Binary Choice With Binary Endogenous Regressors in Panel Data: Estimating the Effect of Fertility on Female Labor Participation

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This article considers the estimation of the causal effect of fertility on female-labor-force participation equations. My main concern is to examine two considerations, the endogeneity of fertility and the impact of controlling for unobserved heterogeneity and for predetermined existing children. Using PSID data, a switching binary panel-data model that accounts for selectivity bias as well as for other forms of time-invariant unobserved heterogeneity is estimated. Individual effects are allowed to be correlated with the explanatory variables, which can be predetermined as opposed to strictly exogenous. Family sex composition is used as an instrument for exogenous fertility movements. The results indicate that exogeneity assumptions of children variables induce a downward bias in absolute value in the estimated negative effect of fertility on participation, although the failure to account for unobserved heterogeneity overstates this effect. Moreover, stronger effects of fertility are found when existing children are treated as predetermined but not strictly exogenous variables.

KEY WORDS: Binary choice; Endogenous variables; Fertility; Labor-force participation; Panel data; Predetermined variables.

The interaction between fertility and female labor supply has received a great deal of attention in the literature. In many early studies, the response to the strong negative correlation observed between these variables was to treat fertility as an exogenous determinant of labor-supply behavior (e.g., see Mincer 1962). However, labor supply and fertility may be jointly determined, either by "basic economic variables" or because in the population the preferences for having children and for working are correlated in some way. Therefore, if fertility variables are endogenous in female-participation equations, this should be taken into account when estimating and interpreting the results of these equations.

One strand of the literature has treated the endogeneity problem, estimating the determinants of fertility and labor supply within a simultaneous-equation framework (see Moffit 1984; Hotz and Miller 1988). An alternative approach is to look for "natural" experiments, such as the occurrence of twins in the first birth (e.g., Rosenzweig and Wolpin 1980; Bronars and Grogger 1994; Angrist and Evans 1998; Jacobsen, Pearce, and Rosenbloom 1999; Angrist 2001). Another solution is to use instrumental variables to check for the endogeneity of fertility [e.g., Angrist and Evans (1998) exploited the exclusion restriction given by the sex of the first two children].

In these studies, allowing for the endogeneity of children makes a difference to the estimated effect of fertility. Nevertheless, their results vary considerably. This is unsurprising given the differences in the children and labor-supply variables used, which range from discrete to continuous variables (see Browning 1992). In this sense, the main drawback of many of these studies is that they treat discrete children and labor-force-participation variables as continuous. In many cases, they use variants of linear probability models to estimate nonlinear relationships using two-stage estimation methods. However, the presence of a dummy endogenous regressor in a binary-choice model makes the analysis differ substantially from that in continuous-variable models. In particular, the standard two-stage method leads to an inconsistency with the statistical assumptions of the nonlinear discrete model, and the alternative linear probability model is incompatible with the observed data.

The econometric framework used in this article accounts for the interaction between dummy endogenous variables. Using PSID data, I analyze the relationship between labor-force participation and fertility decisions, taking into account the self-selection bias as well as other forms of time-invariant unobserved heterogeneity. I propose a switching regression formulation, similar to the one used within a cross-section setting by Manski, Sandefur, McLanahan, and Powers (1992). Specifically, I extend the Manski approach to the panel-data context. Given that the endogeneity between fertility and participation may emerge from sample selection or unobserved heterogeneity, I need panel data to obtain the true exogenous effect of children on participation. I first present a bivariate probit model for panel data and then consider a generalization into a switching probit model with endogenous switching. To account for the dynamics properly, the model I propose (a) includes unobserved individual effects that are allowed to be correlated with the explanatory variables (as shown by Arellano and Carrasco 1996) and (b) allows the explanatory variables to be predetermined but not strictly exogenous. This distinction is crucial in labor-supply equations, since the

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participation decision is also affected by lagged participation and by existing children variables, which must be treated as predetermined.

In my attempt to quantify the effect of fertility on participation, I face an identification problem: The data alone do not suffice to identify this effect. Hence, inference on fertility depends on the prior information available to the researcher about the probability distribution of the endogenous variables. I present alternative sets of estimates obtained under different assumptions about the process generating fertility and participation outcomes. Although there are also nonparametric alternatives to estimate this type of models, prior information assumptions are necessary if one is to do more than bound the probabilities (see Manski 1990). I also use an exclusion restriction, given by the sex of previous children, that will help to identify the parameters of the model (as shown by Angrist and Evans 1998).

Two main conclusions emerged from my analysis. First, the approach that ignores the endogeneity of fertility underestimates the impact of exogenous changes in fertility on female participation. Second, the coefficient on the fertility variable varies considerably depending on whether I allow for unobserved heterogeneity and/or predetermined existing children.

The article is organized as follows. Section 1 presents the model and distinguishes between cross-sectional and panel-data considerations. Section 2 discusses the issue of endogenous fertility, describes the dataset used, and gives some summary statistics. Section 3 contains the estimation results. Finally, Section 4 presents some concluding remarks.

1. MODELS AND ESTIMATORS

1.1 Switching Probit Models

Let y_i^* be the latent process that guides the woman's participation decision, given by the following underlying behavioral model:

$$y_i^* = \alpha_0 + \alpha_1 d_i + \delta_0 x_i + \delta_1 x_i d_i + v_i, \tag{1}$$

where x_i is an exogenous variable and d_i is a dummy variable indicating the presence of a recently born child. I focus on the effect of very young children since most of the children's effect on participation appears to depend on them, more so than, for example, on the total number of children living in the household (see Browning 1992). Variable y_i^* is unobservable. What I observe is a $0-1$ variable, y_i, which indicates the participation outcome for individual i and is defined by

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

where $\mathbf{1}$ denotes the indicator function. This is the so-called "dummy endogenous variable model" (see Maddala 1983).

If $v_i \mid x_i, d_i \sim \mathrm{N}(0, 1)$, Model (2) becomes a standard probit model. If d were an endogenous variable, provided I had an instrument for fertility z such that $d \mid x, z \sim \mathrm{N}(\mu_d(x, z), \sigma_d^2)$, 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 [e.g., see the discussion of Amemiya (1985) and references therein]. 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. Notice that this model is different from the one considered by Mallar (1977), in which the continuous index d^* enters as an endogenous regressor rather than the endogenous binary indicator d, and, therefore, two-stage methods could be used to estimate the model.

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

$$d_i = \mathbf{1}(d_i^* > 0) = \mathbf{1}(\lambda_0 + \lambda_1 x_i + \lambda_2 z_i + \varepsilon_i > 0), \tag{3}$$

where ε_i and v_i are assumed to be jointly normally distributed and z is a variable that 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:

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

Variable y_{i0} indicates the outcome if woman i were not to have a child; $y_{i0} = 0$ if the woman would not participate, and $y_{i0} = 1$ otherwise. Similarly, y_{i1} indicates the outcome if the woman were to have a child. Of the two outcomes y_{i0} and y_{i1}, one is realized and the other is latent. Then the effect of having a child for woman i will be given by the difference $y_{i1} - y_{i0}$. It measures how the participation outcome would vary with fertility if fertility were not self-selected but were, instead, exogenously assigned.

Notice that, provided $\delta_0 < 0$, $\delta_1 < 0$, $\alpha_0 < 0$, and $\alpha_1 < 0$, the pair (y_{i0}, y_{i1}) may take on the values $(0, 0)$, $(1, 1)$, and $(1, 0)$, but the model rules out the outcome $(0, 1)$ (i.e., the possibility that a nonworking woman while not having a child would start 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).

Before I 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 a model is that its forecasts are not restricted to the $(0, 1)$ interval, but nevertheless it has 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 that it requires $y_{i1} - y_{i0}$ to be constant for all women with a given value of x_i, leading then to an incompatibility with the observed data. 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 $d_i = 0$. 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.

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}:

$$y_{i0} = \mathbf{1}(y_{i0}^* \geq 0) = \mathbf{1}(\alpha_0 + \delta_0 x_i + v_{i0} \geq 0)$$
$$y_{i1} = \mathbf{1}(y_{i1}^* \geq 0) = \mathbf{1}\big((\alpha_0 + \alpha_1) + (\delta_0 + \delta_1)x_i + v_{i1} \geq 0\big). \quad (5)$$

As before, I have realized that the participation outcome is

$$y_i = y_{i0}(1 - d_i) + y_{i1} d_i, \quad (6)$$

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

$$\Sigma = \begin{pmatrix} 1 & \rho_{01} & \rho_{0\varepsilon} \\ & 1 & \rho_{1\varepsilon} \\ & & 1 \end{pmatrix}. \quad (7)$$

This model imposes no restrictions on the covariance matrix of $(v_{i0}, v_{i1}, \varepsilon_i)$ and is similar to the one proposed by Manski et al. (1992). The standard bivariate probit arises as a special case of this with $\rho_{0\varepsilon} = \rho_{1\varepsilon}$. 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. Notice that, in the context of the linear probability model, I could allow for two different errors to make the model compatible with the data. However, the shortcomings of this model would still be present. At this point, it is important to stress that in the linear probability model I need to allow for $v_{i0} \neq v_{i1}$ to make the model possible. Nevertheless, in the discrete-choice case, the model with one error is compatible with the observed data, and allowing for two different errors is just a generalization that permits the outcome $(y_{i0}, y_{i1}) = (0, 1)$.

The central problem I face in my attempt to learn the effect of fertility on participation is the failure of the available data to identify $\Pr(y_0 = 1 \mid x, z)$ and $\Pr(y_1 = 1 \mid x, z)$. Instrumental-variables strategies require the assumption of a constant effect of fertility for all individuals in the population, so this solution leads to a nonsensical model in the case of two endogenous and discrete variables. Hence, as was pointed out by Manski et al. (1992), the possibilities for inference depend critically on the available prior information about the process generating the outcomes of interest. One strand of the literature on the estimation of treatment effects has geared toward establishing conditions that guarantee nonparametric identification (e.g., Manski 1990; Angrist and Imbens 1991; Imbens and Angrist 1994; Dehejia and Wahba 1999). In this article, I add assumptions with parametric models, making different suppositions about the covariance matrix of the disturbances $(v_{i0}, v_{i1}, \varepsilon_i)$ to generate different models. Nevertheless, identification based solely on arbitrary functional-form assumptions is very fragile. In this sense, the presence of a regressor in the fertility equation that does not directly affect the participation decision could improve identification of the parameters of the model. I have, therefore, relied on a distributional assumption element, using in addition an exclusion restriction to identify the parameters of the model. In my application, I have used the sex of previous children as an instrument for having a child.

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

$$\begin{aligned} L(\gamma_0, \gamma_1, \beta_1, \beta_0, \alpha, \rho_{0\varepsilon}, \rho_{1\varepsilon}) &= \sum_{y=0,\,d=0} \log P_{00} + \sum_{y=0,\,d=1} \log P_{01} \\ &\quad + \sum_{y=1,\,d=0} \log P_{10} + \sum_{y=1,\,d=1} \log P_{11}, \end{aligned} \quad (8)$$

where

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

Notice that imposing the restriction $\rho_{0\varepsilon} = \rho_{1\varepsilon}$ is equivalent to saying that $\rho_{01} = 1$. However, ρ_{01} is not identified in the likelihood function, and, therefore, the appropriate number of degrees of freedom in a likelihood ratio test is 1.

1.2 Switching Probit Models for Panel Data

I can extend the previous approach to the case of panel-data models. In this setting, there are two basic issues I can account for—the possibility of controlling for time-invariant unobserved heterogeneity and the possibility of modeling dynamic relationships among the variables. Specifically, in labor-supply equations, feedback effects from lagged-dependent variables to current and future values of the explanatory variables, as well as the inclusion of the lagged dependent variable as an additional regressor, are crucial aspects of the economic problem of interest.

To estimate the relationship between two endogenous discrete variables taking into account panel-data considerations, I follow the approach proposed by Arellano and Carrasco (1996). Consider the following error-component switching probit model for N individuals observed T consecutive time periods, which takes into account the dynamics of female labor participation:

$$y_{it} = \begin{cases} y_{it0} = \mathbf{1}(\gamma_0 + \beta_0 x_{it} + \xi_{it0} \geq 0), & \text{iff } d_{it} = 0, \\ y_{it1} = \mathbf{1}(\gamma_1 + \beta_1 x_{it} + \xi_{it1} \geq 0), & \text{iff } d_{it} = 1, \end{cases} \quad (9)$$

where

$$\xi_{itj} = \eta_i + v_{itj}, \qquad j = 0, 1. \quad (10)$$

and the reduced-form fertility choice equation is

$$d_{it} = \mathbf{1}(\lambda_0 + \lambda_1 x_{it} + \lambda_2 z_{it} + \varepsilon_{it} \geq 0). \quad (11)$$

Notice that, given that my main concern is focused on the participation equation, I have specified a reduced-form fertility choice equation instead of a structural one. Nevertheless, (11) is compatible with a structural selection equation in which an unobserved effect is independent of the explanatory variables; otherwise leads and lags should appear in it (see Wooldridge 1995 for a detailed discussion). Therefore, I implicitly allow for an unobserved effect in the fertility equation, provided that the ε_{it} are allowed to be serially correlated.

Denote $w_{it} = (z_{it}, x_{it}, y_{i(t-1)}, d_{i(t-1)})$ and $w_i^t = (w_{i1}, \ldots, w_{it})$. The errors are assumed to have a normal distribution given w_i^t of the form

$$\begin{pmatrix} \xi_{it0} & | \\ \xi_{it1} & | w_i^t \\ \varepsilon_{it} & | \end{pmatrix} \sim \mathrm{N}\left(\begin{Bmatrix} E(\eta_i \mid w_i^t) \\ E(\eta_i \mid w_i^t) \\ 0 \end{Bmatrix}, \Sigma_t\right), \quad (12)$$

where

$$\Sigma_t = \begin{pmatrix} 1 & \rho_{01_t} & \rho_{0\varepsilon_t} \\ & 1 & \rho_{1\varepsilon_t} \\ & & 1 \end{pmatrix}. \quad (13)$$

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

$$E(\eta_i \mid w_i^t) = E\big(E(\eta_i \mid w_i^{t+1}) \mid w_i^t\big). \quad (14)$$

This model can be regarded as a member of the class of random-effects models, since the individual effects are treated as random variables (as opposed to the "fixed-effects" models, in which the effects are treated as parameters to be estimated). Furthermore, in this model the distribution of the individual effects is not completely specified, and the expectation of η_i conditional on discrete variables is saturated. Additionally, in this model, η_i and v_{itj} are not required to be conditionally independent, and it allows for dependence between the explanatory variables and the individual effects through the conditional mean of the latter given the observed time path of w. Moreover, the explanatory variables are allowed to be predetermined, in the sense that, while x_{it} and z_{it} do not depend on current or future values of v_{it}, there may be feedback from lagged values of v to x and z. The model can be rewritten as follows:

$$y_{it} = \begin{cases} y_{i0t} = \mathbf{1}(\gamma_0 + \beta_0 x_{it} \\ \qquad + E(\eta_i \mid w_i^t) + u_{it0} > 0), \quad \text{iff } d_{it} = 0, \\ y_{i1t} = \mathbf{1}(\gamma_1 + \beta_1 x_{it} \\ \qquad + E(\eta_i \mid w_i^t) + u_{it1} > 0), \quad \text{iff } d_{it} = 1, \end{cases} \quad (15)$$

where $u_{itj} = \xi_{itj} - E(\eta_i \mid w_i^t)$, $j = 1, 0$. Notice that, since the model is conditional on w_i^t, it could include $y_{i(t-1)}$ as an additional regressor. In fact, in my application, I consider dynamics so that I need the analysis with predetermined variables.

The model's specification rests on the assumption that the demeaned errors $\xi_{itj} - E(\eta_i \mid w_i^t)(j = 0, 1)$ have a distribution that may change with t but is independent of the individual's history w_i^t. Since the history will affect the shape of the conditional distributions $\eta_i \mid w_i^t$, my assumption implies that in general v_{itj} will only be mean independent of w_i^t, which is a limitation of this approach. However, this is also true of the static random-effects probit model of Chamberlain (1984).

Another approach to estimate binary-choice panel-data models could be considered. For example, within the random-effects framework, it is possible to specify a complete distribution on the individual effects. A convenient possibility suggested by Chamberlain (1984) is to assume the heterogeneity distribution to be $\eta_i \mid x_i^T \sim \mathrm{N}(\mu(x_i^T), \sigma_\eta^2)$ and that the dependence between the effects and the explanatory variables is via a linear regression function. However, an important limitation of this approach is that it requires the availability of strictly exogenous regressors and, as will be shown, allowing for predetermined variables is crucial in labor-supply equations. The reason is that the participation decision is also affected by other existing children variables, which will be included in x. Children aged more than 1 are given, but I 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 labor-supply plans have no effect on fertility decisions at any point in the life cycle (see Browning 1992). Furthermore, in my application z 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.

Another strand of the literature has considered "conditional-effects" specifications in which the full distribution of the effects is left unrestricted (Chamberlain 1985; Manski 1987; Honoré and Kyriazidou 2000). The aim is to derive a set of probabilities that does not depend on the individual effect. This is attractive as a way to ensure that the distribution of the effects does not play any role in the identification of the parameters of interest. However, the main drawbacks of this approach are that identification relies on constraining the variation of the variables over time, thus discarding a large number of observations and, again, all the explanatory variables, except the lagged dependent variable, are required to be strictly exogenous. Therefore, sometimes one may be willing to impose a certain amount of structure in the dependence between the effects and the endogenous variables if this makes it possible to relax other aspects of the economic problem of interest. In this regard, the model considered in this article may represent a useful compromise.

Maximum Likelihood Estimation. I consider identification and estimation in the case in which 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, and I apply it to the case of two mass points. However, this method does not work in the continuous case.

In my case, the vector w_{it} will have a finite support of 2^4 points given by $(\phi_1, \ldots, \phi_{2^4})$, so the vector w_i^t takes on $(2^4)^t$ different values $\phi_j^t (j = 1, \ldots, (2^4)^t)$.

Denote

$$\psi_j^t = E(\eta_i \mid w_i^t = \phi_j^t), \qquad j = 1, \ldots, (2^4)^t. \quad (16)$$

By the law of iterated expectations, I have a relationship that links the parameters ψ_j^t:

$$\psi_j^{t-1} = \sum_{\ell=1}^{2^4} \psi^t_{(\ell-1)(2^4)^{t-1}+j} \Pr(w_{it} = \phi_\ell \mid w_i^{t-1} = \phi_j^{t-1}),$$
$$j = 1, \ldots, (2^4)^{(t-1)}; t = 2, \ldots, T. \quad (17)$$

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

$$E(\eta_i) = \sum_{\ell=1}^{2^4} E(\eta_i \mid w_{i1} = \phi_\ell) \Pr(w_{i1} = \phi_\ell) = 0. \quad (18)$$

The initial 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.

The model can be estimated by ML. I estimate jointly the parameters of "interest" $\gamma_0, \gamma_1, \beta_0, \beta_1, \alpha, \rho_{0\varepsilon}, \rho_{1\varepsilon}$, with the "nuisance" coefficients ψ_j^t. The ψ_j^t are solved recursively using the restrictions (17) and (18) as functions of ψ_j^T and the other parameters of the model. In this case, the joint probability distribution of y and d is given by the following expressions:

$$\begin{aligned}
P_{it}^{00} &= \Pr(y_{it} = 0, d_{it} = 0) \\
&= \Phi(-\gamma_0 - \beta_0 x_{it} - \Psi_j^t, -\alpha z_{it}; \rho_{0\varepsilon}) \\
P_{it}^{01} &= \Pr(y_{it} = 0, d_{it} = 1) = \Phi(-\gamma_1 - \beta_1 x_{it} - \Psi_j^t) \\
&\quad - \Phi(-\gamma_1 - \beta_1 x_{it} - \Psi_j^t, -\alpha z_{it}; \rho_{1\varepsilon}) \\
P_{it}^{10} &= \Pr(y_{it} = 1, d_{it} = 0) = \Phi(-\alpha z_{it}) - P_{it}^{00} \\
P_{it}^{11} &= \Pr(y_{it} = 1, d_{it} = 1) = \Phi(\alpha z_{it}) - P_{it}^{01} \\
&= 1 - P_{00} - P_{01} - P_{10},
\end{aligned} \quad (19)$$

where

$$\Psi_j^t = \sum_{j=1}^{(2^4)^t} \psi_j^t \mathbf{1}(w_i^t = \phi_j^t). \quad (20)$$

2. ESTIMATING THE EFFECT OF FERTILITY ON FEMALE LABOR PARTICIPATION

When an additional child enters a household, one might suppose that the mother's allocation of time would change. Since both an income effect (children are expensive) and a substitution effect (children have high time costs, which raises the reservation wage) operate, the nature of this change is not clear a priori. Typically, any measure of female labor supply is negatively correlated with any measure of young children, which may be simply interpreted as indicating that the substitution effect outweighs the income effect. In many early studies, the usual response to this observation has been to treat children as constraints that are exogenously imposed on the household when making their participation decisions.

However, it may well be the case that fertility is endogenous to labor-force participation and both decisions may be jointly determined. In this 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, irrespective of any true causal effect of children on participation. If endogenous fertility is not accounted for, the estimates of the effect of children on women's labor-market activity will be incorrect and useless to the policy makers concerned with stimulating female employment and/or fertility.

To obtain credible estimates, some authors look for "natural" experiments as instruments for exogenous fertility movements (for example, looking at families that are infertile or experience multiple births). This methodology enables the identification of an exogenous fertility event without any assumptions about the population distribution of preferences. But one problem with this approach is that such families are necessarily few, so these instruments have very little explanatory power because there is so little variation in them. An 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 open to question. Variables used to predict fertility such as religion, number of siblings, ideal family size, and duration of marriage are probably related to social class, which will affect participation via education and wages.

In this article, I exclude from the participation equation a variable that will help to identify the parameters of the model. As Angrist and Evans (1998) did, I use the sex composition of children in families with two or more children. This variable exploits the widely observed phenomenon of parental preferences for a mixed sibling-sex composition in developed countries (see Westoff, Potter, and Sagi 1963; Iacovou 1996). Therefore, a dummy for whether the sex of the next child matches the sex of the previous children provides a plausible predictor for additional childbearing. Thus, this instrument estimates effects for moving from two to three or from three to more children in the population of women with at least two children. Nevertheless, I do not exclude from the sample women with less than two children because they could be relevant to analyze other aspects of the model. Although in my model the absence of the same-sex variable from the participation equation is not crucial for identification (see Manski et al. 1992), it is important to note that the random assignment of child sex does not guarantee that the only reason it affects labor supply is changing fertility (see the discussion of Angrist, Imbens, and Rubin 1996). In fact, Rosenzweig and Wolpin (1998) argued that having children of the same gender allows cost economies that may affect participation decisions. Nevertheless, they recognized that these cost economies might not be important in a developed country context such as the U.S. economy.

The Dataset

Our estimation strategy requires information on basic labor-supply variables and the sex of children. The data for this analysis come from the University of Michigan Panel Study of Income Dynamics (PSID) for the years 1986–1989. This is a longitudinal survey in which over 5,000 households have been interviewed annually since 1968. The PSID contains information about labor supply, number, and age of children, as well as supplementary information on the sex of the children. Because the PSID focused originally on the dynamics of poverty, the initial sample consisted of two independent subsamples—an equal probability sample of U.S. households and a supplemental sample of households with incomes at or below 150% of the poverty line. The PSID combines both subsamples. Therefore, the combination is a sample with unequal selection probabilities. My sample includes individuals from both subsamples. This allows me to have a larger sample size. Furthermore, to the extent that belonging to the low-income subsample is a fixed effect, in some sense accounting for unobserved heterogeneity accounts for this self-selection as well. Nevertheless, the models have also been estimated using the random subsample and, although some variables are not significant, the results on the effects of fertility are very similar. A Wald test of the null hypotheses that the full set of estimates equals between the two samples has been computed and the null hypothesis is accepted (i.e., the test statistics for the linear model that accounts for endogeneity of fertility and panel data issues distributed as a χ^2 with 3 df is 4.039).

Our sample consists of 1,442 married or cohabiting women between the ages of 18 and 55 in 1986. The dependent variable is an indicator of woman labor participation during each year. It is equal to 1 if a woman's annual hours of work are greater than 0 in period t and 0 otherwise. The effect of fertility is specified by a dummy variable that equals 1 if the age of the youngest child at $t+1$ is 1. I want to capture whether a new birth occurs or not, but given 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 at t is 1. In fact, primary results showed that using this definition of fertility did not influence the estimation results, although the significance of the estimated coefficients was smaller.

I am 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, since the correlation between women's labor supply and children may vary among different groups (e.g., race, age, education, and income), I also account for these variables when modeling the effects of children. Moreover, I include in the fertility equation an indicator of same sex and the two components of it (girls and boys). Therefore, our *same sex* instrument is defined as a dummy variable taking the value 1 if previous children in the household have the same sex and 0 otherwise.

The sample characteristics are presented in Table 1. Some simple cross-tabulations confirm that there is a negative relationship between labor-market participation and fertility at all levels of fertility. Table 2 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). These figures indicate that it seems relevant to study the impact of moving from two to more children. One can also see that, among those women who decide not to have an additional child, the percentage of participants is larger than among those women who have an additional child.

Table 1. Means of the Data (standard deviation in parentheses)

Variable	Means
More than 2 kids	.300
(= 1 if mother had more than 2 kids, = 0 otherwise)	(.46)
Two boys	.232
(= 1 if first two children were boys, = 0 otherwise)	(.42)
Two girls	.200
(= 1 if first two children were girls, = 0 otherwise)	(.40)
Same sex	.432
(= 1 if first two children were the same sex, = 0 otherwise)	(.49)
Age	31.293
(mother's age in 1986)	(5.68)
Worked for pay	.769
	(.42)
Education 1	.057
	(.23)
Education 2	.719
	(.45)
Education 3	.233
	(.42)
Black	.227
	(.42)
Husband's income	12.830
	(9.41)
LFP by number of children:	
0	94.52%
1	81.43%
2	77.66%
3	70.56%
4+	59.68%

NOTE: Number of observations per year = 1,442.

Regarding parents' preferences over the sex composition of their offspring, results for our dataset resemble those reported by Ben-Porath and Welch (1976) and Angrist and Evans (1998). In Table 3, I report the sample frequency of women who had an additional child. The first panel shows that the fraction of women who had a second child is almost invariant to the sex of the first child. However, the second panel indicates that women with two children of the same sex are more likely to have a third child: 27.95% of mothers with one boy and one girl have a third child, compared to 34.64% for women with two girls or two boys. Table 4 gives an indication on how well sex composition explains the occurrence of a new birth. The estimates are for probit equations, and the results reveal that having children of the same sex has a significant and positive effect on the probability of having an

Table 2. 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
Percent of women who participate (whole sample)		
With an additional child	66.11	
Without an additional child	78.30	

Table 3. Fraction of Mothers Who Had Another Child, by Sex of Previous Children

	Fraction who had another child (std. error)
Sex of first child, families with one or more children	
(1) One boy	.7089 (.42)
(2) One girl	.6841 (.47)
Difference (1)–(2)	.0248 (.65)
Sex of first two children, families with two or more children	
Two girls	.3493 (.50)
One boy, one girl	.2795 (.49)
Two boys	.3493 (.49)
(3) Both same sex	.3464 (.49)
(4) One boy, one girl	.2795 (.49)
Difference (3)–(4)	.067 (.69)

NOTE: Number of observations = 1,442.

Table 4. Fertility Equation: Probit Estimates Based on the Pooled Sample

Indep. variables	Coefficients	
Same sex	.325 (5.40)	—
Boys	—	.328 (4.30)
Girls	—	.321 (3.91)
Kids 2–6	−2.135 (−13.22)	−2.135 (−13.23)
Educ 2	.028 (.24)	.028 (.24)
Educ 3	.307 (2.45)	.307 (2.44)
Age	−.081 (−16.65)	−.081 (−16.64)
Black	.092 (1.45)	.092 (−1.46)
Husband's income	.003 (1.06)	.003 (1.06)
Constant	1.527 (8.22)	1.527 (8.22)
Log-likelihood	−1,561.13	−1,561.13

NOTE: Dependent variable: occurrence of a new birth $N = 1{,}442$ women between 18–55 years old in 1986. Years = 1986, 1987, 1988, 1989. Figures in parentheses are *t* ratios.

additional child, although there are not significant differences among having boys and having girls.

3. ESTIMATION RESULTS

In this section, I report the estimates from the different models described in Section 1. Two sets of estimates are presented. The first one compares the results from nonlinear and linear models that account for the endogeneity of the fertility variable with those that consider it as strictly exogenous. The second set of results examines the importance of accounting for panel-data issues. In all cases, I report estimates of the effect of children that condition on past labor supply. The coefficients of the fertility equations, which have been jointly estimated with the parameters of the participation equations, are not reported here (see Carrasco 1998 for details).

3.1 Models Without Unobserved Heterogeneity

My analysis begins with the estimation results from nonlinear and linear probability models, both neglecting unobserved heterogeneity. Table 5 presents the coefficients of different probit and linear specifications. Column (a) presents the results from a probit model that treats fertility as strictly exogenous. Columns (b) and (c) report ML estimates from models that treat fertility as endogenous and impose that $y_{i1}^* - y_{i0}^*$ are constant and nonconstant, respectively. Finally, the last two columns present the coefficients of linear models obtained by ordinary least squares (OLS) and two-stage least squares (2SLS). Although linear models are not very useful for predictive purposes, it is interesting to see how the implications from these models differ from nonlinear ones. I have used *same sex* and *girls, boys* variables as instruments, but since the results are not very different and the value of the likelihood function does not change, I only report the estimates using *same sex.*

The results reproduce previous evidence that recently born children reduce the probability of working. However, when endogeneity is accounted for, the effect of fertility becomes more negative. The effect of fertility on the probability of participating has been evaluated. The first row of Table 6 reports the average impact under the alternative assumptions of strict exogeneity. Considering fertility as exogenous reduces the probability of participating by 7.13% and in the endogenous case by 38.71%. The same type of qualitative results is obtained from linear modes. In this case, the gap between the OLS and 2SLS measured effects of fertility could be possibly due to measurement errors since the failure to account for them makes OLS estimates downward biased in absolute value. Notice that this argument cannot be extended to nonlinear models.

Regarding the rest of the covariates, I obtain again similar qualitative effects from nonlinear and linear estimates. In addition, for all the regressors except fertility and its interactions, the coefficients are not much changed whether I control for the endogeneity of fertility or not. The coefficient on existing children is always negative. Based on these estimates, I could obtain evidence that youngest children are more "time consuming" than older preschoolers (in the sense that the latter have a lower negative effect on the probability of participating). I do not obtain a significant effect of age on participation. Anyway, I should not expect the age coefficient to tell me much about the "true" effects of age on participation. Since the younger women in the sample have younger children, the age

Table 5. Female-Labor-Participation Estimates Without Unobserved Heterogeneity

	Probit estimates			Linear estimates	
Indep. variables	*(a)* $\rho_{0\varepsilon}=\rho_{1\varepsilon}=0$	*(b)* $\rho_{0\varepsilon}=\rho_{1\varepsilon}$	*(c)* $\rho_{0\varepsilon}\neq\rho_{1\varepsilon}$	*(d)* *OLS*	*(e)* *2SLS*
Fertility	−.410 (−5.94)	−.651 (−2.45)	−.644 (−2.00)	−.089 (−6.13)	−.216 (−.94)
Kids 2–6	−.106 (−2.21)	−.151 (−2.04)	−.164 (−1.66)	−.019 (−2.08)	−.038 (−.81)
Fert.*kids 2–6	−.189 (−.27)	−.400 (−.55)	−.360 (−.34)	−.058 (−.36)	−3.367 (−.99)
Educ 2	.234 (2.72)	.235 (2.60)	.235 (2.64)	.049 (2.64)	.033 (1.30)
Educ 3	.377 (3.77)	.390 (3.66)	.392 (3.67)	.072 (3.50)	.065 (2.00)
Age	.009 (2.22)	.005 (1.11)	.005 (.82)	.001 (1.81)	−.002 (−.06)
Husband's income	−.009 (−3.65)	−.009 (−3.05)	−.009 (−3.31)	−.002 (−3.71)	−.002 (−3.53)
Black	.058 (1.06)	.060 (1.05)	.060 (1.03)	.010 (.95)	.016 (1.77)
y_{t-1}	1.932 (41.80)	1.926 (40.07)	1.923 (41.29)	.625 (60.61)	.623 (40.00)
Constant	−.854 (−5.21)	−.707 (−2.99)	−.672 (−2.22)	.237 (7.25)	.333 (2.29)
$\rho_{0\varepsilon}$	—	.142 (.96)	.190 (.63)	—	—
$\rho_{1\varepsilon}$	—	—	.125 (.63)	—	—
Log-likelihood	−3,597.94	−3,594.83	−3,594.80	—	—

NOTE: Dependent variable: labor-market participation. External instrument: previous children of same sex. $N = 1{,}442$ women between 18–55 years old in 1986. Years = 1986, 1987, 1988, 1989. Figures in parentheses are heteroscedasticity-robust t ratios.

coefficient reflects more the effect of the age of the youngest child than the effect of age in itself. Husband's income influences negatively on female labor-force participation. This negative coefficient may be interpreted as a disincentive effect. Education coefficients are of the expected sign (positive), and they have a higher magnitude for higher qualifications. Nevertheless, these two variables, education and husband's earnings, are potentially endogenous. Participation in the previous period has a large positive effect, which means that the most recent work experience is indeed an important determinant of actual labor-market status.

Given the values of the likelihood function for models (b) and (c), we cannot reject the null hypothesis $\rho_{0\varepsilon}=\rho_{1\varepsilon}$. 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 not participate while not having one. Although this is a possible situation, since some women may be induced to work by the presence of an infant, this result suggests that women in my sample do not behave in that way.

Table 6. Effect of Fertility on the Probability of Participating Probit Models

	Endogenous fertility	*Exogenous fertility*
	Models without unobserved heterogeneity	
Average effect	−.387	−.071
	Models with unobserved heterogeneity	
Average effect	−.129	−.024

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

3.2 Models With Unobserved Heterogeneity

I now turn to the estimation of models with unobserved heterogeneity as presented in Section 1.2. In panel-data regressions, I do not include variables that are constant in the temporal dimension, such as age, education, or race. Therefore, I only consider as regressors lagged participation, an indicator of sex of the previous children, and an indicator of having a child aged between 2 and 6.

Table 7 contains the estimates for three different nonlinear and linear specifications of the model that includes individual specific effects. Column (a) contains ML estimates for the model that treats fertility as exogenous, while columns (b) and (c) show the results for an endogenous switching probit model, treating existing children and sex of child as exogenous and as predetermined, respectively. The last three columns present the same type of linear estimates. Column (d) contains within groups (WG) estimates. Column (e) reports generalized method of moments (GMM) estimates of the model that treats the variables on existing children and *same sex* as strictly exogenous. I present the two-step results using all lags and leads of x and z as instruments. Finally, column (f) presents GMM estimates of the model that treats existing children and

Table 7. Female-Labor-Participation Estimates With Unobserved Heterogeneity

	Probit estimates			Linear estimates		
Indep. variables	(a) $\rho_{0\varepsilon} = \rho_{1\varepsilon} = 0$	(b) $\rho_{0\varepsilon} = \rho_{1\varepsilon}$ (st. exog.)	(c) $\rho_{0\varepsilon} = \rho_{1\varepsilon}$ (predet.)	(d) WG	(e) GMM[1] (st. exog.)	(f) GMM[2] (predet.)
Fertility	−.249	−.688	−1.931	−.054	−.062	−.175
	(−3.48)	(−1.36)	(−2.66)	(−3.61)	(−2.24)	(−2.50)
Kids 2–6	−.031	−.036	−.391	.021	.005	−.074
	(−.66)	(−.41)	(−1.56)	(.16)	(.28)	(−2.48)
Fert.*Kids 2–6	−.089	.115	−.682	−.222	−.878	−4.068
	(−.74)	(.34)	(−1.64)	(−.97)	(−.57)	(−1.53)
y_{t-1}	1.913	—	.172	.035	—	.413
	(4.13)		(2.90)	(1.69)	—	(3.10)
Constant	−.608	1.227	.253	—	—	—
	(−13.19)	(1.75)	(1.02)			
$\rho_{0\varepsilon}$	—	.226	.738	—	—	—
		(.82)	(4.28)			
Log-likelihood	−7,892.85	−6,435.22	−3,467.23	—	—	—

[1] IV's: All lags and leads of *Kids 2-6* and *Same sex* variables.
[2] IV's: Lags of *Kids 2-6* and *Same sex* up to $t-1$, and of y_{t-1} up to $t-2$.
Heteroscedasticity-robust *t* ratios shown in parentheses.

same sex as predetermined variables. In this case, I use past values of x, z, and y as instruments. Notice that I 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.

The results indicate that, similarly to the previous estimates, the effects of youngest children are stronger when I relax the exogeneity assumption, both in nonlinear and linear models. Stronger differences appear in the effect of fertility when controlling for predetermined existing children. This results in a larger effect of fertility on participation than the one obtained treating *kids 2–6* and *same sex* as exogenous.

The predicted probabilities of participating when individual effects are taken into account have been calculated in probit models. To calculate these probabilities, I have considered the estimated ψ_j^t parameter for each individual, depending on the values of the conditioning variables until t: $\psi_j^t = E(\eta_i \mid w_i^t = \phi_j^t)$, $j = 1, \ldots, (2^4)^t$. Therefore, those individuals with the same conditioning set will have the same parameter ψ. Since there are only a few individuals in some cells, a number of parameters ψ will be very imprecisely estimated. For that reason, all the cells with less than four observations were dropped, and, as a result, the number of parameters ψ was also reduced. The figures are summarized in the second row of Table 6. We can see that the average fertility effect is substantially dampened under the assumption that fertility is exogenously determined. 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.

4. CONCLUDING REMARKS

The contrast between the sets of estimates presented emphasizes the point that different individuals behave differently due to heterogeneous characteristics. My finding that the probability of participating falls more in the model that accounts for endogenous fertility than in the model with exogenous fertility is similar to the one obtained by Rosenzweig and Wolpin (1980) in a cross-section setting and using a natural event (the occurrence of twins in the first pregnancy).

The results from the linear models presented can be related to other linear estimates reported in the literature. Although I obtain similar qualitative results from nonlinear and linear models, my linear estimates do differ from those of Angrist and Evans (1998). Following a two-stage estimation strategy using parental sex preferences and multiple births to estimate the effect of childbearing on employment status, they obtained that linear instrumental-variables estimates are negative but smaller than OLS estimates. Similar qualitative results were obtained by Angrist (2001). In this case, different estimation strategies available when the object of estimation is directly the causal effect of "treatment," instead of the index coefficients, are discussed. These approaches are illustrated using multiple births to estimate labor-supply consequences of childbearing. The results again indicate that treating children as exogenous exaggerates the negative impact on labor supply. Nevertheless, in these articles, panel-data considerations are not accounted for.

My analysis, using panel-data information, reveals the importance of accounting for the dynamics in labor supply as well as for the predeterminedness of children aged more than 1. I identify two types of bias, (1) a downward bias induced by the exogeneity assumptions of children variables that introduces a spurious positive correlation between fertility and participation decisions and (2) an upward bias due to ignoring individual effects, indicating that preferences for children and for participation could be negatively correlated. Moreover, the fertility effects are smaller when existing children are treated as strictly exogenous. These results suggest that I need to be much more circumspect in assuming exogeneity for children variables in labor-participation equations and that dynamic and longitudinal considerations are important.

The framework used in this article can be generalized to other similar applications: Many models consider the impact of a binary variable on another binary variable. The outcomes of interest may be simultaneously determined, and the analysis of these relationships may well require adequately accounting for serially correlated unobserved variables.

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