach is used, in which individual specific effects can be handled flexibly without imposing a parametric structure. I follow Heckman and Singer (1984) approach in which only the constant term varies across the classes. For correlated disturbances, simulation based estimation (MSL) as proposed by Lerman and Manski (1981), McFadden (1989), and Pakes and Pollard (1989), among others is used. A standard approach to simulation draw from the specified distribution is applied.

The results provide the evidence that hours of work decisions are negatively related to the fertility decision. The effect of permanent income is significant, while the effect of transitory income is insignificant. Substantial unobserved heterogeneity, positive first order state dependence and negative serial correlation in the transitory errors are found. Other characteristics of married women are also found to have an effect on the labor supply decision. An overview of the paper is as follows.

A descriptive analysis of the characteristics of married women in Sweden is presented in Section 2, while Section 3 presents the model and empirical specification. Section 4 reports the empirical findings, Section 5 discuss sensitivity analysis and section 6 discusses simulation results. Finally section 7 summarises and draws conclusions.

2 Data and preliminary analysis

The data are drawn from the Swedish Longitudinal Individual Data (LINDA).[1] The sample used in this analysis consists of 98,210 continuously married couples, aged 20 to 60 in 1992. The sample contains eighty two percent observations for women with positive hours of work, while the remaining observations are for women who do not work for pay during the study period. The educational attainment is measured as the

[1] LINDA, a joint endeavour of the Department of Economics at Uppsala University, the National Social Insurance Board (RFV), Statistics Sweden, and the Ministries of Finance and Labour, is a register based data set consisting of a large panel of individuals and their household members; the main administrator is Statistics Sweden. The sampling procedure used ensures that each annual cross section is representative of the population of Sweden for that year.

highest level reported in 1992-2001.[2] Husband's earning is used as a proxy for non-labor income.[3] Annual earnings are expressed in constant (2000) SEK, computed as nominal earnings deflated by the consumer-price index.[4] A dummy variable for place of birth is included to see if there is any difference in the labor supply (hours of work) pattern between Swedish born and foreign born individuals. This dummy variable indicates the status of the individual, where 1 refers to native born and 0 otherwise.

Figure 1 shows the observed frequency distribution of number of years worked during the study period. The figure suggests that there is serial persistence in the participation decision of married women. For example the overwhelming majority of individuals either work in each year or never works, effectively ruling out the possibility that the process underlying the sequences is independent over time.

Figure 2 shows the distribution of observed annual hours of work. The distribution shows that married women have a varied pattern of hours worked with some bunching at 2000 hours and at the zero hour. This pattern suggests that hours of work are sensitive to changes in the structure of individual heterogeneity. One source of this heterogeneity can be differences in observable characteristics such as age, civic status, education, non-labor income and the number of children.

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[2] Three dummy-variables for educational attainment are used: One for women who have at most finished grundskola grade (9 years education); One for women who have more than 9 but less than 12 years of education; and one for women who have education beyond gymnasium (high school).

[3] Permanent non-labor income (y_{mp}) is the time average ($\bar{y}_{i.}$) of husband's earnings and transitory income (y_{mt}) is the deviation from the time average ($\bar{y}_{i.}$) of husband's earnings.

[4] 1 US Dollar = 8.94698 Swedish Kroner (June 1, 2000).

Table 1 reports observable individual characteristics for the full sample and various sub samples. It is observed that the women who work in all 10 years are better educated, have fewer young children, and have higher husband's earnings than those who never work. Woman with a single transition from work are older, less educated and have fewer dependent children than women with a single transition to work. The women who experience a single transition to work or who experience multiple transitions are younger than average, and have considerably more dependent children in all age groups. Their husband's earnings are slightly bellow average.

Figure 3 presents typical examples of the "raw" correlation between the age of youngest child and mother's annual hours of work for the years 1992, 1996, 1998, and 2001. As can be seen there is a distinct upward slope to these curves. This reproduces the almost universal finding that hours worked is increasing in the age of youngest child.

3 Empirical model and estimation methods

As mentioned earlier, the standard regression approach is not appropriate when the distribution of hours worked exhibits censoring at zero. In a dynamic random effect frame work, the Tobit model is described as:

$$y_{it}^{*} = x_{it}\beta + g(y_{it-1})\gamma + u_{it} \qquad (1)$$

$$y_{it} = \max\{y_{it}^{*}, 0\}$$

$$u_{it} = \alpha_i + \varepsilon_{it} \qquad t=1,\ldots,T \text{ and } i=1,\ldots,N$$

and

$$\varepsilon_{it} = \rho\varepsilon_{it-1} + v_{it}$$

$v_{it} \sim N(0, \sigma_v^2)$, orthogonal to α_i

where y_{it} is an observed response that equals zero with positive probability but is continuously distributed over strictly positive values. g(.) allows lagged values of the observed responses.[5] x_{it} is a vector of explanatory variables such as age, number of children, education, non-labor income, whether the women is an immigrant or Swedish born, etc. The component α_i is an unobserved individual specific random disturbance which is constant over time, and ε_{it} is an idiosyncratic error which varies across time and individuals. If the random effect is correlated with fertility and/or income variables, then

$$\alpha_i = \sum_{s=0}^{T} \left[\delta_{1s} \left(\# Kids0-2 \right)_{is} + \delta_{2s} \left(\# Kids3-5 \right)_{is} + \delta_{3s} \left(\# Kids6-17 \right)_{is} \right] + \sum_{s=0}^{T-1} \delta_{4s} y_{mis} + \eta_i \qquad (2)$$

where η_i is assumed independent of x_{it} and v_{it}. It is also assumed that $\eta_i / X_i \sim N(0, \sigma_\eta^2)$ (see Chamberlain, 1984; Jacubson, 1988; Hyslop, 1999).

A random effect specification is applied in the Tobit model which allows unobserved heterogeneity, first order state dependence and serial correlation in the error components. The draw back with the random effects approach comes from the difficulty in establishing a distribution of individual specific effects. The distribution of the unobserved component of the model for any one observation is linked through α_i to the unobserved components of all the other observations in the same cross sectional unit. Thus with the addition of α_i to the model, the likelihood function becomes somewhat more complicated than that of a simple Tobit model. Moreover, misspecification on the distributional assumption of unabsorbed heterogeneity may lead to inconsistent estimate

[5] The issue has been discussed in Wooldridge (2002).

(Arabmazar and Schmidt, 1982 Goldberger, 1983). An alternative approach used in this paper is to formulate a latent class model. The underlying theory of this model posits that individual behavior depends on observable attributes and on latent heterogeneity that varies with factors that are unobserved by the analyst (Greene and Hensher, 2002). I follow Heckman and Singer (1984) approach in which only the constant term varies across the classes. In this approach, the unobserved heterogeneity is incorporated in a very flexible way without imposing a parametric structure. I assume that the continuous distribution of unobserved individual specific effects can be approximated by estimating the location of the support points and the mass (probability) in each interval. In this case the integration is replaced by a summation over the number of support points for the distribution of unobserved heterogeneity. Associated with each support point is a probability, π_m, where $\sum_{m=1}^{M} \pi_m = 1$ and $\pi_m \geq 0$. To be specific, it is argued that there are M types of individuals and that each individual is endowed with a set of unobserved characteristics, for m=1,..,M. The implication of these unobserved heterogeneity parameters are straightforward, and a high value simply implies a high preference for work. The problem with this approach is that it requires a fairly rich panel. There should be a substantial amount of within group variation.

However, the likelihood function of the dynamic panel censored model is usually intractable since the dimension of an integral involved in its calculation is as large as the number of censoring periods in the model. Under such circumstances, for a model with general correlated disturbances, simulation based estimation (MSL) as proposed by Lerman and Manski (1981), McFadden (1989), and Pakes and Pollard (1989), among others, can be used (Lee, 1997; Lee, 1999). I used the standard approach to random draws from the specified distribution for the simulation based estimation method (MSL).[6] Simulated maximum likelihood method has also been applied to estimate the random effect Tobit model for normal (continuous) heterogeneity distribution (not reported here).

The initial condition problem in dynamic Tobit model with unobserved effects is an important theoretical and practical problem. A common approach is to assume that either the initial condition is exogenous and can be treated as fixed (e.g., Heckman 1978, 1981a, 1981c) or that the process is in equilibrium at the beginning of the sample period (e.g., Card and Sullivan, 1988). The assumption of the non randomness/fixed on initial condition implies that the disturbances that generate the process are serially independent. Unfortunately if the process has been in operation prior to the time it is sampled, or if the disturbances of the model are serially dependent as in the presence of individual specific random effects, the initial conditions are not exogenous (Hsiao, 2003). The assumption that the process is in equilibrium also raises problems in many applications, especially when time varying exogenous variables are driving the stochastic process (Hsiao, 2003). In order to overcome the practical problem of not being able to find the conditional distribution of the initial value, Heckman (1981) proposes approximating the conditional distribution of the initial condition. For the initial period the individual is observed (t=1), a static binomial probit model is estimated in Heckman (1981). This procedure approximates the initial conditions for the model. Heckman (1981) reports that this approximation performs well in a binary

[6] The draw back with this approach is that good performance requires a very large number of draws. With a large sample and a large model, this entails a huge amount of computation and is thus very time consuming.

choice model leading to only a small asymptotic bias. Following Heckman (1981), I approximate the initial conditions for the static Tobit model. In order to control for endogenous initial condition I also assume that the initial period is correlated with the other periods through the distribution of unobserved heterogeneity of initial and other period.

4 Results

The results for all specifications are reported based on 10% (random draw) sub-sample [7] Table 2 contains the results of the estimated static Tobit approach. The first column shows the results when I treat all years as pooled (standard Tobit). This result serves as a benchmark against which I can compare the results that use the panel structure. As expected, the presence of children reduces labor supply, and the presence of young children reduces hours of work even more. An additional child aged 0-2 reduces women's annual hours of work by -885 hours (marginal effect). The effect of permanent income is significantly positive while the coefficient on transitory income is insignificant.

In order to see the effect of individual unobserved heterogeneity, I estimate a random effect Tobit model by MLE using Gaussian quadrature. In column 2, when the individual specific effect is allowed, the result shows that 71% of the latent error variance can be explained by unobserved heterogeneity. Allowing unobserved

[7] 10% sub sample and full sample produce almost similar result in all specification in the static model. It is mentioned that good performance of simulated maximum likelihood method (MSL) requires a very large number of draws. And with a large sample and a large model, this entails a huge amount of computation and thus very time consuming. Therefore 10% sub sample has been used in the simulated maximum likelihood estimation methods and the results reported here are based on 10% sub-sample in all specification.

heterogeneity, the estimated effect of young children aged 0-2, 3-5, and, 6-17 drop 29%, 49%, and 32% respectively. In column 3, the random effect Tobit model is re-estimated by random intercept latent class Tobit model. In this approach it is assumed that the continuous distribution of unobserved individual specific effects can be approximated by estimating the location of the support points and the mass (probability) in each interval. I consider two support points.[8] The results show that the estimated support points and accompanying probabilities of unobserved heterogeneity variance are significant. The first estimated support point (θ_1 = 407.26) and the corresponding probability (π_1 = 0.83) indicate a relatively strong preference for work by 83% of the sample (compared to the sample information that 69% actually worked all 10 years of the study period). The second estimated support point (θ_2 =-1677.59) and the corresponding probability (π_2 = 0.17) indicates low preference for work by 17% (compared to the sample information that 11.3% don't work at all during the study period).

In column 4, the correlated random effect specification is estimated using simulated maximum likelihood (MSL) method. In this specification it is assumed that the fertility and/or income variables are correlated with unobserved taste. The Wald statistic (at the bottom in column 4) rejects the hypothesis of no correlation between the number of children aged 0-2 and the unobserved heterogeneity.[9] The $\chi^2(1)$ value is 44.11. The

[8] The model is also estimated with three classes and found that the model is fitted well with two classes (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.

[9] Wald statistics are calculated for the fertility variables and for transitory income y_{mt}. The number of children aged 3-5 is dropped because of estimation problem.

hypothesis that the number of children aged 6-17 is uncorrelated can not be rejected by the Wald test. The $\chi^2(1)$ value is 0.41. The likelihood ratio tests (not reported) also show similar results.

Table 3 presents the results from the random effect Tobit models for inter-temporal labor supply model. The first, second, third, and fourth column pertain to the "no initial condition", "exogenous initial condition", "correlated initial condition", and "correlated initial condition with AR(1)" specification respectively. The interaction term between lag dependent and the number of children aged 0-2 is included in these specifications. The estimated effects of initial parameter of corresponding specifications are presented in bold letters. In column 1 the random intercept latent class model with first order state dependence SD(1) is estimated. As expected, the estimated state dependence has a significant effect on the model and the coefficient is 72.98. However the state dependence in labor supply is quite large when the initial condition is allowed (column 2). The estimated coefficient (SD(1)) is 247.23. Including initial condition has significant effects on fertility and non-labor income. The results also show that the heterogeneity variance is very sensitive to the initial condition. The estimated probability of strong preference group is declined from 0.82 to 0.62 and the probability of low preference group is increased from 0.18 to 0.38.

In column 3, controlling for endogenous initial condition, the latent class model with first order state dependence is estimated. In this specification it is assumed that the initial period is correlated with the other periods through the distribution of unobserved heterogeneity. The results show that the estimated effects of the covariates are somewhat larger in magnitude than in the exogenous initial condition specification. The results also show that the estimated state dependence and unobserved heterogeneity is almost identical to before. However the second initial support point of heterogeneity variance is still insignificant which suggests that the model may not be well specified.

It is assumed that the disturbances of the model are serially dependent due to the presence of individual specific random effects. If this is the case then the initial conditions are not exogenous. In column 4, controlling for correlated initial condition, the latent class model with first order state dependence and serially correlated error components is estimated. For the AR(1) error component, simulation based estimation methods (MSL) is used in this specification. Allowing for correlation with initial condition, the results find a large and statistically significant AR(1) coefficient (-0.89). However, the effect of state dependence, unobserved heterogeneity and all covariate effects are each individually significant and very close to those in column 3 except the second support point of initial period which is insignificant in column 3 but significant in column 4.

5 Sensitivity analysis

So far I have focused on the Tobit model which is applicable only if the underlying dependent variable contains negative values that have been censored to zero in the empirical realization of the variables. In the Tobit analysis at least some of the observations (0's) must be censored, otherwise the observed dependent variable would always equal the latent dependent variable and the true model would then be a linear regression. Thus the OLS estimators are biased downward (e.g., Greene, 1997). To check whether the observed dependent variable is equal to the latent dependent variable, I re-estimate the model using OLS. In principle the OLS estimates would be similar to Tobit estimates if there is no data censoring.

Table 4 presents the results from the linear models. The first and second column presents the simple and random effect linear estimate. The results are consistent with Tobit specification. That is the presence of children reduces labor supply, and the presence of young children reduces hours of work even more. An additional child aged 0-2 reduces women's annual hours' of work by -698 in the simple linear model (Table 4 column 1) and -885 in the Tobit model (Table 2 column 1). Moreover 78% latent error variance can be explained by the unobserved heterogeneity in the linear model (Table 4 column 2). In contrast 71% latent error variance can be explained by the unobserved heterogeneity in Tobit specification (Table 2 column 2).

In column 3, the dynamic model with first order state dependence SD(1) is estimated.[10] The findings show that including state dependence has substantial significant effect on the model. The estimated state dependence effect is 175 in the dynamic model. Including first order state dependence, the unobserved heterogeneity effect declined from 0.78 to 0.41. In column 4 the dynamic model with first order state dependence SD(1) and serially correlated error components AR(1) is estimated. The results show that the addition of AR(1) coefficient has a positive and statistically significant effect on the model. The AR(1) coefficient is 0.38.

[10] The initial condition is not considered in this specification. The log of lag dependent variable is used in the right hand side variables

6 Simulated responses

Figure 4 shows simulated responses to a birth in year 1 for simple linear (OLS) and simple Tobit model. During the first year, the annual hours of work declined 54% and 58% in simple linear and simple Tobit model respectively. There is a distinct upward slope after the birth during the first year in both models. The women increase their annual hours of work with the age of youngest child. During first year the annual hours of work are 557 and 488 hours in simple linear and simple Tobit model respectively while that of 1494 and 1463 when the youngest child become 16 years old. The shift in hours of work at years 3 and 6 may indicate the pre-school and school going ages.

In Figure 5, the responses for random effect linear and Tobit model gives two distinct results in terms of average prediction of annual hours of work. Figure 6 shows the simulated responses to a birth in year 1 for dynamic linear and dynamic Tobit model. The women decrease their annual hours of work to 490 in the dynamic linear and 653 in the dynamic Tobit model.

Figure 7 shows simulated responses to a birth in year 1 for all linear models such as simple linear (OLS), RE linear and dynamic SD(1) linear. Similarly Figure 8 shows simulated responses to a birth in year 1 for all Tobit models such as simple Tobit, RE Tobit, RE latent class Tobit and dynamic SD(1) Tobit. The simulated responses from each of these models increase hours of work as the child ages. The differences of simulated hours of work from each of these models are quite noticeable. During the first year, an additional child reduces the annual hours of work by 54% in the simple linear

(OLS), 51% in RE linear and 42% in dynamic linear. However the annual hours of work in the Tobit models are reduced by 58%, 62% and, 48% respectively.

Figure 9, which is based on the dynamic with SD(1) Tobit model, shows remarkably stronger responses to a birth in year 1 for University educated (highly educated) women than for high-school educated (middle educated) women. While Figure 10 shows two distinct responses of immigrant and native born mothers in Sweden.

7 Summary and conclusions

This paper has analyzed the dynamic specification of labor supply model of married women in Sweden using longitudinal data LINDA. The empirical specification used is a dynamic model with endogenous initial condition, unobserved heterogeneity and serially correlated error components. A finite mixture model is formulated allowing for unobserved heterogeneity in very flexibly without imposing a parametric structure.

In both linear and Tobit specifications, the results indicate that hours of work are strongly affected (inversely) by the ages of children. Inter-temporal labor supply decisions seemed to be characterized by a substantial amount of unobserved heterogeneity, first order state dependence and serially correlated error components. The correlated random effects (CRE) Tobit specification rejects the hypothesis that the number of children aged 0-2 is exogenous to women’s hour’s decisions in the static model. The Tobit analysis suggests that the first order state dependence and unobserved heterogeneity are very sensitive to the initial condition.

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Table1: Sample Characteristics of Married Women Aged 20-64 in 1992-2001

	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	44.78 (7.50)	46.17 (6.52)	45.70 (7.84)	47.11 (7.25)	38.32 (7.05)	37.40 (7.50)
Education[(a)] (Grundskola)	0.16 (0.37)	0.12 (0.32)	0.44 (0.50)	0.29 (0.45)	0.14 (0.35)	0.12 (0.33)
Education[(a)] (Gymnasium)	0.48 (0.50)	0.46 (0.50)	0.47 (0.50)	0.52 (0.50)	0.54 (0.50)	0.57 (0.49)
Education[(a)] (Universitet)	0.36 (0.48)	0.42 (0.49)	0.09 (0.29)	0.19 (0.39)	0.32 (0.47)	0.31 (0.46)
No. Children Aged 0-2 years	0.07 (0.28)	0.02 (0.14)	0.09 (0.32)	0.03 (0.20)	0.24 (0.51)	0.33 (0.53)
No. Children Aged 3-5 years	0.13 (0.38)	0.07 (0.27)	0.14 (0.40)	0.06 (0.26)	0.40 (0.60)	0.44 (0.58)
No. Children Aged 6-17 years	0.93 (1.00)	0.88 (0.97)	0.82 (1.04)	0.62 (0.88)	1.46 (1.10)	1.12 (1.03)
Husbands earnings (SEK1000)	268.16 (165.87)	278.71 (163.31)	223.35 (162.70)	263.89 (197.94)	258.66 (155.69)	252.43 (175.66)
Born in Sweden=1	0.92 (0.27)	0.94 (0.24)	0.85 (0.36)	0.88 (0.33)	0.90 (0.30)	0.93 (0.26)
Hours of work (h)	1414.10 (764.66)	1778.62 (386.37)	0.00 (0.00)	939.64 (817.21)	920.04 (800.67)	986.82 (753.66)
Sample size	98210	67720	11100	3160	8320	7910

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: Static Tobit Estimate of Married Women Aged 20-64 in 1992-2001

	Simple Tobit (1)	*Random Effect Tobit* (2)	*Random Effect Tobit (latent class)* (3)	*Correlated Random Effect Tobit (MSL)* (4)
Permanent income	11.62 (5.13)	9.98 (3.39)	5.55 (0.83)	9.59 (1.28)
Transitory income	-0.002 (7.78)	5.58 (3.62)	12.32 (1.05)	5.85 (4.43)
No. Kids aged 0-2	-935.85 (37.90)	-660.06 (21.35)	-792.21 (20.85)	-802.60 (19.86)
No. Kids aged 3-5	-315.48 (26.66)	-161.45 (15.50)	-211.19 (12.97)	-193.68 (15.39)
No. Kids aged6-17	-99.04 (10.69)	-67.01 (7.61)	-70.21 (5.30)	-79.88 (9.37)
Unobserved Heterogeneity				
$Var(\eta_i)^{(a)}$	-	0.71	-	-
First support point (θ_1)	-	-	407.27 (69.43)	-
Second support point (θ_2)	-	-	-1677.59 (73.54)	-
Probability (π_1)	-	-	0.83	-
Probability (π_2)	-	-	0.17	-
Log likelihood	-72290.27	-66105.13	-67305.00	-67546.70
Wald statistic for H_0:CRE=0				
#kid0-2	-	-	-	44.11 (0.00)
#kid6-17	-	-	-	0.68 (0.41)
y_{mt}	-	-	-	1.64 (0.20)

Notes: Estimated standard errors in parentheses. All specifications include 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) Var (η_i) is expressed as a fraction of the total error variance.

Table 3: Dynamic Tobit Estimate of Married Women Aged 20-64 in 1992-2001

	Dynamic Tobit No initial condition (1)	*Dynamic Tobit Exogenous initial condition* (2)	*Dynamic Tobit Correlated initial condition* (3)	*Dynamic Tobit Correlated initial condition with AR(1)* (4)
Permanent income	-7.43 (0.43)	4.69(2.51) **18.77 (5.80)**	5.22 (2.54) **21.72 (10.21)**	5.23 (1.06) **21.75 (4.23)**
Transitory income	0.79 (0.02)	3.06 (1.49) **18.39 (10.45)**	4.64 (3.55) **18.15 (16.85)**	4.70 (0.68) **18.26 (3.59)**
No. Kids aged 0-2	-491.73 (14.51)	474.66(30.21) **-799.27(18.37)**	501.60(29.43) **-840.13(43.42)**	500.95(27.95) **-840.17(40.42)**
No. Kids aged 3-5	-188.89 (7.05)	-97.19(15.12) **-159.22(10.26)**	-75.19 (16.12) **-127.95(40.13)**	-75.59 (12.43) **-127.99(30.35)**
No. Kids aged6-17	-76.99 (2.58)	-42.72 (7.38) **-99.91(13.53)**	-34.45 (7.06) **-66.37 (16.94)**	-34.39 (5.79) **-66.30 (11.52)**
Unobserved Heterogeneity				
First support point (θ_{11})	-32.14 (1.17)	-974.39 (148.55)	-1124.58 (178.73) **-1535.67 (438.96)**	-1124.53 (107.26) **-1536.89 (65.84)**
Second support point (θ_{12})	-1645.64 (5.37)	-1541.99 (150.23)	-1592.99 (177.38) **436.53(437.27)**	-1593.19 (106.07) **437.10(67.42)**
Probability (π_1)	0.82	0.62	0.61	0.60
Probability (π_2)	0.18	0.38	0.39	0.40
Log of lag dependent (log h_{t-1})	72.98 (0.94)	247.23 (3.06)	251.78 (2.88)	251.44 (2.79)
(log h_{t-1})* (No. Kids aged 0-2)	-35.87 (2.96)	-165.85 (5.64)	-166.46 (5.43)	-166.39 (5.36)
AR1coefficient, ρ	-	-	-	-0.89 (0.16)
Log likelihood	-66800.60	-65510.20	-65346.00	-65342.70

Notes: Estimated standard errors in parentheses. All specifications include 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. The estimated coefficient of initial year of corresponding specifications is presented in bold letters.

Table 4: Linear Estimate of Married Women Aged 20-64 in 1992-2001

	Standard OLS (1)	*Random effect GLS* (2)	*Dynamic* (4)	*Dyamic with AR(1)* (5)
Permanent income	9.06 (4.12)	0.69 (11.56)	2.01 (4.89)	4.33 (5.03)
Transitory income	-0.99 (6.23)	2.31 (2.97)	2.61 (2.81)	8.98 (3.08)
No. Kids aged 0-2	-698.48 (28.55)	-496.33 (17.87)	182.44 (22.05)	189.58 (24.49)
No. Kids aged 3-5	-269.64 (21.40)	-149.40 (14.00)	-83.76 (13.16)	-121.51 (14.84)
No. Kids aged6-17	-86.33 (8.73)	-72.79 (7.64)	-52.34 (6.63)	-57.99 (7.63)
Var(η_i) [(a)]	-	0.78	0.41	0.44
Log of lag dependent (log h_{t-1})	-	-	174.98 (2.21)	154.32 (2.40)
(log h_{t-1})* (No. Kids aged 0-2)	-	-	-116.81 (4.01)	-117.38 (4.08)
AR1coefficient(ρ)	-	-	-	0.38

Notes: Estimated standard errors in parentheses. All specifications include 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) Var(η_i) is expressed as a fraction of the total error variance.

Figure 1: Distribution of Years of Work of Married Women Aged 20-64 in 1992-2001

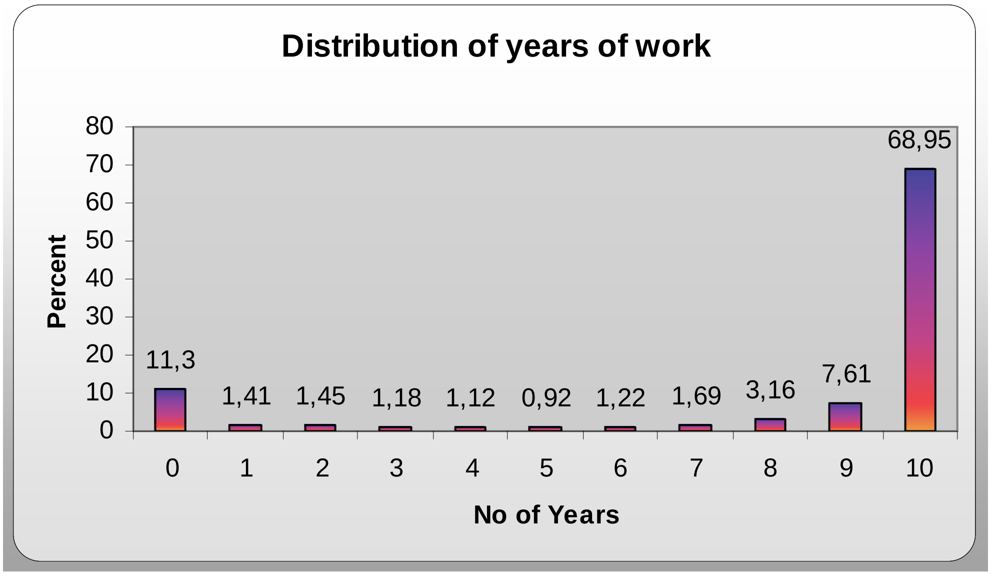
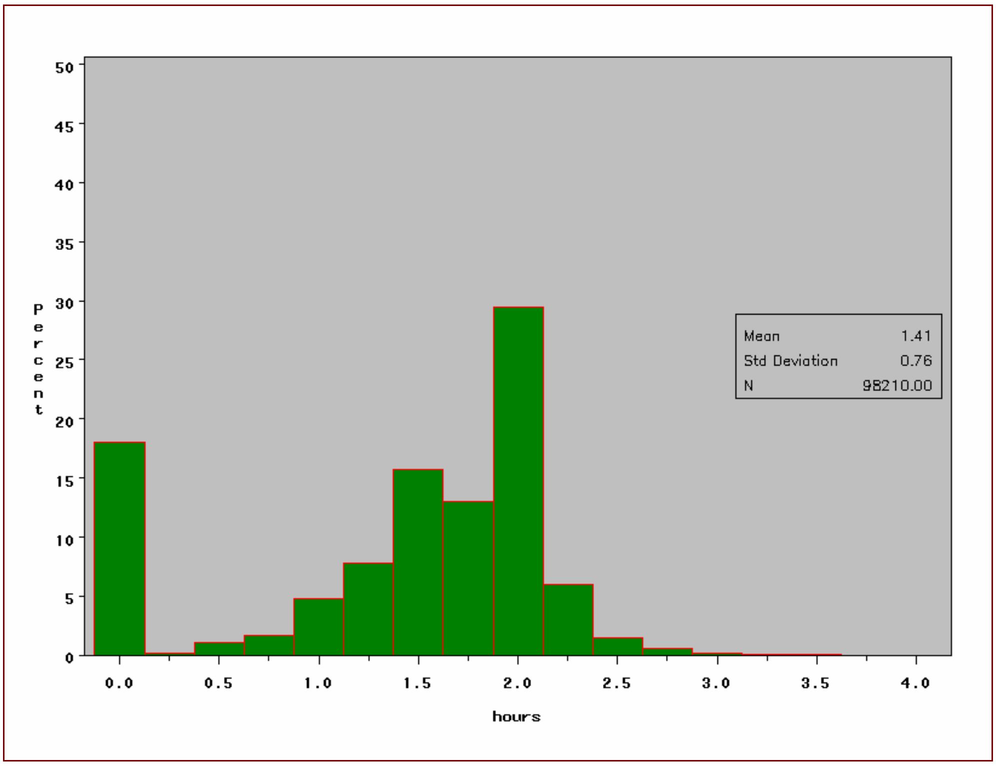


Figure 2: Distribution of Annual Hours of Work of Married Women Aged 20-64 in 1992-2001



Hours in thousand

Figure 3: Distribution of Hours of Work Against Age of Youngest Child of Married Women in Sweden.

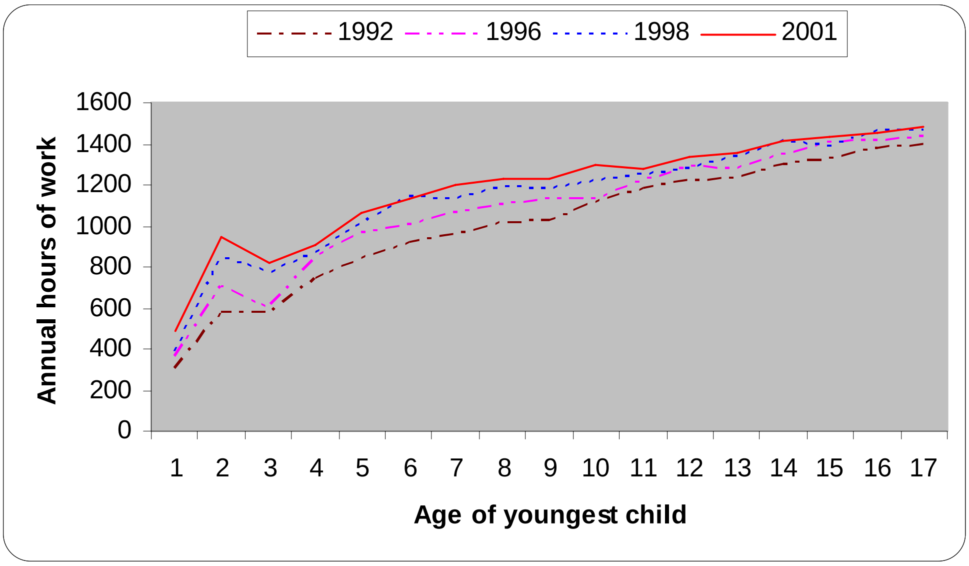


Figure 4: Simulated Response of Hours of Work to a Birth During First Year.

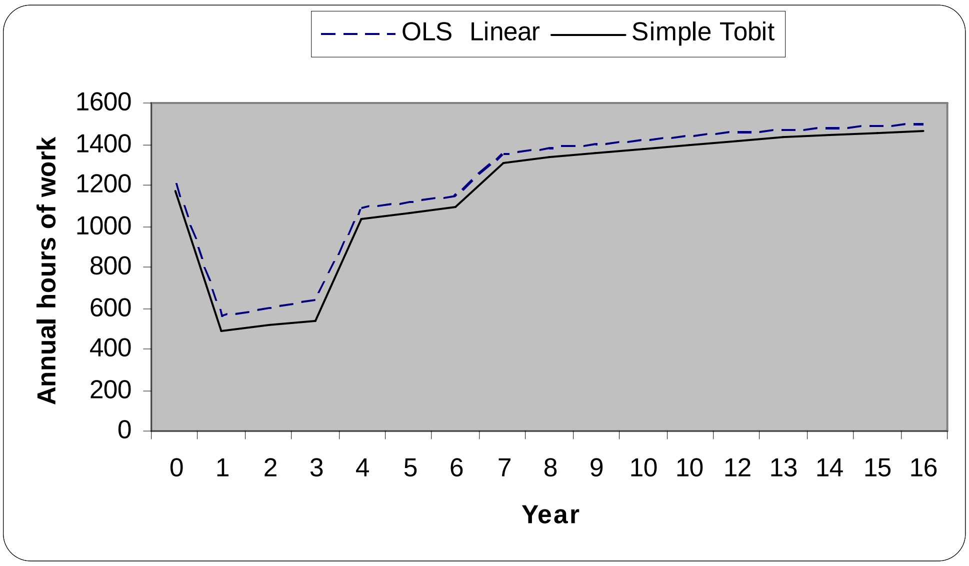


Figure 5: Simulated Response of Hours of Work to a Birth During First Year.

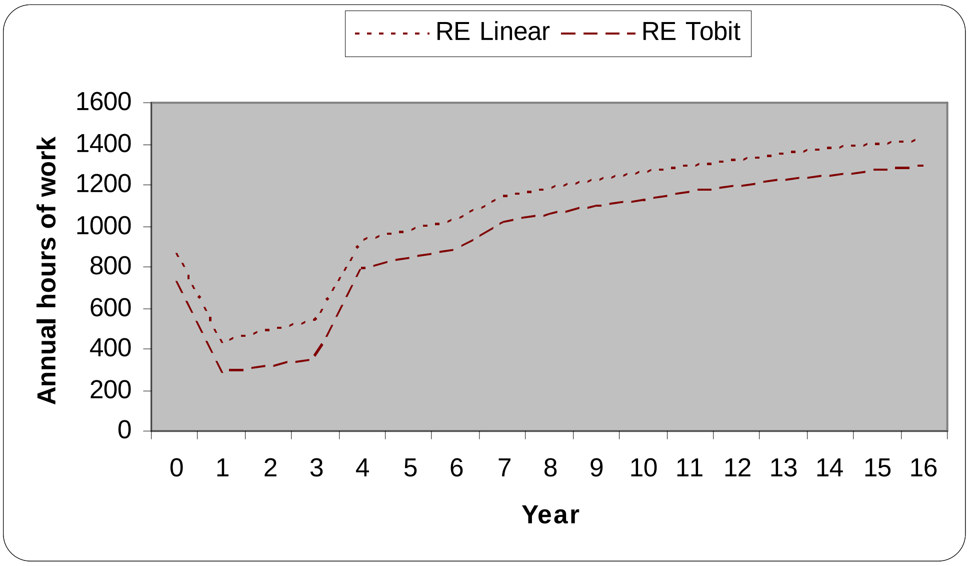


Figure 6: Simulated Response of Hours of Work to a Birth During First Year.

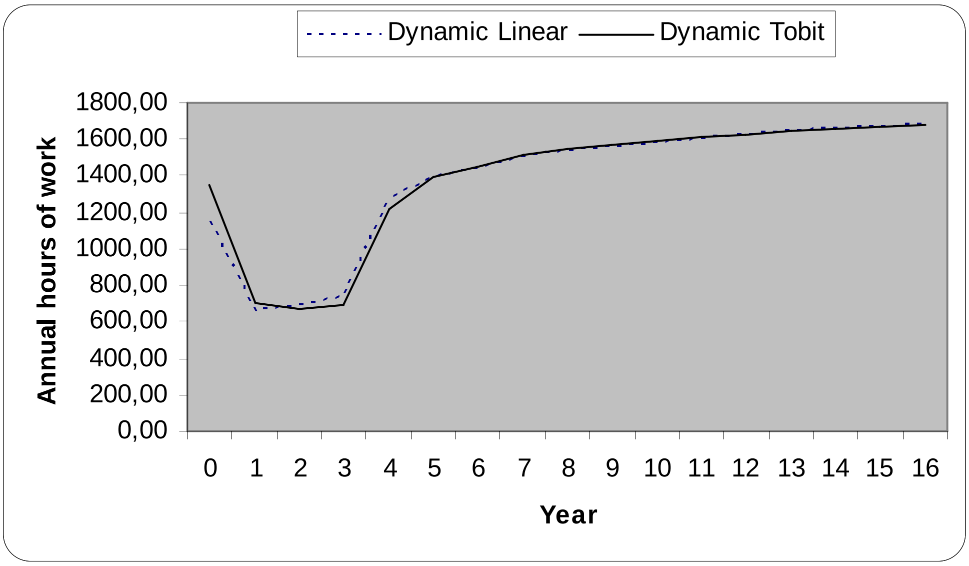


Figure 7: Simulated Response of Hours of Work to a Birth During First Year

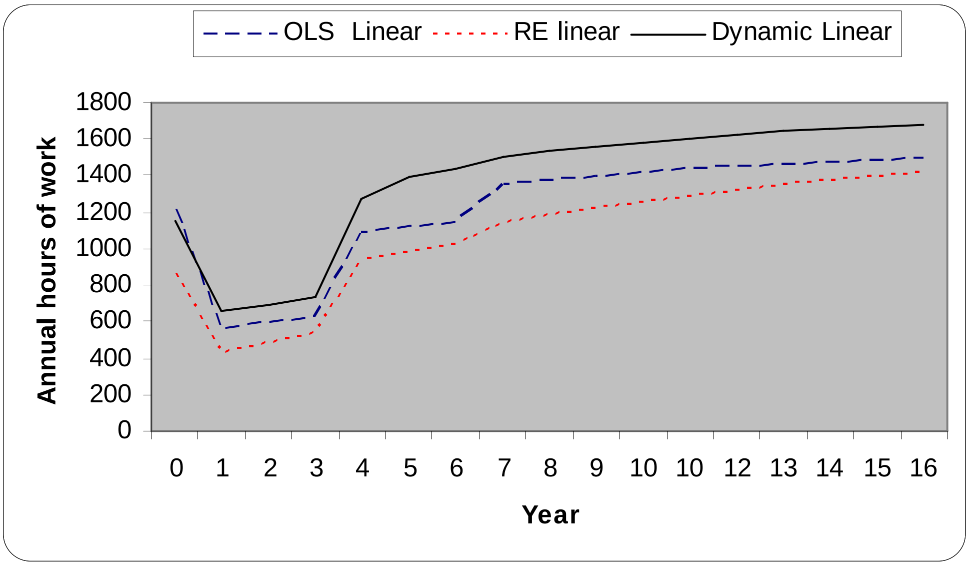


Figure 8: Simulated Response of Hours of Work to a Birth During First Year

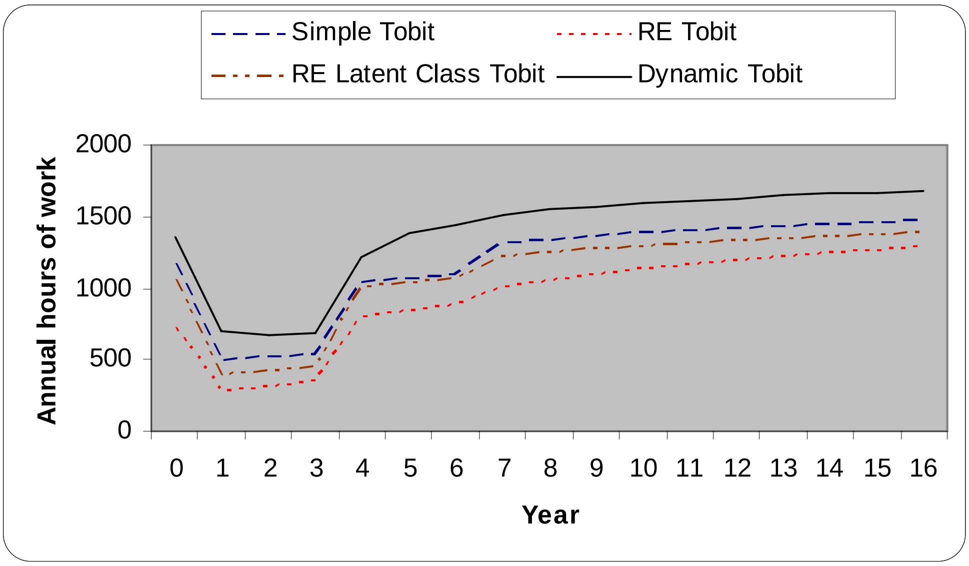


Figure 9: Simulated Response of Hours of Work to a Birth During First Year

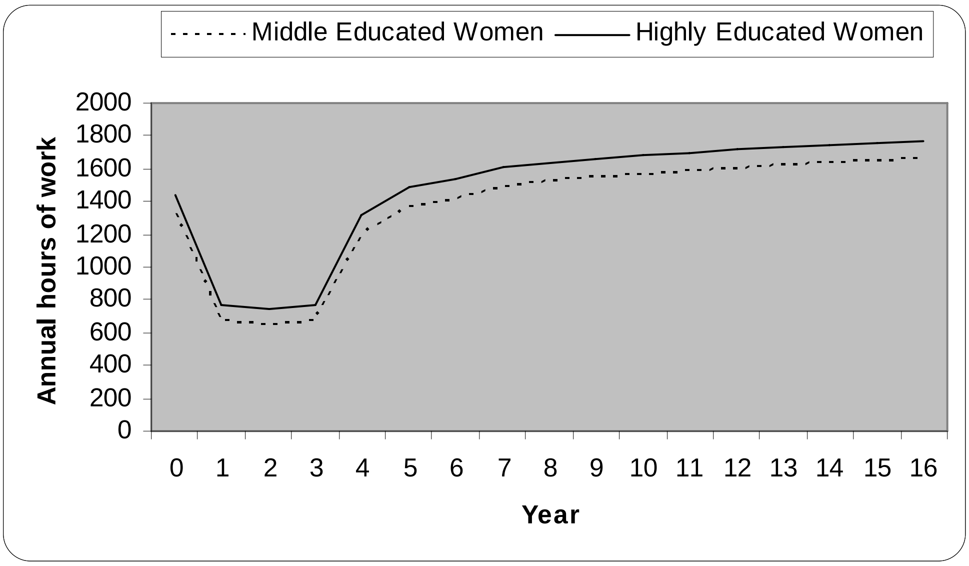
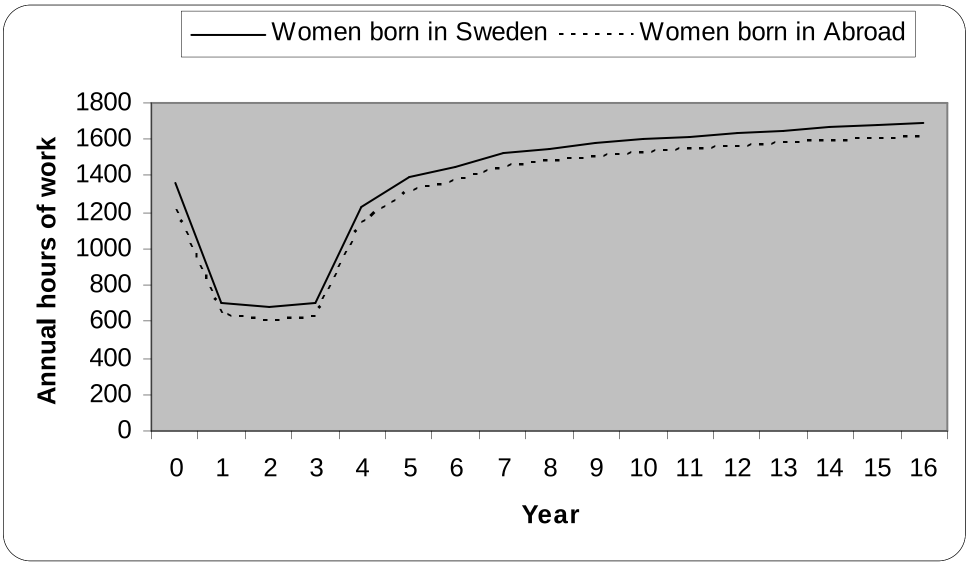


Figure 10: Simulated Response of Hours of Work to a Birth During First Year



Poverty dynamics in Ethiopia: state dependence and transitory shocks

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Abstract

This paper focuses on the persistency of poverty in rural and urban households in Ethiopia by estimating dynamic probit models. Unobserved heterogeneity, first order state dependence and serially correlated error component are allowed for. The empirical results for both rural and urban areas show that each of these components is statistically significant in characterising the dynamics of poverty in Ethiopia. Furthermore, risk of poverty increases with the number of household's size. Moreover, land size is highly correlated (negatively) with that risk of poverty and the most important two cash crops (Coffee and Chat) has significant role in the alleviation of poverty in Ethiopia. Finally, the effect of true state dependence and transitory shocks in poverty persistency appears to be stronger among urban households than rural households.

Key words: Poverty persistency, state dependence, unobserved heterogeneity

1 Introduction

Existing studies (see Bane and Ellwood, 1986; Stevens, 1994) on the dynamics of poverty commonly use a spell approach to compute the underlying probabilities as functions of the number of durations in a particular spell. This approach, although powerful in capturing the effects of duration in poverty or out of poverty, it does not provide explicitly the magnitude of previous states on the risk of being poor in the present state, which provides an opportunity to estimate state dependency of the motion of poverty. That is, if the risk of entering into poverty is dependent on being in poverty in the previous period, after controlling for unobserved individual effects and serially correlated error components, then, it implies that there is much to be gained from policy interventions that reduce poverty in the current period on the evolution of poverty in subsequent periods. This suggests for the need to actually quantify the true state dependency of the poverty evolution and its contribution to the risk of being in poverty or not. This paper contributes to the literature on poverty dynamics by estimating an econometric model of poverty dynamics that explicitly takes into account the effect of the lag dependent variable, unobserved heterogeneity and serially correlated error components.

The rest of the paper is organized as follows: section 2 describes the data and variables, section 3 provides the methodological framework, discusses the underlying econometric model and methods of estimation, section 4 discuss the results, and Section 5 draws conclusion.

2 Data and variables

A panel data set covering rural and urban households of four waves in the period 1994-2000 was used in the analysis. The data set originally consisted of approximately 3000 households, equally divided between rural and urban households. The nature of the data, the sampling methods involved in collecting it, and other features are discussed in detail in Bigsten et al. (2005). It is one of the few longitudinal data sets available for Africa. The data covers households' livelihood, including asset-accumulation, labour market participation as well as health and education and other aspects of household level economic activities.

To measure poverty, we used consumption expenditure reported by respondents based on their recollections of their expenses in the recent past. The components of consumption expenditure are selected carefully to allow some room for comparisons between rural and urban households. The consumption-baskets include food as well as clothing, footwear, personal care, educational fees, household utensils, and other non-durable items.

Major food expenses among households in Ethiopia are difficult to measure, particularly in rural areas, because of problems related with measurement units, prices, and quality. The consumption period could be a week or a month depending on the nature of the food item, the household budget cycle, and consumption habits. Own-consumption is the dominant source of food consumption in rural Ethiopia, particularly with regard to vegetables, fruits, spices and stimulants like coffee and chat. Cereal, which makes up the bulk of food consumption, is increasingly obtained from markets as farmers swap high cash-value cereals such as *teff* for lower-value ones, such as maize and sorghum. Even so, food in rural areas is derived from own sources, which makes valuation difficult. The situation is better in the urban setting, where the bulk of consumption items are obtained from markets and measurement problems are less.

The poverty-line, to identify the poor population, was computed as follows; The major food items frequently used by the poor were first picked to be included in the poverty line 'basket'. The calorie content of these items was evaluated and their quantities scaled so as to give 2,200 calorie per day; the minimum level nutritionists require an adult person must consume to subsist in Ethiopia. The cost of purchasing such a bundle would be computed using market prices and constitutes the food poverty line. Taking the average food-share at the poverty line made adjustment for non-food items. Using the estimated poverty lines in each year for all the sites we adjusted consumption expenditure for all households by using the poverty line of one of the sites as price deflator. Thus, consumption expenditure was adjusted for temporal and spatial price differences. The poor were thus defined as those unable to meet the cost of buying the minimum consumption basket. In this study, we use the household as our unit of analysis, so that poverty dynamics is studied at the level of a household. Differences in individual attributes are adjusted using adult-equivalence scales in consumption.

The variables that we use to analyse poverty dynamics for households in rural areas are: household demographics (household size, sex of the head of the household, age of the head of the household, mean age in the household), dummy for major crops raised (coffe, chat and teff), wealth variables (cash values of durables, size of land, number of oxen owned) and quadratic terms to capture economies of scale and experience in farming. Table 1 (in appendix) provides a list of variables that we used for the analysis, particularly in reporting regression tables.

For households in urban areas, apart from demographic and educational variables, we used occupational categories, city of residence, the educational and occupational background.

Our main interest is the dynamics of poverty. Table 1 gives a broad picture of the dynamics. In rural areas, about 7 percent of the households can be classified as poor throughout the period. In urban areas, the corresponding share is around 15 percent. In rural areas almost 21 percent of the households have not been in any year, while in urban areas this share is 39 percent. The rest of the households have spent at least one period outside of poverty. Thus, in rural areas, poverty tends to be less persistent as compared to urban areas. Also, we observe that in both areas, the proportion of households who remained poor through out the period was quite low.

Tables 2a and 2b report demographic and other characteristics of the household stratified by the number of times in poverty. A visual inspection of these two tables shows some interesting things. For instance, in both rural and urban areas, poverty is persistent among households whose head are relatively older, have larger members, have little education, little asset, or engaged in self-employment etc. suggesting the structural nature of poverty. Although these correlates of poverty are also interrelated, they also point at the existence of some unobserved characteristics of the household that for instance allows for the co-existence of low ownership of land, oxen and asset at old age with a large family. Thus, it is useful and important to address unobserved household heterogeneity as a possible source of endogeneity of determinants of poverty dynamics. Finally, the dynamics of poverty can also be affected by unobserved random shocks that could persist over time and are common to all households. This could be caused by a number of factors such as drought, price shocks, policy changes and structural factors. Controlling for these factors brings out the true state dependence of the dynamics of poverty that provides a proper structure to the time-path of poverty irrespective of individual characteristics and persistent random shocks.

3 A Model of Poverty Dynamics

In the literature, poverty persistence is estimated in several ways. Some use variance-component models (Lillard and Willis, 1978, Abowd and Card, 1989; Baker, 1997; Cappelari, 2000); others use non-parametric transition probability distributions, such as life-cycle tables, and parametric hazard functions (Bane and Ellwood, 1986; Stevens, 1994, 1999, Antolin, et al 1999; Devicienti, 2001, 2003; Hansen and Wahlberg, 2004, Biewen 2003). What is common in these approaches is the effort to capture the effect of past history of poverty on current and future risk of being in poverty. In almost all cases, past history of poverty is found to be an important determinant of current or future poverty. The problem however with this finding is that it does not distinguish all three possible sources of poverty persistence over time. For example, the first source of poverty persistence is unobserved individual characteristics, such as ability, motivation, mental and physical disabilities, that pre-dispose some more than others to stay in or out of poverty for long time The second source of poverty persistence is the effect of time-varying shocks that are not specific to individuals, such as price fluctuations, natural calamities, general economic stagnation or slow-down, etc. The third is the behavioural and preference shifts that may be associated with the fact of being in poverty at least once in the past. This implies that regardless of household characteristics, once a household slips into poverty, it could trigger physical and other dispositions that allow poverty to persist over time. In the first case, poverty is driven by unobserved household attributes that may not change over time. In the second case, the events leading to poverty are correlated over time. In the last case, poverty is truly state dependent so that alleviating current poverty can lead to reduction of poverty in future too. Identifying and quantifying these causes of poverty dynamics is very important for policy purposes.

To capture the underlying causes of poverty persistence, we specify a general model of poverty as follows:

$$P_{it} = \Phi(P_{it-1}, Z_{it}, \alpha_i) \tag{1}$$

where P_{it} is equal to 1 if the i^{th} household is poor at time t and zero otherwise. The vector Z_{it} captures covariates of poverty and α_i controls for unobserved heterogeneity to each household. True state dependence in poverty dynamics is exists if current poverty is significantly correlated with lagged poverty.

In most applications that use parametric hazard functions, be it proportional or logistic, the state dependence is routinely captured by a dummy variable of duration in poverty (for exit probabilities) or out of poverty (for re-entry probabilities). For example, with a logistic specification, a typical model of poverty dynamics is specified as follows:

$$h_{it}(d) = \frac{\exp[\alpha(d) + X_{it}^{'}\beta)]}{1 + \exp[\alpha(d) + X_{it}^{'}\beta]} \tag{2}$$

where h_{it} (d) is the probability that a household *i* leaves the poverty state at duration *d,* given that it has remained in poverty up to *d-1*. Discrete intervals are commonly used to capture the duration dependence of the hazard rate of exiting or re-entering poverty. This specification combines into one the three sources of poverty persistence if the model is estimated without controlling for unobserved household characteristics. In this case, duration dependence is reported to be much stronger. Most studies do adjust for unobserved household characteristics through a joint maximum likelihood estimation of exit and re-entry rates where the hazard rates depend on spell-specific unobserved heterogeneity (e.g. Meghir and Whitehouse, 1997; Stevens, 1999; Devicienti, 2003; and Hansen and Wahlberg, 2004). Under this condition, a number of studies found that the effect of duration in or out of poverty has little role in determining poverty persistence[1]. There are few studies (Biewen 2004, Cappelari and Jenkins, 2004) that attempt to link current state of poverty with its lag, and to our knowledge none that control for serial correlation in the error components. With this limitation in mind, the empirical model used here is a dynamic probit model which controls for state dependence, unobserved heterogeneity and serial correlation -

$$P_{i0} = 1\{\beta_0 X_{i0} + u_{i0} > 0\} \tag{3}$$

$$P_{it} = 1\{\gamma P_{it-1} + \beta X_{it} + u_{it} > 0\} \qquad (i = 1,..., N; t = 1,.....T) \tag{4}$$

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

$$\varepsilon_{it} = \rho\varepsilon_{it-1} + v_{it},$$

$v_{it} \sim N(0, \sigma_v^2)$ orthogonal to α_i. $Corr\left(u_{i0,} u_{it}\right) = \rho_t$ t=1, 2,…, T

[1] see Devicienti, 2003 for review of the evidence

The approach to modelling the dynamics of individual poverty status considered in this paper is a dynamic random effects probit model where P_{it} denotes the poverty status of individual i=1,2,…,N. X_{it} is a vector of observable characteristics. β is a set of associated parameters to be estimated. The parameter γ represents the true sate dependence that refers to a situation in which the experience of poverty causes a subsequently higher risk of continuing to be poor. α_i represents for all unobserved determinants of poverty that are time invariant for a given household. In the poverty context these might be factors such as intelligence, ability, motivation or general attitude of household members. And finally ε_{it} represents the idiosyncratic error term which is serially correlated over time.

However, in dynamic model, the individual's poverty status in the initial period may be correlated with the factors captured by unobserved determinants of poverty (α_i).For example low intelligence or a lack of abilities will contribute to the risk of being poor at time t=0. To address this issue, we follow Heckman (1981) suggestion and approximate the initial conditions using static probit model (for equation 3). In order to empirically implement the model, we need to specify the stochastic nature of unobserved heterogeneity. For this, we choose a latent class specification which allows for unobserved heterogeneity (α_i), first order state dependence (γ) and serial correlation (ρ) overtime. We follow the Heckman and Singer (1984) approach in which only the constant term varies across the classes. It is assumed that there exists M different set of unobserved determinants of poverty (α_i) each observed with probability π_m (where π_m>0 and $\sum \pi_m$ =1, m=1,2,…M). This specification allows the arbitrary correlation between initial and other periods. It is straightforward to estimate the model with maximum likelihood techniques. However for correlated disturbances the likelihood function of the above dynamic probit model requires the evolution of T-dimensional integrals of normal density functions. Under such circumstances, simulation based estimation (MSL) as proposed by Lerman and Manski (1981), McFadden (1989), and Pakes and Pollard (1989), among others, can be used (Lee, 1997). In this case we use simulated maximum likelihood method (for more details see Lee 1997, Hyslop 1999, Islam 2005) and a standard approach to simulation draw has been applied.

4 Results

Based on the econometric model fully specified in section 3, we report results on the nature of poverty dynamics in Ethiopia. We start with a simple static probit model that sets the binary variable of being in poverty or not as functions of several regressors. We then compare it respectively with a model that controls for unobserved household heterogeneity, state dependence and serial correlation. We report the results separately for rural and urban households.

Table 3 provides probit estimates for the probability of falling into poverty with and without controlling for unobserved household heterogeneity in Column 1 and 2 respectively, and dynamic effects with and without controlling for serial correlation in Column 3 and 4 respectively. The key variables used to determine the probability of falling into poverty are the age of the head of the household and its square, which essentially capture life-cycle effects on household welfare such as experience, family formation, asset accumulation, and other inter-generational differences. Mean age within the household and its square is used to measure overall dependency in the household, which affects directly the probability of falling into poverty. The larger the number of dependents (the lower mean age of the household), the higher could be the probability of falling into poverty, and vice versa. The square term captures the effect of having elderly dependents. We have size of the household, education of the wife, agricultural systems, types of major crops cultivated, distance to the nearest market, total value of household asset, size of land and its interaction with household size as potential determinants of poverty.

Column 1 shows the result for simple probit (pooled) model. As expected, the probability of poverty increases with the number of household's size and the coefficient is 0.088. Coffee and Chat are two most important exported cash crops in Ethiopia. The estimated results show that the mean probability of coffee producing households being poor is -0.06 and that of for chat producing households is -0.31. This implies that as exportable crops coffee and Chat has significant role in the alleviation of poverty in Ethiopia. The results show that the coefficient of off-farm employment is statistically significant and positive, which means that off-farm employment is associated with a higher probability of poverty. The results also show that the land size is highly correlated (negatively) with the probability of being in poverty. It is noteworthy that good access to markets has also significant effects.

Column 2 contains the estimated results of latent class probit model which allows for household specific unobserved heterogeneity. The estimated distribution of unobserved heterogeneity (shown at the bottom) indicates that there are two types of households each observed with probability. The estimated probability (0.35) of type 1 households indicates that about 35 percent households have relatively higher risk of being poor due to permanent unobserved heterogeneity[2]. The majority, 65 percent, of the households belongs to the type 2 where the households have a relatively lower risk of being poor.

Columns 3 report the results from the dynamic model where the first order state dependence SD(1) (lag dependent variable) is included in the list of explanatory variables discussed above. The model allows the correlation between unobserved heterogeneity of initial and other periods. The result is quite interesting. The estimated lag dependent effect (true state dependence) is significant and the coefficient is 0.33. It suggests that even after controlling for observed and unobserved household specific characteristics, past experience was connected to a higher future poverty risk. This means that the households who experienced poverty during the preceding year have a higher risk of staying in poverty than the household who was not poor the previous year. In comparison to the results for the static random effects model in column 2, these results show the addition of lag dependent variable has a significant effect on covariates. For example the estimated coefficients for chat have decline 52%. It is also observe that there is a dramatic improvement in the fit of the model, as measured by the log likelihood, if the dynamic is modelled.

Column 4 contains the results of latent class probit specification which allows for unobserved heterogeneity, first order state dependence SD (1) and first order serial correlation AR(1) in the error components. The results show that the estimated serial

[2]This is because the estimated value (1.81) of support point for type 1 household is higher than the estimated value (0.97) of type 2 household.

correlation coefficient AR (1) is negative and statistically significant, with a magnitude of about -0.19[3].The result indicates that even after controlling for unobserved heterogeneity and first order state dependence SD(1), there is a negative transitory shock in poverty persistency which persist longer than one year but deteriorate in effect over time.[4]

Similar latent class probit regression is applied for the urban households in Table 4. As was the case with the rural sample household's size is positively related with poverty. The results show that the wife primary education is negative and statistically significant in all specifications. This suggests that if the wife has completed primary education, that will significantly decrease the chance of the household falling into poverty.

The model (column 3 Table 4) that allows household specific heterogeneity and first order state dependence SD (1) show almost the same pattern as for the rural sample. However the estimated proportion of type 1 households is 35 percentages and the proportion of type 2 households is 65 percentages. The results show that including first order state dependence has very little effect on unobserved heterogeneity (There is a little change of the estimated unobserved heterogeneity if the lag dependent variable is allowed). It is also observed that the proportion of type 1 in rural households is 26 percent lower than the proportion of type 1 households in urban households.

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[3] This confirms the negative transitory shocks in other studies. For example, Chay and Hyslop (1998) estimate dynamic models of welfare and labor force participation and find that the estimated AR(1) coefficient is always negative and statistically significant except for the exogenous initial condition models.

[4] The issue about transitory shock is discussed in Lillard and Willis (1978).

Again, the model (column 4 Table 4) which allows household specific unobserved heterogeneity, first order state dependence SD(1) and first order auto regressive error components AR(1) shows that the addition of transitory component of the error has significant effect on the model. The model found a statistically significant effect of transitory components in poverty persistency and the coefficient AR(1) is -0.45. However, the effect of transitory shocks in poverty persistency in urban households is stronger than that of in rural households. The results show that the estimated effects of the covariates and heterogeneity distribution are very sensitive to AR (1). The estimated proportion of type 1 households is now 4 percent and the estimated value of support point for type 1 household is -1,192 which is relatively higher than the other (type 1) support point (-1,923). This implies that type 1 (4 percent) households has stronger heterogeneity effect than the type 2 household (96 percent). The result also show a substantial increase in the estimated state dependence when first order autoregressive error components AR (1) is allowed. The estimated true state dependence is 1.49 which is almost three times larger (in magnitudes) than the model without AR (1). The model also shows that the degree of true state dependence is 60 percent lower in rural households than the urban households. This implies that the poverty in urban households is more persistent than the rural households.

5 Conclusion

This study focuses on the persistence of poverty in Ethiopia. We consider latent class probit models which allow for three components that generate serial persistence in poverty: a permanent household specific effect to control for unobserved heterogeneity, a serially correlated error component and state dependence components to control for the effects of previous poverty status on the current poverty status. According to Heckman (1981) the former two is termed as “spurious” state dependence where the source of persistence is unobserved. The last one is termed as true “state” or structural state dependence where the past experience has an actual behavioural effect. The empirical results for both rural and urban areas show that each of these components is statistically significant in characterising the dynamics of poverty in Ethiopia. The results show that the urban household display a greater degree of true state dependence than the rural households. This indicates that an urban household that experienced poverty during the preceding year has higher risk (almost twice) of staying in poverty than a rural household. Our result also shows that the majority of the households in rural area belong to the type 2 heterogeneity group where the households have a relatively lower risk of being poor due to permanent unobserved heterogeneity. However this proportion in urban area is quite high. Furthermore the effect of transitory shocks in poverty persistency appears to be stronger among urban households than rural households.

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Table 1: Percentage of Households by Poverty Status: 1994-2000

Poverty Status	Rural	Urban
Always poor	7.3	15.4
Once poor	28.9	20.4
Twice Poor	23.0	18.3
Thrice Poor	20.0	16.0
Never Poor	20.8	39.4

Source: Bigsten and Shimeles (2005)

Table 2a: Descriptive Statistics for Selected Variables by the Number of Times in Poverty During 1994-2000: Rural Households

Variable	Never Poor	Once Poor	Twice Poor	Three Times poor	Always Poor
Household size (numbers)	4.9	5.8	6.4	6.9	8.3
Age of head of household (years)	44	46	47	47	48
Female headed households (%)	23	22	18	22	16
Household head with primary education. (%)	12	10	7	7	3
Wife completed primary school (%)	4	2	2	1	1
Land size (hectare)	1.1	0.9	.7	0.7	0.5
Asset value(birr)	225	173	152	87	92
Off-farm employment (%)	24	38	39	45	29
No of oxen owned	2	1.7	1.4	1.1	0.78

Source: Bigsten and Shimeles (2005)

Table 2b: Descriptive Statistics for Selected Variables by the Number of Times in Poverty During 1994-2000: Urban Households

Variable	Never Poor	Once Poor	Twice Poor	Three Times poor	Always Poor
Household size (no)	5.7	6.3	6.6	6.9	7.6
Age of head of households(years)	47	49	50	48	51
Female headed households (%)	40	44	46	39	43
Head of household with primary educ. (%)	60	44	30	27	20
Wife with primary education (%)	33	21	16	12	8
Private business (%)	3	2	2	0.0	0.0
Own account employee (%)	19	17	15	12	16
Civil servant (%)	21	15	11	9	9
Public sector employee (%)	9	7	5	6	5
Private sector employee (%)	6	5	5	3	3
Casual worker (%)	4	6	7	14	32
Unemployed (%)	4	4	7	4	9
Resides in the capital (%)	68	71	79	78	87

Source: Bigsten and Shimeles (2005)

Table 3: Estimated probit effect (Rural areas).

	Simple Probit (1)		Latent Class Probit (2)		Latent Class Dynamic SD(1) Probit (3)		Latent Class Dynamic SD(1)+AR(1) Probit (4)	
	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio
Const	1.044	12.23	-	-	-	-	-	-
Hhsize	0.088	16.33	0.092	9.94	0.100	13.11	0.099	10.50
Teff	0.011	0.87	-0.002	-0.08	-0.012	-0.58	-0.003	-0.06
Coffee	-0.130	-5.85	-0.171	-3.51	-0.012	-0.45	0.007	0.10
Chat	-0.647	-10.12	-0.692	-7.58	-0.387	-4.48	-0.323	-4.17
Landsize	-0.105	-8.44	-0.124	-5.16	-0.068	-4.47	-0.063	-2.14
Oxen	-0.016	-1.99	-0.013	-0.76	-0.005	-0.21	-0.005	-0.27
Off-farm	0.166	9.87	0.184	3.95	0.151	3.21	0.129	3.18
Market	-0.004	-7.42	-0.005	-6.12	-0.002	-3.11	-0.002	-2.81
Grozone	-0.412	-10.26	-0.464	-7.58	-0.512	-1.24	-0.463	-7.97
Wifeprim	-0.396	-5.18	-0.392	-2.61	-0.211	-1.49	-0.176	-1.30
Meanage	-0.018	-2.68	-0.023	-3.48	-0.010	-1.61	-0.006	-0.76
Agehhh	0.005	1.69	0.006	0.89	-0.003	-0.61	-0.005	-0.69
Meanage2	0.011	1.33	0.018	2.14	0.007	0.97	0.005	0.45
Agehhh2	0.001	0.25	0.001	0.16	0.008	1.51	0.008	1.23
Assetval	-0.064	-13.65	-0.064	-8.25	-0.058	-5.26	-0.057	-7.32
Land*Hhsize	-0.003	-1.308	-0.002	-0.77	-0.006	-2.65	-0.006	-1.69
LagP	-	-	-	-	0.331	8.54	0.598	6.64
AR(1)	-	-	-	-	-	-	-0.188	3.55
Type 1	-	-	1.807	9.50	1.149	7.74	0.788	2.74
Type 2	-	-	0.968	5.03	0.858	6.39	0.596	2.34
Pr Type 1	-	-	0.35	-	0.26	-	0.26	-
Pr Type 2	-	-	0.65	-	0.74	-	0.74	-
Log Likelihood	2956.59	-	2933.88	-	2826.82	-	2822.59	-

Notes: The estimated coefficients of initial year of corresponding specifications are not reported.

Table 4: Estimated probit effect (Urban areas)

	Simple Probit (1)		Latent Class Probit (2)		Latent Class Dynamic SD(1) Probit (3)		Latent Class Dynamic SD(1)+AR(1) Probit (4)	
	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio
Constant	-0.330	-1.13	-	-	-	-	-	-
Hhsize	0.113	10.73	0.143	9.86	0.139	14.04	0.113	12.17
Hhhfem	0.169	3.10	0.260	3.20	0.171	6.29	0.099	3.45
Addis	0.143	0.89	0.114	0.39	0.144	4.54	0.123	3.29
Awasa	-0.019	-0.09	-0.088	-0.26	0.038	0.70	0.096	1.59
Bahadar	-0.408	-1.50	-0.551	-1.08	-0.051	-0.67	0.113	0.88
Dessie	0.192	0.94	0.093	0.25	0.416	3.89	0.447	3.79
Iredawa	-0.101	-0.55	-0.209	-0.65	0.167	2.59	0.294	3.99
Jimma	0.140	0.79	0.127	0.41	0.267	3.67	0.352	4.78
Amhara	-0.141	-1.54	-0.202	-1.37	-0.136	-3.72	-0.070	-2.12
Oromo	-0.139	-1.42	-0.231	-1.48	-0.132	-4.21	-0.098	-2.46
Tigrawi	-0.626	-4.16	-0.880	-3.29	-0.529	-6.95	-0.273	-3.46
Gurage	-0.066	-0.63	-0.112	-0.70	-0.113	-2.49	-0.122	-2.24
Wifeprime	-0.465	-6.84	-0.516	-5.41	-0.388	-7.31	-0.265	-5.07
Unemp	0.522	4.72	0.609	4.23	0.489	4.37	0.323	3.54
Fedn	-0.220	-1.65	-0.215	-0.96	-0.112	-2.48	-0.088	-1.59
Ffarmer	0.072	0.95	0.116	0.92	0.089	3.60	0.005	0.15
Fgempl	-0.530	-4.04	-0.667	-3.18	-0.486	-3.96	-0.364	-3.35
Fsempl	-0.427	-3.87	-0.465	-2.55	-0.319	-4.38	-0.233	-3.37
Meanage	-0.036	-3.56	-0.029	-1.82	-0.019	-2.86	-0.011	-1.37
Meanage2	0.034	2.54	0.024	1.11	0.019	2.18	0.015	1.28
Agehhh	0.003	0.40	0.009	0.77	-0.003	-0.70	-0.009	-1.46
Agehhh2	0.004	0.50	0.001	0.02	0.007	1.48	0.009	1.44
Avalue	-0.005	-11.15	-0.004	-23.87	-0.003	-7.17	-0.003	-6.28
LagP	-	-	-	-	0.543	10.77	1.490	18.76
AR(1)	-	-	-	-	-	-	-0.452	-12.39
Type 1	-	-	0.053	0.11	-0.470	-11.57	-1.192	-6.08
Type 2	-	-	-1.37	-2.78	-1.329	-5.11	-1.923	-9.39
Pr Type 1	-	-	0.38	-	0.35	-	0.04	-
Pr Type 2	-	-	0.62	-	0.65	-	0.96	-
Log Likelihood	1828.77	-	1739.42	-	1693.56	-	1662.76	-

Notes: The estimated coefficients of initial year of corresponding specifications are not reported.

Appendix Table (1): Definition of Variables used in the study

Variable definition	Explanation
Rural Households	
Household Characteristics	
Hhsize	Household size
Agehhh	Age of head of the household
Agehhh2	Squared age of the head of the household
Meanage	Mean age of the household
Meanage2	Squared mean age of the household
Wifeprime	Dummy for a wife completing primary school
Landsz	Land size
Assetval	Value of household assets (durables)
Oxen	Number of oxen owned
Types of crops planted	
Teff	Dummy if major crop grown is teff
Coffee	Dummy if major crop grown is coffee
Chat	Dummy if major crop grown is chat
Other means of income	
Offfarm	Off farm income
Regional variables	
Market	Access to local market
Urban Households	
Household Characteristics	
Hhsize	Household size
Agehhh	Age of head of household
Agehhh2	Squared age of head of household
Meanage	Mean age in the household
Meanage2	Squared mean age in the household
Hhhfem	Dummy if household head is female
Hhhprime	Dummy if household head completed primary school
Wifeprime	Dummy if wife completed primary school
Avalue	Value of household assets (durables)
Occupation	
Fedn	Father of household head has primary education
Ffarmer	Father of household head is farmer
Fgempl	Father of household head is government employed
Fsempl	Father of household head is self employed
Unemp	Household head is unemployed
Regional Dummies	
Addis	
Awasa	
Bahadar	
Dessie	
Iredawa	
Jimma	
Amhara	
Oromo	
Tigrawi	
Gurage	