Binary Choice with Binary Endogenous Regressors in Panel Data: Estimating the Effect of Fertility on Female Labour Participation*

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October 1998

Abstract

This paper considers the estimation of binary choice panel data models with discrete endogenous regressors. We present a switching probit model which accounts for selectivity bias as well as for other forms of time invariant unobserved heterogeneity. Individual effects are allowed to be correlated with the explanatory variables, which can be predetermined as opposed to strictly exogenous. This model is applied to estimate a female participation equation with endogenous fertility and predetermined existing children and with individual effects using PSID data. We use the family sex composition as an instrument for exogenous fertility movements. The results indicate that assuming the exogeneity of fertility induces a downward bias in absolute value in the estimated negative effect of fertility on participation, although the failure to account for unobserved heterogeneity exaggerates this effect. Moreover, the estimates that deal with the endogeneity of fertility and control for fixed effects, but treat existing children as strictly exogenous produce a smaller effect of fertility that those obtained treating this variable as predetermined.

KEYWORDS: Binary choice, panel data, endogenous variables, predetermined variables, labour force participation, fertility.

JEL CLASSIFICATION NOS: C21, C23, C25, J13.

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*I am indebted to Manuel Arellano for his excellent supervision. I would like to thank Juan Carlos Berganza for his helpful comments and Ernesto Villanueva for providing me with the data. I have also benefited from the suggestions of Samuel Bentolila, Richard Blundell, Olympia Bover, Ignacio Garcia, Costas Meghir, Pedro Mira, Enrico Rettore, Javier Suarez and other professors and students at CEMFI. The author assumes full responsibility for any error.

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1 Introduction

Behavioral equations relating jointly dependent qualitative variables very often arise in a wide variety of microeconomic problems. There are many models which consider the impact of a binary variable on another binary variable, such as those that arise from the joint determination of (a) employment probabilities and training; (b) housing ownership status and transportation mode; and (c) fertility and female labour force participation. Many other examples could be given. In all these cases, it is suspected that individuals make choices of belonging to one group or another on the basis of unobserved factors that affect outcomes but are not due to the decision being evaluated. That is to say, in these models the decision of an individual is based on individual self-selection.

There are a number of empirical works that have studied the problem of sample selection in the setting of continuous variables. One prototypical problem in the econometrics of self-selection bias is that of the estimation of the impact of unionism (a discrete variable) on wage differentials (a continuous variable).[1] Another major use of the self-selection models is in evaluating the benefits of social programs.[2] This strand of the literature has originated a variety of techniques to estimate the effect of self-selection (*e.g.* Heckman (1976b) suggested a two-stage estimation method for such models).

However, there are significantly fewer results on selection for discrete choice models with an endogenous and discrete explanatory variable. The presence of a dummy endogenous regressor in a binary choice model makes the analysis differ substantially from that in conventional binary choice models. More precisely, the standard two-stage method leads to an inconsistency with the statistical assumptions of the nonlinear discrete models. Moreover, the alternative linear probability model is incompatible with the observed data when dummy endogenous regressors are present.

The purpose of this paper is to present a framework which accounts for the interaction between dummy endogenous variables. Specifically, we present a bivariate probit model for panel data and then we extend the model to consider a switching probit model with en-

[1] See Lee (1978) and Abowd and Farber (1982).

[2] For example, Willis and Rosen (1979) apply the model to analyze the returns of education.

dogenous switching. The model proposed here is sufficiently flexible to take into account the individual self-selection and the time invariant unobserved heterogeneity between individuals. As in Arellano and Carrasco (1996), individual effects are allowed to be correlated with the explanatory variables, through the conditional expectation of the effects, which is let to be non-parametric. Furthermore, the explanatory variables can be predetermined as opposed to strictly exogenous.[3] The proposed model is estimated by maximum likelihood, by specifying the joint probability distribution of the two discrete endogenous variables.

We apply this model to analyze the relationship between labour force participation and fertility decisions using PSID data. Throughout the paper, we look at some of the issues that arise in modeling the effects of children on female labour force participation. The majority of studies find a negative correlation between fertility and female labour supply. However, the interpretation of these correlations remains unclear.[4] Many of these studies implicitly assume that all of the observed negative correlation is due to a "direct" effect. This is to assume that the unobserved heterogeneity is irrelevant and that the error term is serially uncorrelated. Nevertheless there is evidence that fixed effects may be important and that the error term is also likely to be autocorrelated.[5] Therefore, to obtain a true exogenous effect of children on participation we need panel data in order to specify a labour participation equation so that it has serially uncorrelated residual. Then, since children aged more than one are given we can treat them as predetermined, and we need only worry about the endogeneity of recently born children.

A recurrent problem with estimating the causal link running from fertility to female labour participation has been the difficulty in finding enough well-measured variables that are correlated with fertility but not with labour supply, that is, valid instruments.[6] A number of studies have used instrumental variables to take into account the endogeneity of

[3] This includes models with lagged dependent variables as well as models with other forms of unspecified feedback.

[4] An important exception to these empirical labour supply traditions is Mincer (1963), in which the inappropriateness of including a fertility variable among the set of labour supply regressors is suggested.

[5] It is generally accepted that the presence of children, and especially young children, decreases the labour supply of the mother (see for instance Mroz (1987)) and that women plan the number and timing of their children according to labour market factors (see for instance Waite and Stolzenberg (1976)). This makes it necessary to analyze jointly both decisions.

[6] The survey by Nakamura and Nakamura (1992) seems to argue that a search for exogenous variation is not only difficult, it is not even fruitful (pp. 60-61).

fertility variables.[7] However, the results vary considerably from one study to another, which is unsurprising given that they use different sets of instruments to estimate different labour supply variables (e.g. Cramer (1980) uses the ideal family size and religion as instruments, Schultz (1978) uses the wife's origin and Rosenzweig and Wolpin (1980) use twins-pairs).

In this paper we use the sex of previous children as instrument. This follows from the finding, well-documented in the demography literature, that parents prefer "balanced" families in terms of the sex composition of their children, and are more likely to have an additional child if the previous ones are of the same sex. It is argued in this paper that this instrument is a good predictor of fertility, but not of participation, in the sense that sex of children does not influence directly this decision.

We first examine the extent to which the use of actual fertility in labour participation equations provides biased representations of the impact of an exogenous change in family size on participation. Given the panel structure of our data, we then consider the impact of controlling for unobserved heterogeneity and for predetermined existing children on participation.

The paper is organized as follows. Section 2 presents the model and distinguishes between cross-sectional and panel data considerations. Section 3 discusses the issue of endogenous fertility, describes the data set used and gives some summary statistics. Section 4 contains the estimation results. Finally, Section 5 presents some concluding remarks.

2 Models and estimators

2.1 Switching probit models

Let y_i^* be the woman disutility from working based on her valuation of time in the household. This variable is unobservable. What we observe is a dummy variable, y_i, which indicates labour force participation and it is defined by

$$y_i = \begin{cases} 1, & \text{if } y_i^* > 0; \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

[7] See Browning (1992) for an excellent survey of work in this area.

We start by considering the following model for y_i

$$y_i = \mathbf{1}\left(y_i^* > 0\right) = \mathbf{1}\left(\alpha_0 + \alpha_1 d_i + \delta_0 x_i + \delta_1 x_i d_i + v_i \geq 0\right), \quad (2)$$

This is the so called "dummy endogenous variable model", where **1** denotes the indicator function, x_i is an exogenous variable, and d_i is a dummy variable ($d_i = 1$ if the woman has an additional child, 0 otherwise).[8]

If $v_i \mid x_i, d_i \sim N(0,1)$, model (2) becomes a standard probit model. If d were an endogenous variable, provided we had an instrument for fertility z such that $d \mid x, z \sim N\left(\mu_d\left(x,z\right), \sigma_d^2\right)$ the reduced form for y would also be a probit model and, therefore, the parameters in (2) could be easily estimated by using a two-stage method (see for example the discussion in Amemiya (1985) and references there in). However, since d is a binary indicator its distribution cannot be normal, and as a consequence, two-stage or instrumental-variable methods are not valid alternatives for estimating this type of nonlinear models.

Given the inappropriateness of the standard instrumental variable method for analyzing the relationship between two endogenous discrete variables, we account for the endogeneity among fertility and participation by considering a bivariate probit model. We specify a reduced form probit for fertility:

$$d_i = \mathbf{1}\left(\lambda_0 + \lambda_1 x_i + \lambda_2 z_i + \varepsilon_i \geq 0\right), \quad (3)$$

where ε_i and v_i are assumed to be jointly normally distributed and where z is a variable which affects y only through d.

To measure the effect of fertility in this model, holding x_i and v_i constant, it is useful to define the latent binary variables:

$$\begin{aligned} y_{i0} &= \mathbf{1}\left(y_{i0}^* \geq 0\right) = \mathbf{1}\left(\alpha_0 + \delta_0 x_i + v_i \geq 0\right) \\ y_{i1} &= \mathbf{1}\left(y_{i1}^* \geq 0\right) = \mathbf{1}\left(\left(\alpha_0 + \alpha_1\right) + \left(\delta_0 + \delta_1\right) x_i + v_i \geq 0\right) \end{aligned} \quad (4)$$

Then the effect of having a child for woman i will be given by $y_{i1} - y_{i0}$. It answers the question: how does that particular woman change participation behaviour if her fertility decision switches from $d = 0$ to $d = 1$? Notice that provided $\delta_0 < 0$ and $(\delta_0 + \delta_1) < 0$ the

[8] Note that in this specification the effect of x varies among individuals with different values for d.

pair (y_{i0}, y_{i1}) make take on the values $(0,0)$, $(1,1)$ and $(1,0)$, but the model rules out the outcome $(0,1)$ (that is, the possibility that a nonworking woman starts working following the birth of a new child). This situation does not put the model in contradiction with the observed data, since the model is still able to generate all possible outcomes for the pair (y_i, d_i).[9]

Before we consider a generalization of this model, it is of some interest to relate the previous discussion to the linear probability model. A well known problem of such model is that its forecasts are not restricted to the $(0,1)$ interval, but it has nevertheless been suggested as a simple alternative specification when dummy endogenous explanatory variables are present (see Heckman and MaCurdy (1985)). The advantage of the linear probability model is that it can be estimated using linear instrumental variable methods. However, interpretation of the results is difficult given the following incompatibility with the observed data.

Let us consider

$$y_i = \alpha_0' + \alpha_1' d_i + \delta_0' x_i + \delta_1' x_i d_i + v_i' \tag{5}$$

Here,

$$y_{i1} - y_{i0} = \alpha_1' + \delta_1' x_i \tag{6}$$

Therefore, the linear probability model requires $y_{i1} - y_{i0}$ to be constant for all women with a given value of x_i. Notice that to be able to have $y_{i1} - y_{i0} = -1$ rules out the possibility of observing women with $y_i = 1$ and $d_i = 1$ or women with $y_i = 0$ and $d_i = 0$. A similar argument applies in the case of $y_{i1} - y_{i0} = 1$. The conclusion is that in general the only way for the model not to be in contradiction with the observed data is that $y_{i1} - y_{i0} = 0$, therefore imposing no effect of children on participation!.[10]

Turning to the bivariate probit, a generalization that permits the outcome $(y_{i0}, y_{i1}) = (0,1)$ can be achieved by specifying two different errors in the index formulation for y_{i0} and y_{i1}:

$$\begin{aligned} y_{i0} &= \mathbf{1}\left(y_{i0}^* \geq 0\right) = \mathbf{1}\left(\alpha_0 + \delta_0 x_i + v_{i0} \geq 0\right) \\ y_{i1} &= \mathbf{1}\left(y_{i1}^* \geq 0\right) = \mathbf{1}\left(\left(\alpha_0 + \alpha_1\right) + \left(\delta_0 + \delta_1\right) x_i + v_{i1} \geq 0\right) \end{aligned} \tag{7}$$

[9] It is important to stress that for each woman we observe the pair (y_i, d_i), but only y_{i1} or y_{i0}.

[10] Note that in the continuous case this problem does not arise, since there is an infinite set of values of y which are compatible with the homogeneity restriction.

As before, we have

$$y_i = y_{i0}(1 - d_i) + y_{i1} d_i. \tag{8}$$

and $(v_{i0}, v_{i1}, \varepsilon_i)$ are assumed to be jointly normally distributed with zero mean vector and covariance matrix

$$\Sigma = \begin{pmatrix} 1 & \rho_{12} & \rho_{1\varepsilon} \\ & 1 & \rho_{2\varepsilon} \\ & & 1 \end{pmatrix}. \tag{9}$$

The standard bivariate probit arises as a special case of this model with $\rho_{12} = 1$. The difference between the two models can be appreciated by noticing that $y_{i1} - y_{i0}$ is random in both models, whereas the gain in the latent variables $y^*_{i1} - y^*_{i0}$ is constant in the former but random in the latter. The more general model is therefore a switching regressions model in the latent variables with endogenous switching. If $y^*_i = y^*_{i0}(1 - d_i) + y^*_{i1} d_i$ were observed and $v_{i0} \equiv v_{i1}$, this would make instrumental variables inferences consistent. In the discrete choice context, however, the situation is different since although $y^*_{i1} - y^*_{i0}$ is constant, $y_{i1} - y_{i0}$ remains random.[11]

The log-likelihood function of the model, from which maximum likelihood estimates can be obtained in a straightforward manner, is as follows:

$$\begin{aligned} L\left(\gamma_0, \gamma_1, \beta_1, \beta_0, \alpha, \rho_{1\varepsilon}, \rho_{2\varepsilon}\right) &= \sum_{y=0,d=0} \log P_{00} + \sum_{y=0,d=1} \log P_{01} + \\ &+ \sum_{y=1,d=0} \log P_{10} + \sum_{y=1,d=1} \log P_{11}. \end{aligned} \tag{10}$$

where

$$\begin{aligned} P_{00} &= \Pr(y = 0, d = 0) = \Phi\left(-\gamma_0 - \beta_0 x, -z'\lambda; \rho_{1\varepsilon}\right), \\ P_{01} &= \Pr(y = 0, d = 1) = \Phi\left(-\gamma_1 - \beta_1 x\right) - \Phi\left(-\gamma_1 - \beta_1 x, -z'\lambda; \rho_{2\varepsilon}\right), \\ P_{10} &= \Pr(y = 1, d = 0) = \Phi\left(-z'\lambda\right) - P_{00}, \\ P_{11} &= \Pr(y = 1, d = 1) = \Phi\left(z'\lambda\right) - P_{10} = 1 - P_{00} - P_{01} - P_{10}. \end{aligned}$$

[11] In other words, in the standard bivariate probit model, the change in the disutility from working when having a child is constant. However, since the change in the disutility only produces switch in actions if a threshold is crossed, we can still observe different behaviour for different individuals.

2.2 Switching probit models for panel data

We can extend the previous approach to the case of panel data models. One of the main advantages of panel data is that they allow us to relax and test some implicit assumptions in the cross-section analysis. In this setting, there are two basic issues we can account for. First of all, the possibility of controlling time invariant unobserved heterogeneity. The second reason for which the panel is essential with respect to a cross-section sample is the possibility of modelling dynamic relationships among the variables. In some models, feedback effects from lagged dependent variables to current and future values of the explanatory variables are crucial aspects of the economic problem of interest. In addition, adequately representing dynamics usually requires including lagged dependent variables as additional regressors, which are predetermined by definition.

Despite the interest of this problem, there are not well established econometric techniques for estimating the relationship between two endogenous discrete variables taking into account panel data considerations. In this paper, following the approach proposed by Arellano and Carrasco (1996) to estimate random effects probit models without the strict exogeneity assumption, we present a semi-parametric random effects switching probit model, with unrestricted conditional means of the individual effects given the explanatory variables.

Let us consider the following error-component switching probit model for N individuals observed T consecutive time periods that takes into account the dynamics of female labour supply

$$y_{it} = \begin{cases} y_{it1} = \mathbf{1}\left(\gamma_{1t} + \beta_1 x_{it} + \omega_{it1} \geq 0\right), & \text{iff } d_{it} = 1; \\ y_{it0} = \mathbf{1}\left(\gamma_{0t} + \beta_0 x_{it} + \omega_{it0} \geq 0\right), & \text{iff } d_{it} = 0. \end{cases} \tag{11}$$

where

$$\omega_{ijt} = \eta_i + v_{ijt} \quad j = 1, 0; \tag{12}$$

and the fertility choice equation

$$d_{it} = \mathbf{1}\left(\lambda_0 + \lambda_1 x_{it} + \lambda_2 z_{it} + \varepsilon_{it} \geq 0\right); \tag{13}$$

We have in mind the typical microeconometric panel where T is small and N is large. Let us also denote $w_{it} = \left(z_{it}, x_{it}, y_{i(t-1)}, d_{i(t-1)}\right)$ and $w_i^t = (w_{i1}...w_{it})$. The errors are assumed to have a normal distribution given w_i^t of the form[12]

$$\left(\begin{array}{c|c} \omega_{it1} & \\ \omega_{it0} & w_i^t \\ \varepsilon_{it} & \end{array}\right) \sim N\left(\left\{\begin{array}{c} E\left(\eta_i \mid w_i^t\right) \\ E\left(\eta_i \mid w_i^t\right) \\ 0 \end{array}\right\}, \Sigma\right), \tag{14}$$

where

$$\Sigma = \begin{pmatrix} 1 & \rho_{12} & \rho_{1\varepsilon} \\ & 1 & \rho_{2\varepsilon} \\ & & 1 \end{pmatrix}. \tag{15}$$

In this model η_i and v_{ijt} are not required to be conditionally independent, and in general they will be correlated.

As in Arellano and Carrasco (1996), the sequence of conditional means $\{E\left(\eta_i \mid w_i^s\right), s = 1, ..., T\}$ is left unrestricted, except for the fact that they are linked by the law of iterated expectations:

$$E\left(\eta_i \mid w_i^t\right) = E\left(E\left(\eta_i \mid w_i^{t+1}\right) \mid w_i^t\right). \tag{16}$$

This model accounts for the self-selectivity problem as well as other forms of time-invariant unobserved heterogeneity. In addition, we allow for dependence between the explanatory variables and the individual effects through the conditional mean of the latter given the observed time path of w, which is let to be nonparametric. Although some other ways of controlling for unobserved heterogeneity could be considered, there are only a few results in the literature on binary choice panel data models. Some authors, following the work by Heckman and Singer (1984) for semiparametric duration models, have specified an individual effect with a mass point distribution (Moon and Stotsky (1993)). Another strand of the literature has considered "conditional effects" specifications in which the full distribution of the effects is left unrestricted (Manski (1987), Honoré (1992 and 1993)). This is attractive as a way to ensure that the distributions of the effects does not play any role in the identification of the parameters of interest. However, sometimes one may be willing to impose a certain amount of structure in the dependence between the effects and the endogenous variables if in exchange this makes it possible to relax another aspects of the economic

[12] In our application we do not condition on d_{it-1} since this variable coincides with x_{it}.

problem of interest. In this regard, the semi-parametric random effects model considered in this paper may represent an useful compromise.

Moreover, the model specifies x and z as a predetermined but not strictly exogenous variables, in the sense that while x_{it} and z_{it} do not depend on current or future values of the error term v_{it}, there may be feedback from lagged values of v to x and z. This distinction is crucial in labour supply equations, since the participation decision is also affected by other existing children variables, which will be included in x. In our application, this variable will be a dummy indicating whether there is any child aged between 2 and 6. Children aged more than one are given, but we must treat them as predetermined. Assuming that children are strictly exogenous is much stronger than the assumption of predeterminedness, since it would require us to maintain that labour supply plans have no effect on fertility decisions at any point in the life cycle (see Browning, 1992). Furthermore, z will also be a predetermined variable. This variable will be an indicator of the sex of previous children, so it reflects fertility decisions. Therefore, this variable must be treated as predetermined and not strictly exogenous.

The model can be rewritten as follows

$$y_{it} = \begin{cases} y_{i1t} = \mathbf{1}\left(\gamma_{1t} + \beta_1 x_{it} + E\left(\eta_i \mid w_i^t\right) + u_{i1t} > 0\right), & \text{iff } d_{it} = 1; \\ y_{i0t} = \mathbf{1}\left(\gamma_{0t} + \beta_0 x_{it} + E\left(\eta_i \mid w_i^t\right) + u_{i0t} > 0\right), & \text{iff } d_{it} = 0. \end{cases} \tag{17}$$

where

$$u_{ijt} = \eta_i + v_{ijt} - E\left(\eta_i \mid w_i^t\right) \quad j = 1, 0;$$

Notice that since the model is conditional on w_i^t it could include $y_{i(t-1)}$ as an additional regressor.

2.2.1 Maximum likelihood estimation

We consider identification and estimation in the case where x_{it} and z_{it} are discrete random variables. The following estimation procedure is valid for discrete random variables with finite support of J mass points, although we apply it to the case of two mass points. As it has been mentioned, in our case x will be an indicator of having a child between the ages of 2 and 6 and z will be an indicator of same sex. However, this method does not work in the continuous case.

The vector w_{it} will have a finite support of 2^4 points given by $(\phi_1 ... \phi_{2^4})$. The vector w_i^t takes on $(2^4)^t$ different values ϕ_j^t $\left(j = 1, ..., (2^4)^t\right)$.

Let us denote

$$\psi_j^t = E(\eta_i \mid w_i^t = \phi_j^t) \quad (j = 1, ..., (2^4)^t). \tag{18}$$

By the law of iterated expectations we have

$$\begin{aligned} \psi_j^{t-1} &= \sum_{\ell=1}^{2^4} \psi_{(\ell-1)(2^4)^{t-1}+j}^t \Pr\left(w_{it} = \phi_\ell \mid w_i^{t-1} = \phi_j^{t-1}\right) \\ (j &= 1, ..., (2^4)^{(t-1)};\ t = 2, ..., T). \end{aligned} \tag{19}$$

Moreover, since the model includes a constant term, it is not restrictive to assume that $E(\eta_i) = 0$. Therefore,

$$E(\eta_i) = \sum_{\ell=1}^{2^4} E(\eta_i \mid w_{i1} = \phi_\ell) \Pr(w_{i1} = \phi_\ell) = 0. \tag{20}$$

Let us consider the partition $\phi_j = (\phi_{1j}, \phi_{2j})$ where $\phi_{2j} = \left(y_{i(t-1),} d_{i(t-1)}\right)$ is $(0, 0)$, $(0, 1)$, $(1, 0)$ or $(1, 1)$. Then the probabilities in (19) factorize as:

$$\begin{aligned} \Pr(w_{it} &= \phi_\ell \mid w_i^{t-1} = \phi_j^{t-1}) = \\ &\Pr\left[(z_{it}, x_{it}) = \phi_{1\ell} \mid w_i^{t-1} = \phi_j^{t-1}, \left(y_{i(t-1)}, d_{i(t-1)}\right) = \phi_{2\ell}\right] \\ &* \Pr\left[\left(y_{i(t-1)}, d_{i(t-1)}\right) = \phi_{2\ell} \mid w_i^{t-1} = \phi_j^{t-1}\right]. \end{aligned} \tag{21a}$$

Notice that the second term on the right-hand side contains the probabilities specified by the model. The first term consists of unspecified conditional probabilities for the x, and so they are additional reduced form parameters:

$$\begin{aligned} \pi_{t\ell}^{jk} &= \Pr\left[(z_{it}, x_{it}) = \phi_{1\ell} \mid w_i^{t-1} = \phi_j^{t-1}, \left(y_{i(t-1)}, d_{i(t-1)}\right) = \phi_{2k}\right] \\ (t &= 2, ..., T;\ \ell = 1, ..., 2^{T+1};\ j = 1, ..., (2^4)^{t-1};\ k = 1, ..., 4). \end{aligned} \tag{22}$$

The probabilities $p_\ell = \Pr(w_{i1} = \phi_\ell)$ are also left unrestricted and just add 2^4 parameters to the full likelihood function of the data.

Let us define the indicator variables

$$I_{ij}^t = \mathbf{1}(w_i^t = \phi_j^t) \tag{23}$$

The joint probability distribution of y and d is given by the following expressions

$$\begin{aligned}
P_{it}^{00} &= \Pr\left(y_{it}=0, d_{it}=0\right) = \Phi\left(-\gamma_{0t} - \beta_0 x_{it} - \sum\nolimits_{j=1}^{(2^4)^t} \psi_j^t I_{ij}^t, -\alpha z_{it}; \rho_{1\varepsilon}\right), \\
P_{it}^{01} &= \Pr\left(y_{it}=0, d_{it}=1\right) = \Phi\left(-\gamma_{1t} - \beta_1 x_{it} - \sum\nolimits_{j=1}^{(2^4)^t} \psi_j^t I_{ij}^t\right) - \\
&\quad -\Phi\left(-\gamma_{1t} - \beta_1 x_{it} - \sum\nolimits_{j=1}^{(2^4)^t} \psi_j^t I_{ij}^t, -\alpha z_{it}; \rho_{2\varepsilon}\right), \\
P_{it}^{10} &= \Pr\left(y_{it}=1, d_{it}=0\right) = \Phi\left(-\alpha z_{it}\right) - P_{it}^{00}, \\
P_{it}^{11} &= \Pr\left(y_{it}=1, d_{it}=1\right) = \Phi\left(\alpha z_{it}\right) - P_{it}^{01} = 1 - P_{00} - P_{01} - P_{10}.
\end{aligned} \tag{24}$$

The contribution to the log-likelihood for the ith individual is given by

$$\begin{aligned}
L_i &= \sum_{t=1}^{T} [(1-y_{it})(1-d_{it}) \log p_{it}^{00} + y_{it}(1-d_{it}) \log p_{it}^{10} + \\
&\quad + (1-y_{it}) d_{it} \log p_{it}^{01} + y_{it} d_{it} \log p_{it}^{11}]
\end{aligned}$$

$$+\sum_{t=2}^{T} \left\{ \sum_{\ell=1}^{2^{T+1}} \sum_{j=1}^{(2^4)^{t-1}} I_{ij}^{t-1} [\sum_{k=1}^{4} \mathbf{1}\left[\left(y_{i(t-1)}, d_{i(t-1)}\right) = \phi_{2k}\right] \log \pi_{t\ell}^{jk}] \right\}$$

$$+\sum_{\ell=1}^{2^4} \mathbf{1}(w_{i1} = \phi_\ell) \log p_\ell; \tag{25}$$

The ψ_j^t are solved recursively using the restrictions (19) and (20) as functions of ψ_j^T and the other parameters of the model.[13] The log-likelihood is maximized as a function of the $\gamma_0, \gamma_1, \beta_0, \beta_1, \psi_j^T, \alpha, \rho_{1\varepsilon}$ and $\rho_{2\varepsilon}$.

Note that in the case of x and z being strictly exogenous there is no sequential updating of the conditional expectations of the individual effects, since we always condition on the same set of variables. Therefore, the number of parameters ψ to be estimated is in that case smaller.

[13] Since we can have only a few individuals in some cells, a number of parameters ψ will be very imprecisely estimated. For that reason in the estimates of the model that treats x and z as predetermined variables all the cells with less than four observations were dropped and as a result the number of parameters ψ was also reduced.

3 Estimating the effect of fertility on female labour participation

When an additional child enters a household, we may suppose that the mother's allocation of time will change. Since both an income effect (children are expensive) and a substitution effect (children have high time costs and this rises the reservation wage) operate, the nature of this change is not clear *a priori*. Typically, any measure of female labour supply (for example, participation or hours if participating) is negatively correlated with any measure of young children,[14] which we may interpret simply as indicating that the substitution effect outweighs the income effect. Causal observation and a number of studies from different places and different times have found this. The usual response to this observation has been to include children variables as "nuisance" variables in female labour supply equations.

However, things may not be so simple: it is not clear that fertility is exogenous to labour force participation. Both decisions may be jointly determined, either by "basic economic variables" or because the population preferences for having children and for working are correlated in some way, in which case at least part of the observed relationship between them is spurious. This is the so called selection bias problem, which implies that those women with children would behave differently from those women with no child, independent of any true causal effect of children on participation. Whatever the explanation, if endogenous fertility is not accounted for, we can not obtain consistent estimates of labour supply conditional on fertility which allow us to draw robust and credible indication of the effects of children on women's labour market activity.

The fast increase in female labour force participation rates during the last decades and the decline in the fertility rates have originated a growing awareness among economists of the importance of the interrelationship between fertility behaviour and female labour supply. An understanding of the exogenous effects of children on labour supply (if there are any) is critical to a number of policy issues, mainly those aimed at fostering female labour force participation as well as fertility. For example, we could interpret the exogenous effect of children as due partly to the time needs of them. It is usually argued that career

[14] Influential studies of female labour supply which document this correlation include Lehrer and Nerlove (1986) and Nakamura and Nakamura (1992).

interruptions to look after children lead to lower wages for women.[15] If this is the case then it may be that a policy making child care cheaper would reduce the "wage gap" between women with and without children.[16]

In studies of female labour supply that do not make any correction for the possible endogeneity of fertility the coefficient on children can only be interpreted as measuring the exogenous effect if it is assumed that the error term in the participation equation is serially uncorrelated and there are not correlated individual effects. As emphasized before, this is difficult to maintain, so to obtain credible estimates we have to find suitable variables which to instrument fertility with. Some authors look for "natural" experiments; for example by looking at families that are infertile or experience multiple births. One problem with this approach is that such families are necessarily a few,[17] so these instruments have very little explanatory power because there is so little variation in them (leading to a lack of precision in estimates).

The alternative approach is to simply maintain some exogeneity assumption, that is, to look for variables for which a case can be made for excluding them from the participation equation and which have as much explanatory power as possible. A wide number of instruments have been used in the literature. Many of them are highly correlated with fertility but it is not clear that they are determined outside the model, in which case the results are opened to question. For example, religion,[18] number of siblings, ideal family size and duration of marriage are all probably related to social class, which will affect participation via education and wages.

In this paper we use an instrument based on the sibling sex mix in families with two or more children. This instrument exploits the widely observed phenomenon of parental preferences for a mixed sibling-sex composition in developed countries.[19] In particular,

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[15] See, for example, Mincer and Polanchek (1974).

[16] Note that how efficacious such a policy would in fact be depends on how responsive the female labour force participation is to the price of child care.

[17] For example, Rosenzweig and Wolpin (1980) start off with 12,605 women who had had a child but have only 87 who experienced twin births in the first pregnancy.

[18] Membership of the Catholic faith has long been used as an indicator of fertility, but as contraceptive use among Catholics increases (Ryder and Westoff (1972)) this instrument has declined in power.

[19] The preferences for children when they might have useful for productive capacities are not considered here.

parents of same-sex siblings are substantially more likely to have an additional child.[20] Child sex is essentially randomly assigned. Therefore, conditional on the sex of the previous children, a dummy for whether the sex of the next child matches the sex of the previous children provides a plausible instrument for additional child-bearing. Thus, our instrument only estimates effects for moving from 2 to 3 or more children in the population of women with at least two children,[21] but our conclusions may have important implications for other groups of women.

3.1 The data set

Our estimation strategy requires information on basic labour supply variables and the sex of mother's children. The data for this analysis come from the University of Michigan Panel Study of Income Dynamics (hereafter PSID) for the years 1986, 1987, 1988 and 1989. This is a longitudinal survey in which over 5000 households have been interviewed annually since 1968. The PSID contains information about labour supply, number and age of children as well as supplementary information on the sex of the children.

Our sample consists of 1442 married or cohabiting women between the ages of 18 and 55 in 1986. The dependent variable is an indicator of woman labour participation during each year. It is equal to 1 if the woman's annual hours of work is greater than zero in period t.

The effect of fertility is specified by a dummy variable which equals 1 if the age of the youngest child in $t+1$ is 1. Since we want to capture whether a new birth occurs or not, we look at childbirth rather than conception decisions.[22] Due to the timing of the survey (each time period is equal to one year) and that the reported age is the one at the time of the interview, it is not clear that this decision is better taken when the fertility variable is defined as 1 if the age of the youngest child in t is 1. In fact, primary results showed that using this definition of fertility did not influence the estimation results, although the

[20] Westoff, Potter and Sagi (1963) were among the first to report preferences for a mix. In a survey of desired fertility and a follow-up study of actual fertility among couples with two children, they found that parents of two boys or two girls both desired and ultimately had more children than parents of mixed pairs. Another papers using sex-preference instruments to estimate the effect of fertility on female labour supply are those of Iacovou (1996) and Angrist and Evans (1998).

[21] However, we will not drop the women with less than 2 children, since they could be relevant to analyze other aspects of the model.

[22] Our purpose is to measure the exogenous effect of a newborn on labour participation decisions.

significance of the estimated coefficients was smaller.

We are also interested in considering the effect of children aged more than 1. It is specified by a dummy that equals 1 if the woman has a child aged between 2 and 6. Besides it is important to bear in mind that correlation between women's labour supply and children may vary between different groups. It might be variation across race, age, education and income, so inappropriate pooling across heterogeneous groups could lead to inconsistent estimates. Therefore, we also account for these variables when modelling the effects of children. Moreover, since we make the assumption that the sex of the previous children affects a woman's propensity to have a further child but does not affect her labour participation decision, we instrument the fertility variable with an instrument set consisting of an indicator of same sex and with the two components of it (two or more girls and two or more boys).

The sample characteristics are presented in Table 1.1 and a description of the data set construction can be found in Appendix. Some simple cross-tabulations (Table 1.2) confirm that there is a negative relationship between labour market participation and fertility at all levels of fertility. For example, among women with no children, 95.36% are engaged in market work. The number falls to 80.10% for women with one child, to 75.13% for women with two children, 69.81% for three children and 58.5% for mothers of four or more.

Table 1.3 reports the fraction of women with two or more children by age and time of survey. Between 1986 and 1989 the fraction of women aged less than 25 increased from 34.01% to 53.24%. The increase in the fraction of women aged between 26 and 35 and those aged more than 36 is less sharp (from 64.75% to 73.76% and from 80.24% to 82.62% respectively).

Finally, Table 1.4 shows the sample fraction of women who participate by fertility decisions. As we can see, among those women who decide not tohave an additional child the percentage of participants is larger than among those women who have an additional child.

3.2 Instruments for fertility: The preference for balanced families

There is a large body of research in the demography literature on parent's preferences over the sex composition of their offspring. There is a consensus that significant preferences exists, although these vary between cultures, and within the same culture over time.

Reviewing the research on sex-preferences using US. data, Williamson (1983) concludes that there have been three consistent findings. First, there is a slight preference for male first births. Second, there is a preference for more males among families that prefer an odd number of children. Third, most families would prefer at least one child of each sex. In other words, families with more equal number of boys and girls are less likely to have another child than those with more unequal numbers of boys and girls. This third result has been analyzed for many researches. For example, Ben-Porath and Welch (1976) found that in the 1970 Census, 56% of families with either two boys or two girls has a third birth, whereas only 51% families with one boy and one girl had a third child. Angrist and Evans (1998) using the 1980 US Census found that only 31.2% of women with one boy and one girl have a third child, compared to 38.8% and 36.5% for women with two girls and two boys respectively.

Tables 2 and 3 reports results for our data set similar to those reported by Ben-Porath and Welch (1976) and Angrist and Evans (1998). Table 2 shows the fraction of women with at least one child who had a second child, in subgroups categorized by the sex of the first child. The third row of this table shows the difference by sex. Our data set indicate that the fraction of women who had a second child is almost invariant to the sex of the first child. Although attitudinal surveys suggests that many couples would prefer more boys than girls, or prefer the first child to be a boy, the results in Table 2 suggest that parents are not more or less likely to have a second child if they have a girl first.

Table 3 documents the relationship between the fraction of women who have a third child and the sex of the first two children. The first three rows show the sample characteristics for women in the following groups: those with two girls, those with one boy and one girl and those with two boys. The next two rows report separate results for women with two children of the same sex and for women with one boy and one girl. The final row reports the differences between the same-sex and mixed sex group averages.

We observe that women with two children of the same sex are more likely to have a third child: only 38.44% of mothers with one boy and one girl have a third child, compared to 44.75% and 40.10% for women with two girls and two boys respectively.

Table 4 gives an indication of how well our instrument explains the occurrence of a new birth. We examine how the sex of previous children exogenously alters fertility based on the pooled sample. The estimates are for probit equations which include indicators of sex of previous children, education, age, husband's income, race and age of the youngest child. The results reveal that having children of the same sex has a significant and positive effect on the probability of having an additional child, although there are not significant differences among all boys and all girls.

Some other indirect evidence in favour of the same-sex exclusion restriction comes from families with only one child. In particular, we can ask whether the labour supply of mothers is affected by the sex of an only child. In our sample the fractions of mothers with one boy or one girl that worked for pay are 0.81 and 0.82 respectively. The difference between these two figures is -0.0169 with a standard error of 0.302. Thus, there is no significant association between the probability a mother works and the sex of her first-born children. This finding supports the claim that the sex of children of itself is not related to labour supply.

4 Estimation results

In this section we report the estimates from the different models described in Section 2. Our basic motivation is to examine two considerations: endogeneity of fertility and the impact of controlling for unobserved heterogeneity and for predetermined existing children. Firstly, we compare the results from linear and non linear models that instrument the fertility variable with those that consider it as strictly exogenous. Secondly, we examine the importance of accounting for panel data considerations through the estimation of linear and probit models which include individual specific effects and that treat the explanatory variables as strictly exogenous and as predetermined.

We also report estimates of the effect of children that take account of the dynamics of female labour participation. Most of the evidence on dynamics points to the fact that the estimates of the effects of children on current labour supply that do not condition on past labour supply are likely to be misleading.[23] So it seems important to include lagged

[23] See for example Nakamura and Nakamura (1985).

participation as an additional regressor, trying to pick up part of the heterogeneity effects.

4.1 Models without unobserved heterogeneity

4.1.1 Linear estimates

Linear probability models are estimated in order to obtain results which do not depend on distributional assumptions. Although, as it has been shown in previous sections, the interpretation of the results from these linear models is difficult, identification of the parameters of the model does not require any hypothesis on the distribution of the error terms. Therefore we can get an idea of the identifying power of the instruments compared to the non-linear estimates. Tables 5 and 6 report estimates with and without including lagged participation as a regressor. We compare the coefficients obtained by OLS regression with those obtained using two-stage least squares (2SLS) (as in Heckman and MaCurdy (1985)).

OLS estimates suggest that the presence of an infant reduces the probability of work by 0.155. However, 2SLS estimates using *Same sex* as an instrument are markedly different from the estimates obtained under strict exogeneity, implying stronger effects of small children on participation.[24] This gap between OLS and 2SLS estimates is possibly due to measurement errors.

Looking at other coefficients in the regressions, we see that the children between 2 and 6 years coefficient is of the expected sign, although it does not seem to significantly influence the probability of participating for those women with a smaller child. We do not obtain a significant effect of age on participation. Anyway, we should not expect the age coefficient to tell us much about the "true" effects of age on participation. Since the younger women in the sample have younger children, the age coefficient reflects more the effect of the age of the youngest child that the effect of age in itself. The husband's income influences negatively on female labour force participation. The education coefficients are of the expected sign (positive), and they have a higher magnitude for higher qualifications.[25]

[24] We have also performed 2SLS estimates using *All boys* and *All girls*, the two components of *Same sex*, as separate instruments. In that case the effect of fertility is somewhat smaller. However, the additional predictive power provided by separating the two components of *Same sex* does not change the results very much or lead to an appreciable increase in precision.

[25] These two variables, education and husband's earnings, are potentially endogenous because the may be partly determined by fertility.

The 2SLS estimates obtained differ from some of the IV estimates previously reported in the literature on children and labour supply. In his review article, Browning (1992, p.1469) points out that it is not clear from these estimates whether children really have no effect on female labour supply, or whether the instruments are too weak or are poorly specified. Our 2SLS estimates are even larger (in absolute value) than the corresponding OLS estimates. Nevertheless, it may be mentioned that Rosenzweig and Wolpin (1980) using twins as instruments also found that the use of actual fertility in participation equations understated the impact of exogenous changes in fertility on female work status.

4.1.2 Probit estimates

As it has been mentioned in Section 2.1, linear probability models are not appropriate for estimating the relationship between two endogenous and discrete variables. Therefore, we estimate different probit specifications of our model, which are shown in Tables 7 and 8.

First column of Table 7 presents the results from a probit model that treats fertility as strictly exogenous, that is, in this model it is assumed that $\rho_{1\varepsilon} = \rho_{2\varepsilon} = 0$. Column (b) reports maximum likelihood estimates from the model that treats fertility as endogenous and imposes that $y^*_{i1} - y^*_{i0}$ is constant (that is, $\rho_{12} = 1$). Third column contains estimates of the switching probit model (that is, $\rho_{12} \neq 1$).

We have utilized *Same sex* and *All girls, All boys* variables as instruments, but since the results are not very different and the value of the likelihood function does not change, we only report the estimates using the *Same sex*.

The results are qualitatively consistent with the obtained for the linear models: the coefficient on fertility is significantly negative when the equation is estimated under strict exogeneity, and it becomes more negative under endogeneity.

The coefficients on the children between 2 and 6 years old variables are always negative. Based on these estimates we could obtain evidence that infants are more "time intensive" than older preschoolers (in the sense that the latter have a less negative effect on the probability of participating). One reason for the increasing participation of mothers as their children age could be the decreasing time cost (for example, the cost of alternative supervision falls as children age). Another reason is that even if child care costs were constant, mothers might still prefer to have children with them at home when there are infants, or that time spent with infants may be more exhausting than the same number of hours spent with an older child (see Becker (1985)).

Regarding the effects of the rest of covariates, we obtain similar qualitative effects than in the linear estimates and, again, we obtain that for all the regressors except fertility and its interactions the coefficients are not much changed whether we instrument fertility or not.

Given the values of the likelihood function for models (b) and (c), we cannot reject the null hypothesis $\rho_{12} \neq 1$. This result is not surprising, since the difference between these two models is that model (b) does not allow for the possibility that a woman would participate in the case of having a child, but while not having one does not participate. In a sense, this is a *perverse* situation, and this result suggests us that women in our sample do not behave in that way. The effect of lagged participation (see Table 8) is always positive as expected, but when we allow for state dependence the estimator of fertility is somewhat smaller.

The estimations of the fertility equation are shown in Table 9. As we can see, in all cases mothers of girls or boys are more likely than mothers with boys and girls to have an additional child. Moreover, the estimated coefficients are very similar in all specifications.

To evaluate the exogenous effect of fertility on the probability of participating in the labour force, we calculate the average impact for all women for both models: the one in which fertility is treated as endogenous and the one in which is treated as exogenous.[26] As we can see in the first row of Table 10, considering fertility as exogenous considerably understates the effect: in the exogenous case the probability of participating is reduced by 7.13%, while in the endogenous one by 38.71%. The contrast between these two sets of estimates may be due to measurement errors, but emphasizes the point that different individuals behave differently due to heterogeneous characteristics and that estimates which instrument fertility are probably most useful for predicting the consequences of policy innovations. Another informative way of highlighting the effects of fertility on the probability of participating is by calculating the implicit predicted probabilities for some individual types and seeing how these probabilities change when various factors change. From third and fourth rows

[26] These average effects are calculated using the models without state dependence.

of Table 10 we can see that for those women with higher education the effect of fertility is smaller than for those with lower education: in the first case the effect of fertility reduces the probability of participation by 33.81% while in the second case by 41.91%. Last two rows of Table 10 shows that when husband's income is low the probability of participating is reduced by 36.66% and by 38.93% when husband's income is high.

4.2 Models with unobserved heterogeneity

We now turn to the estimation of models with unobserved heterogeneity as presented in Section 2.3. In the panel data regressions we do not include variables which are constant in the temporal dimension, such as age, education or race. Therefore, we only consider as a regressor an indicator of sex of the previous children and an indicator of having a child aged between 2 and 6 years old. This variable is treated as strictly exogenous and as predetermined.

4.2.1 Linear estimates

Table 11 contains the estimates for three different linear specifications of the model that includes individual specific effects. Column (a) contains within groups estimates from a linear model that the treats fertility as a strictly exogenous variable. Column (b) reports GMM estimates of the model that deals with the endogeneity of fertility but treats the existing children and same sex variables as strictly exogenous. We present the two-step results using all lags and leads of x and z as instruments. Finally, Column (c) presents GMM estimates of the model that treats fertility as endogenous and existing children and same sex as predetermined variables. In this case, we use past values of x, z and y as instruments. Table 12 reports similar estimates to those in Table 11 but including lagged participation as a regressor.

In both tables, we can observe that relative to the rest of estimates, the within groups estimates show a downward bias (in absolute value) in the coefficient on fertility.[27] This result is unsurprising, since the WG estimator introduces biases due to lack of strict exogeneity of

[27] Note that we would expect the "same sex" instrumental variable to be correlated with the fixed effect. The reason is that it will be a predictor of preferences for children, given that the sample includes women with less than two children.

explanatory variables. However, the stronger differences appear when comparing columns (b) and (c). We can see that controlling for predetermined existing children imply stronger effects of smallest children on participation: the fertility coefficient is much bigger (in absolute value) than the corresponding GMM estimates that consider existing children as strictly exogenous. According to these results, it seems important account for the dynamics of fertility in relation to labour force participation decisions in order to obtain credible indication of the effects of children on participation.

4.2.2 Probit estimates

We now turn to the estimation of the model with unobserved heterogeneity as presented in Section 2.3. Table 13 reports the results from a model that treats the age and the sex of existing children as strictly exogenous variables. We consider three different models. The first column contains ML estimates for the model that treats fertility as exogenous, while the second and third columns show the results for an endogenous switching probit model. The difference between these two columns is that column (b) treats existing children as exogenous and column (c) as predetermined.

The results indicate that, similarly to the previous estimates, if endogenous fertility is not taken into account, an additional child appears to be associated with a smaller decrease in participation than in the endogenous case. Again, we can appreciate stronger differences in the effect of fertility when we control for predetermined existing children. Table 15 shows the predicted probabilities of participating when individual effects are taken into account. To calculate these probabilities we have to consider the estimated ψ_j^t parameter for each individual, depending on the values of the conditioning variables until t:

$$\psi_j^t = E(\eta_i \mid w_i^t = \phi_j^t) \quad (j = 1, ..., (2^4)^t)$$

Therefore, those individuals with the same conditioning set will have the same parameter ψ. In terms of predicted probabilities, we can see that the average effect on the probability of participating decreases by 0.129 when endogenous fertility is taken into account and only by 0.024 when it is considered as strictly exogenous.

Regarding the comparison between estimates with and without unobserved heterogeneity, it turns out that the estimates of the coefficients are upward biased when individual effects are not considered. Comparing the results from Table 15 to the ones in Table 10, we can see that the failure in controlling for unobserved heterogeneity overestimates considerably the reduction in the probability of participating.

So we can conclude that the exogeneity assumptions on fertility and existing children variables induce a downward bias in absolute value in the estimated fertility effect. This bias can be due to any measurement error in the fertility variable, that introduces a spurious positive correlation between this fertility measure and the dependent variable. However, the bias due to ignoring individual effects increases the effect of fertility in participation. This result indicates us that preferences for children and for participation could be negatively correlated.

5 Conclusions

In this paper we propose a switching probit model for panel data to analyze the relationship between dummy endogenous variables. This econometric framework enables us to take into account the self-selection bias as well as other forms of time invariant unobserved heterogeneity. Furthermore, the explanatory variables can be predetermined as opposed to strictly exogenous, which is a crucial point in our application. We apply this model to the estimation of the relationship between fertility and female labour force participation decisions. It allows us to investigate to what extent are these considerations important in determining the exogenous effect of fertility on participation. We use the sex of previous children as an instrument for exogenous fertility movements. One important limitation of this instrument is that it estimates the effect for moving from 2 to 3 or more children in the population of women with at least 2 children. The resulting estimates therefore do not necessarily describe the impact of moving from 0 to 1 or from 1 to 2 children. However, since our results indicate that the effect of the third and subsequent child is actually to decrease labour market participation, and the marginal effect of a second and subsequent children is usually less than that of the first child, our conclusions may have implications for other groups of women.

Two important conclusions emerged from our analysis. First, the standard approach with no instrumenting fertility leads to underestimates of the impact of exogenous changes in fertility on female work status. Second, the coefficient on the fertility variable varies considerably depending on whether we allow for unobserved heterogeneity and/or predetermined existing children. In particular, this variable has a smaller effect (is less negative) when we control for fixed effects and for predetermined existing children. Moreover, this effect is even smaller when we treat existing children and same sex variables as strictly exogenous.

Therefore, the fertility effects obtained suggests the importance of accounting for the dynamics in determining the causal effect of fertility on participation. The estimates that exploit the sex mix as an instrumental variable show us that children lead to an increase in female labour participation, so those policies aimed to increase fertility could play a causative role in increasing female participation.

APPENDIX

The data used in this analysis come from the Michigan Panel Study of Income Dynamics. We have selected those women older than 18 years old and less than 55 years old in 1986 and those classified as married or cohabiting.

Variables:

Participation: The variable takes the value 1 if the annual hours worked in t is greater than 0.

Fertility: The variable takes the value 1 if the age of the youngest child is 1 and there has been an additional child.

Kids 2-6: The variable takes the value 1 if the age of the youngest child is 2, 3, 4,5 or 6.

Education: Highest grade or year of school completed. We consider the following categories: Education 1 (1-10), Education 2 (11-15) and Education 3 (16 and 17), postgraduate).

Husband's Income: The values for this variable represent the head's average hourly earnings in dollars and cents per hour. This variable includes labour, part of farm income and business income, wages, bonuses, overtime, commissions, professional practice, from roomers and boarders.

Non-white: The variable takes the value one for black, American Indian and Asian women, and 0 for white women.

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Table 1.1

Means of the data
(Standard deviation in parentheses)

Variable	
More than 2 kids	0.404
(=1 if mother had more than 2 kids, =0 otherwise)	(0.49)
Two boys	0.282
(=1 if first two children were boys, =0 otherwise)	(0.45)
Two girls	0.235
(=1 if first two children were girls, =0 otherwise)	(0.42)
Same sex	0.517
(=1 if first two children were the same sex, =0 otherwise)	(0.50)
Age	31.293
(mother's age in 1986)	(5.68)
Worked for pay	0.769
	(0.42)
Education 1	0.057
	(0.23)
Education 2	0.719
	(0.45)
Education 3	0.233
	(0.42)
Black	0.227
	(0.42)
Husband's Income	12.830
	(9.41)
Number of observations per year	1442

Table 1.2

Labour force participation by number of children

Number of children

	0	1	2	3	4+
Market work	95.36%	80.10%	75.13%	69.81%	58.50%

Table 1.3

Percent of women with two or more children

Sample	PSID 1986	PSID 1989
Women 18-25	34.01%	53.24%
Women 26-35	64.75%	73.76%
Women 36-55	80.24%	82.62%

Table 1.4

Percent of women who participate

Sample	
With an additional child	66.11%
Without an additional child	78.30%

Table 2

Fraction of mothers with one child who had another child, by sex of first child

Sex of first child, families with one or more children	Fraction who had another child (std.error)
(1) One boy	0.6980 (0.4593)
(2) One girl	0.6817 (0.4661)
Difference (1)-(2)	0.0163 (0.6544)

Table 3

Fraction of mothers with two children who had another child, by sex of first two children

Sex of first two children, families with two or more children	Fraction who had another child (std.error)
Two girls	0.4475 (0.4980)
One boy, one girl	0.3844 (0.4868)
Two boys	0.4010 (0.4907)
(1) Both same sex	0.4222 (0.4942)
(2) One boy, one girl	0.3844 (0.4868)
Difference (1)-(2)	0.0378 (0.6937)

Table 4

Fertility equation
Probit estimates

Indep. variables		
Same sex	0.325	-
	(5.40)	-
All boys	-	0.328
		(4.30)
All girls	-	0.321
		(3.91)
Kids 2-6	-2.135	-2.135
	(-13.22)	(-13.23)
Educ 2	0.028	0.028
	(0.24)	(0.24)
Educ 3	0.307	0.307
	(2.45)	(2.44)
Age	-0.081	-0.081
	(-16.65)	(-16.64)
Black	0.092	0.092
	(1.45)	(-1.46)
Husband's Income	0.003	0.003
	(1.06)	(1.06)
Constant	1.527	1.527
	(8.22)	(8.22)
Log-likelihood	-1561.13	-1561.13

Dependent variable: occurrence of a new birth.
N = 1442 women between 18-55 years old in 1986. Years = 1986, 1987, 1988, 1989.
Figures in parentheses are *t*-ratios.

Table 5

Female labour participation without unobserved heterogeneity
Linear estimates

Method	OLS	2SLS
Instruments		Same sex
Indep. variables		
Fertility	-0.155	-0.987
	(-8.40)	(-5.80)
Kids 2-6	-0.078	-0.232
	(-6.59)	(-6.70)
Fert.*Kids2-6	0.214	-3.687
	(1.03)	(-1.27)
Educ 2	0.156	0.145
	(6.58)	(6.09)
Educ 3	0.232	0.264
	(8.81)	(9.74)
Age	0.002	-0.009
	(1.95)	(-3.70)
Husband's Income	-0.004	-0.004
	(-6.70)	(-7.25)
Black	0.026	0.037
	(1.98)	(4.97)
Constant	0.663	1.176
	(16.19)	(11.21)

Dependent variable: labour market participation
N = 1442 women between 18-55 years old in 1986. Years = 1986, 1987, 1988, 1989.
Figures in parentheses are heteroskedasticity robust t-ratios.

Table 6

Female labour participation without unobserved heterogeneity
Linear estimates with state dependence

Method	OLS	2SLS
Instruments		Same sex
Indep. variables		
Fertility	-0.089	-0.216
	(-6.13)	(-0.936)
Kids 2-6	-0.019	-0.038
	(-2.08)	(-0.808)
Fert.*Kids2-6	-0.058	-3.367
	(-0.36)	(-0.998)
Educ 2	0.049	0.033
	(2.64)	(1.304)
Educ 3	0.072	0.065
	(3.50)	(2.00)
Age	0.001	-0.002
	(1.81)	(-0.06)
Husband's Income	-0.002	-0.002
	(-3.71)	(-3.53)
Black	0.010	0.016
	(0.95)	(1.77)
y_{t-1}	0.625	0.623
	(60.61)	(40.00)
Constant	0.237	0.333
	(7.25)	(2.29)

Table 7

Female labour participation without unobserved heterogeneity
Probit estimates

Model	$\rho_{1\varepsilon} = \rho_{2\varepsilon} = 0$	$\rho_{12} = 1$	$\rho_{12} \neq 1$
	(a)	(b)	(c)
Indep. variables			
Fertility	-0.491	-1.107	-0.801
	(-8.21)	(-5.52)	(-3.67)
Kids 2-6	-0.268	-0.365	-0.411
	(-6.64)	(-7.81)	(-11.83)
Fert.*Kids2-6	0.718	0.027	0.671
	(0.99)	(0.30)	(0.68)
Educ 2	0.470	0.467	0.454
	(6.35)	(6.38)	(9.11)
Educ 3	0.745	0.765	0.758
	(8.71)	(8.97)	(13.01)
Age	0.006	-0.001	-0.003
	(1.91)	(-0.24)	(-1.07)
Husband's Income	-0.013	-0.013	-0.13
	(-6.61)	(-6.34)	(-8.99)
Black	0.089	0.089	0.09
	(1.93)	(1.96)	(3.08)
Constant	0.438	0.773	0.890
	(3.20)	(4.73)	(7.77)
$\rho_{1\varepsilon}$	-	0.364	0.816
	-	(3.19)	(1.89)
$\rho_{2\varepsilon}$	-	-	0.106
			(0.67)
Log-likelihood	-4577.50	-4571.07	-4570.66

Table 8

Female labour participation without unobserved heterogeneity
Probit estimates with state dependence

Model	$\rho_{1\varepsilon} = \rho_{2\varepsilon} = 0$	$\rho_{12} = 1$	$\rho_{12} \neq 1$
	(a)	(b)	(c)
Indep. variables			
Fertility	-0.410	-0.651	-0.644
	(-5.94)	(-2.45)	(-2.00)
Kids 2-6	-0.106	-0.151	-0.164
	(-2.21)	(-2.04)	(-1.66)
Fert.*Kids2-6	-0.189	-0.400	-0.60
	(0.79)	(-0.55)	(-0.34)
Educ 2	0.234	0.235	0.235
	(2.72)	(2.60)	(2.64)
Educ 3	0.377	0.390	0.392
	(3.77)	(3.66)	(3.67)
Age	0.009	0.005	0.005
	(2.22)	(1.11)	(0.82)
Husband's Income	-0.009	-0.009	-0.009
	(-3.65)	(-3.05)	(-3.31)
Black	0.058	0.060	0.060
	(1.06)	(1.05)	(1.03)
y_{t-1}	1.932	1.926	1.923
	(41.80)	(40.07)	(41.29)
Constant	-0.854	-0.707	-0.672
	(-5.21)	(-2.99)	(-2.22)
$\rho_{1\varepsilon}$	-	0.142	0.190
		(0.96)	(0.63)
$\rho_{2\varepsilon}$	-	-	0.125
			(0.63)
Log-likelihood	-3597.94	-3594.83	-3594.80

Table 9

Probit estimates of the fertility equation
Models without unobserved heterogeneity

Model	without y_{t-1}		with y_{t-1}	
	$\rho_{12} = 1$	$\rho_{12} \neq 1$	$\rho_{12} = 1$	$\rho_{12} \neq 1$
Indep. variables				
Same sex	0.355	0.365	0.328	0.328
	(5.99)	(5.77)	(5.43)	(5.03)
Kids 2-6	-2.150	-2.156	-2.136	-2.137
	(-13.31)	(-12.59)	(-13.18)	(-12.32)
Educ 2	0.022	0.032	0.028	0.028
	(0.62)	(0.35)	(0.13)	(0.30)
Educ 3	0.289	0.308	0.307	0.308
	(3.97)	(2.90)	(1.46)	(2.81)
Age	-0.080	-0.081	-0.081	-0.081
	(-15.95)	(-17.05)	(-13.34)	(-18.37)
Black	0.098	0.117	0.087	0.089
	(1.69)	(1.66)	(1.28)	(1.24)
Husband’s Income	0.004	0.002	0.003	0.003
	(1.21)	(0.82)	(1.06)	(1.00)
Constant	1.522	1.554	1.525	1.526
	(9.31)	(7.72)	(4.73)	(7.78)

Table 10
Effect of fertility on the probability of participating
Models without unobserved heterogeneity

	Endogenous fertility	Exogenous fertility
Average effect	-0.387	-0.071
Standard[1]	-0.391	-0.162
Low education	-0.419	-0.192
High education	-0.338	-0.134
Low husband's income	-0.366	-0.146
High husband's income	-0.389	-0.190

Notes: The average effect is calculated as the mean of $E(y_{i1} - y_{i0})$.

1. Standard: white women with the mean age in our data (33 years), with the mean husband's income (13), without kids aged between 2 and 6 years old, with medium level of education.

Table 11

Female labour participation with unobserved heterogeneity
Linear estimates

Method	(a) WG	(b) GMM[1] (St.Exog.)	(c) GMM[2] (Predet.)
Instruments		Same sex	
Indep. variables			
Fertility	-0.054	-0.062	-0.133
	(-3.66)	(-2.24)	(-2.24)
Kids 2-6	0.027	0.005	-0.096
	(0.20)	(0.28)	(-3.19)
Fert.*Kids2-6	-0.216	-0.878	-2.358
	(-0.97)	(-0.57)	(-1.25)

[1] IVs: All lags and leads of "Kids 2-6" and "same sex" variables.
[2] IVs: Lags of "Kids 2-6" and "same sex" up to $t-1$.

Table 12

Female labour participation with unobserved heterogeneity and state dependence
Linear estimates

Method	(a) WG	(b) GMM (St.Exog.)	(c) GMM (Predet.)
Instruments		Same sex	
Indep. variables			
Fertility	-0.054	-0.093	-0.175
	(-3.61)	(-2.76)	(2.50)
Kids 2-6	0.002	-0.017	-0.074
	(0.16)	(-0.95)	(-2.48)
Fert.*Kids2-6	-0.223	-1.611	-4.068
	(-0.97)	(-0.86)	(-1.53)
y_{t-1}	0.035	0.556	0.413
	(1.69)	(5.37)	(3.10)

These estimates also include lags of participation up to $t-2$ as instruments.

Table 13

Female labour participation with unobserved heterogeneity
Probit estimates

Model	$\rho_{1\varepsilon} = \rho_{2\varepsilon} = 0$	$\rho_{12} = 1$ (St.Exog.)	$\rho_{12} = 1$ (Predet.)
	(a)	(b)	(c)
Indep. variables			
Fertility	-0.146	-0.688	-0.984
	(-2.48)	(-1.363)	(-10.68)
Kids 2-6	0.068	-0.036	-0.389
	(1.31)	(-0.411)	(-1.801)
Fert.*Kids2-6	0.304	0.1146	-0.708
	(0.33)	(0.343)	(-1.464)
Constant	2.716	1.227	-
	(0.170)	(1.748)	
$\rho_{1\varepsilon}$	-	0.226	0.755
	-	(0.816)	(9.857)
Log-likelihood	-8014.88	-6435.22	-2585.19

Table 14

Probit estimates of the fertility equation
Model with unobserved heterogeneity

Model	$\rho_{12} = 1$ (St.Exog.)	$\rho_{12} = 1$ (Predet.)
	(a)	(b)
Indep. variables		
Same sex	0.193	0.156
	(4.010)	(2.160)
Kids 2-6	-1.734	-1.553
	(-16.672)	(-11.46)
Constant	-0.988	-1.026
	(-42.589)	(-29.091)

Table 15
Effect of fertility on the probability of participating
Model with unobserved heterogeneity

	Endogenous fertility	Exogenous fertility
Average effect	-0.129	-0.024
Without kids 2-6	-0.151	-0.043
With kids 2-6	-0.109	0.016