NBER WORKING PAPER SERIES

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Working Paper 14995
http://www.nber.org/papers/w14995

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2009

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NBER Working Paper No. 14995
May 2009
JEL No. C13,C34,C5,C63,I1,I12,I18,I38

ABSTRACT

We employ a latent class model to assess the impact of Mexico's Seguro Popular ("SP") program on the number of prenatal visits in a cross-sectional sample of 4,381 women who gave birth during 2002-2005. We specify an ordered probit model to permit a pregnant woman's probability of membership in one of three latent classes to depend on observed covariates. In the ordered probit model, enrollment in SP is explicitly treated as an endogenous variable. We model the number of prenatal visits, conditional upon membership in a particular latent class, as a Poisson regression. We employ the EM algorithm to reduce the computational burden of model estimation. At any iteration of the algorithm, the parameters of the model of latent class membership can be estimated separately from the parameters of the model of prenatal care utilization. We find that enrollment in SP was associated with a mean increase in 1.65 prenatal visits during pregnancy. Approximately 59 percent of this treatment effect is the result of increased prenatal care among women in the first latent class, that is, women who had with little or no access to care. The remaining 41 percent of the treatment effect is the result of a shift in membership from the second to the third latent class, which we interpret as increased recognition of complications of pregnancy prior to labor and delivery. Our model has a better fit and predicts a larger impact of SP than alternative models that relax the assumption of endogeneity, do not impose ordering on the latent classes, or incorporate only two latent classes. Our findings are consistent with prior work on the favorable impact of SP on maternal health (Sosa-Rubí, Galárraga, Harris 2009).

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1. INTRODUCTION

Since the seminal paper of Deb and Trivedi (Deb and Trivedi 1997), latent class models have become increasingly common in the econometric analysis of the demand for health care. In these models, the econometrician assumes that each individual belongs to one of a fixed number of latent classes, but the specific class to which an individual belongs remains unobserved. Based on these assumptions, she jointly estimates the probability of membership in each class, as well as the demand for health care conditional upon membership in each specific class (Atella, Brindisi et al. 2004; Deb, Munkin et al. 2006). In most applications, investigators have assumed that the unknown probabilities of class membership are fixed parameters. In a few papers, analysts have modeled these probabilities as functions of observed covariates (Nagin and Land 1993; Roeder, Lynch et al. 1999; Greene and Hensher 2003; Clark, Elité et al. 2005; Bago d'Uva 2006; Clark and Etile 2006; Bago d'Uva and Jones 2008; Greene, Harris et al. 2008).

Latent class models have made significant progress in addressing the heterogeneous effects of health-sector policies, such as those policies aimed at improving access to medical care (Deb and Trivedi 1997; Deb and Holmes 2000; Jimenez-Martin, Labeaga et al. 2002; Conway and Deb 2005). These models have demonstrated how such unobserved or partially observed factors as health status and attitudes toward health risks can determine consumers' demand responses. However, such models have not squarely confronted the serious problem that health-care coverage is endogenous in non-experimental databases (Cameron, Trivedi et al. 1988; Atella and Deb 2008). Even in contexts where the government exogenously introduces a change in eligibility criteria or insurance coverage for specific types of health care, the individual's decision to take advantage of the new policy may still be voluntary (Sosa-Rubí, Galárraga et al. 2009). As a consequence, unobserved factors may influence both the decision to participate and the demand for medical care conditional upon participation (Cameron, Trivedi et al. 1988).

Here, we extend the latent class framework to take account of this knotty problem of endogeneity. We assume, as have other investigators, that the probability of latent class membership is a function of observable covariates. Unlike prior work, we permit one of these covariates to be endogenous to the model of latent class determination. We show how the EM algorithm, an iterative procedure that has been widely used to estimate latent class models, can be extended to our model. At each stage of the iterative EM algorithm, we separately estimate two distinct subsets of parameters: the parameters of the model of latent class membership, which contains the endogenous variable; and the parameters of the model of demand conditional on class membership.

We apply our approach to an evaluation of the impact of Seguro Popular (or "People's Insurance"), a public health policy inaugurated in Mexico in 2001 to improve access of the poor to quality medical care (Gakidou, Lozano et al. 2006; King, Gakidou et al. 2009; Sosa-Rubí, Galárraga et al. 2009). We study the effect of a household's participation in Seguro Popular ("SP") on the demand for prenatal care by pregnant women who delivered babies during 2002–2005. Analyzing cross-sectional data from the 2006 National Survey of Health and Nutrition (Encuesta Nacional de Salud y Nutrición, or "ENSANUT") (Instituto Nacional de Salud Pública 2006), we specify a Poisson count-data model for the number of prenatal visits, conditional upon membership in one of three latent classes. We further specify an ordered probit model for the determination of class membership. The household's participation in SP enters as a covariate not only in the former Poisson model, but also as an endogenous covariate in the latter ordered probit model. Consequently, enrollment in Seguro Popular can influence the distribution of class membership as well the conditional demand for prenatal care. Our specification has significantly better fit to our data than alternative restricted models that specify only two latent classes, do not account for the endogeneity of SP, or do not model class membership. Moreover, our model predicts significantly larger impacts of SP – as well as public policies designed to promote participation in SP – than alternative models.

Based upon our findings, we interpret the three latent classes of pregnant women in Mexico as representing: (1) poor women without access to prenatal health care services; (2) women with access to prenatal care but without identified complications of pregnancy; and (3) women with access to prenatal care and identified pregnancy complications. Our empirical finding that SP moves pregnant women from the first to the second class suggests that SP has improved access among women who previously had little no prenatal care. Moreover, our finding that SP moves some women from the second to the third class suggests that SP has permitted identification of pregnancy complications might have otherwise gone unrecognized before labor.

2. ECONOMETRIC MODELS

2.1. General Latent Class Model

Our cross-sectional sample consists of independent observations on M pregnant woman, indexed $i = 1,\ldots,M$. For each pregnant woman, we observe the number n_i of prenatal visits, as well as other covariates to be described below.

We assume that each woman belongs to one of three latent classes, indexed by $k = 1,2,3$, but we cannot observe the class to which she belongs. Extension of our analysis to an arbitrary number of classes is straightforward. We denote by $f_k\left(n_i; X_i, \beta\right)$ the conditional distribution of the number of prenatal visits n_i, given that woman i belongs to class k, where is a vector X_i of observed covariates and β is an unknown parameter vector. We shall specify a parametric form for this distribution shortly.

Let $\pi_k\left(Z_i, \theta\right)$ denote the probability that pregnant woman i belongs to class k, where Z_i is a vector of observed covariates that may differ from X_i, and where θ is an unknown parameter vector. These probabilities are constrained so that $\sum_{k=1}^{3} \pi_k\left(Z_i, \theta\right) = 1$ for all $i = 1,\ldots,M$. Below, we specify parametric forms for the dependence of the latent class probabilities π_k on observed covariates.

2.2. Estimation via the EM Algorithm

The foregoing assumptions imply a mixture of count-data models. The log likelihood is

$$(1) \qquad L\left(n, X, Z \middle| \beta, \theta\right) = \sum_{i=1}^{M} \ln\left[\sum_{k=1}^{3} \pi_k\left(Z_i, \theta\right) f_k\left(n; X_i, \beta\right)\right]$$

The log likelihood function in (1) is not separable in the parameters β and θ. However, the EM algorithm offers an iterative approach to maximization of (1) that permits us to estimate the parameters β and θ separately during each successive iteration. The EM algorithm has been widely employed to maximize the log likelihood function in latent class models (Wedel, Desarbo et al. 1993).

We applied the EM algorithm to the maximization of the log likelihood in (1) as follows. Assume that we have estimates $\left(\beta^{(t)},\theta^{(t)}\right)$ at iteration $t=1,2,\ldots$ of the algorithm. We update these parameter estimates in two steps: the E-step and the M-step. In the E-step, we evaluate the posterior probability that woman i belongs to class k as

(2) $$p_{ik}^{(t)} = \frac{f_k\left(n_i;X_i,\beta^{(t)}\right)\pi_k\left(Z_i,\theta^{(t)}\right)}{\sum_{j=1}^{3} f_j\left(n_i;X_i,\beta^{(t)}\right)\pi_j\left(Z_i,\theta^{(t)}\right)} \text{ for } k=1,2,3$$

Equation (2) is a version of Bayes formula, in which the prior probabilities are $\pi_k\left(Z_i,\theta^{(t)}\right)$ and the likelihoods are $f_k\left(n_i;X_i,\beta^{(t)}\right)$. We then define the log likelihood of the extended data (sometimes called the "complete-data log likelihood"), consisting of the observed data $\left\{n_i,X_i,Z_i\right\}$ as well as the class variable $\left\{k_i\right\}$ for each woman $i=1,\ldots,M$, as if each woman's latent class were known:

(3) $$L\left(n,X,Z,k|\beta,\theta\right)=$$

$$\sum_{i=1}^{M}\ln\left[\pi_{k_i}\left(Z_i,\theta\right)f_{k_i}\left(n_i;X_i,\beta\right)\right]=\sum_{i=1}^{M}\left[\ln\pi_{k_i}\left(Z_i,\theta\right)+\ln f_{k_i}\left(n_i;X_i,\beta\right)\right]$$

Given the estimates $\left(\beta^{(t)},\theta^{(t)}\right)$ at iteration t, the expected value of this extended log likelihood is

(4) $$Q\left(\beta,\theta,\beta^{(t)},\theta^{(t)}\right)=\sum_{i=1}^{M}\sum_{k=1}^{3}\left[p_{ik}^{(t)}\left(\ln\pi_k\left(Z_i,\theta\right)+\ln f_k\left(n_i;X_i,\beta\right)\right)\right]$$

where the expectation is taken over the posterior distribution given in (2). In the M-step, we maximize this expression with respect to (β,θ) in order to obtain updated values of the parameters $\left(\beta^{(t+1)},\theta^{(t+1)}\right)$. A critical feature of the maximization problem in this M-step is that the expectation $Q\left(\beta,\theta,\beta^{(t)},\theta^{(t)}\right)$ of the extended log likelihood in (4) is separable in the parameters β and θ. It is well known that the EM procedure converges to the maximum of the likelihood function (1) (Redner and Walker 1984) (Xu and Jordan 1996).

2.3. Poisson Conditional Distributions

In what follows, we assume that the conditional distribution of prenatal visits n_i, given that pregnant woman i belongs to latent class k is Poisson:

(5) $$f_k\left(n_i;X_i,\beta\right)=\frac{\lambda_{ik}^{n}\exp\left(-\lambda_{ik}\right)}{n!}$$, where $\lambda_{ik}=\exp\left(X_i'\beta_k\right)$, for $k=1,2,3$

and where $\beta=\left(\beta_1,\beta_2,\beta_3\right)$. Although we shall not do so here, we could generalize our analysis to any conditional distribution for the count variable n_i, such as the negative binomial (Deb and Trivedi 1997).

Given the Poisson conditional distributions in (5), the expected log likelihood (4) in the M-step simplifies to

(6) $$Q\left(\beta,\theta,\beta^{(t)},\theta^{(t)}\right)=$$

$$\sum_{k=1}^{3}\sum_{i=1}^{M}\left[p_{ik}^{(t)}\left(n_iX_i'\beta_k-\exp\left(X_i'\beta_k\right)\right)\right]-M\ln\left(n_i!\right)+\sum_{k=1}^{3}\sum_{i=1}^{M}p_{ik}^{(t)}\ln\pi_k\left(Z_i,\theta\right)$$

The maximizing solution for each β_k is obtained by setting the corresponding derivatives of $Q\left(\beta,\theta,\beta^{(t)},\theta^{(t)}\right)$ with respect to each β_k equal to zero. That is,

(7) $$\sum_{i=1}^{M} p_{ik}^{(t)} X_i \left(n_i - \exp\left(X_i'\beta_k\right)\right) = 0 \text{ for } k = 1,2,3$$

where (7) is a vector equation that holds for each coordinate of X_i. This is equivalent to separately solving three weighted Poisson regressions, where the weights for regression k are the posterior probabilities $p_{ik}^{(t)}$. This procedure for obtaining the updated parameters $\beta^{(t+1)}$ at iteration $t+1$ does not depend on the specification of our model for the probabilities $\pi_k\left(Z_i,\theta\right)$, to which we now turn.

2.4. Basic Model: Mixture of Poisson Distributions

We develop our models for $\pi_k\left(Z_i,\theta\right)$ in stages. We begin with the conventional mixture model, where the probability of belonging to each latent class is a fixed parameter that does not depend on observables.

(8) $$\pi_k\left(Z_i,\theta\right) = \theta_k \text{ for } k = 1,2,3$$

This is the model underlying nearly all of the latent class literature. Given (5), our model is a finite mixture of Poisson distributions. The expected log likelihood in the M-step simplifies to

(9) $$Q\left(\beta,\theta,\beta^{(t)},\theta^{(t)}\right) = \sum_{k=1}^{3}\sum_{i=1}^{M}\left[p_{ik}^{(t)}\left(n_i X_i'\beta_k - \exp\left(X_i'\beta_k\right)\right)\right] - M\ln\left(n_i!\right) + \sum_{k=1}^{3}\sum_{i=1}^{M} p_{ik}^{(t)} \ln\theta_k$$

The maximizing value for each θ_k at the M-step is given by

(10) $$\theta_k^{(t+1)} = \frac{1}{M}\sum_{i=1}^{M} p_{ik}^{(t)} \text{ for } k = 1,2,3$$

2.5. Ordered Probit Model for the Mixing Probabilities

We modify our basic model so that the probabilities π_k are functions of the observable variables Z_i. Specifically, for all $i = 1,\ldots,M$,

(11) $$k_i^* = Z_i'\alpha + \varepsilon_i, \quad \text{where} \quad \varepsilon_i \sim \text{i.i.d. } N(0,1) \quad \text{and} \quad k_i = \begin{cases} 1 & \text{if} \quad k_i^* \le 0 \\ 2 & \text{if} \quad \kappa \ge k_i^* > 0 \\ 3 & \text{if} \quad k_i^* > \kappa \end{cases}$$

Equation (11) is an ordered probit model, where α and κ are unknown parameters. We assume that the unit normal error term ε_i is independent of the covariates Z_i. Denoting $\theta = (\alpha, \kappa)$, and letting $\Phi(\cdot)$ represent the unit normal cumulative distribution function, we have:

(12) $$\pi_1(Z_i, \theta) = \Phi(-Z_i'\alpha)$$

$$\pi_2(Z_i, \theta) = \Phi(\kappa - Z_i'\alpha) - \Phi(-Z_i'\alpha)$$

$$\pi_3(Z_i, \theta) = \Phi(Z_i'\alpha - \kappa)$$

Maximization of the expected log likelihood $Q\left(\beta, \theta, \beta^{(t)}, \theta^{(t)}\right)$ in (6) with respect to the parameters $\theta = (\alpha, \kappa)$ at the M-step is similarly obtained by setting the corresponding derivatives equal to zero. Letting $\varphi(\cdot)$ denote the unit normal density function, we have

(13) $$\sum_{i=1}^{M} \left(p_{i2}^{(t)} - p_{i3}^{(t)}\right) \varphi(\kappa - Z_i'\alpha) = 0$$

$$\sum_{i=1}^{M} \left[\left(p_{i3}^{(t)} - p_{i2}^{(t)}\right) \varphi(\kappa - Z_i'\alpha) + \left(p_{i2}^{(t)} - p_{i1}^{(t)}\right) \varphi(-Z_i'\alpha)\right] Z_i = 0$$

The second expression in (13) is a vector equation that holds for each coordinate of Z_i.

2.5. Ordered Probit with a Binary Endogenous Variable

We further modify our ordered probit model, introducing an observed binary endogenous variable y_i. Specifically, for all $i = 1,\ldots,M$,

$$k_i^* = Z_i'\alpha + \delta y_i + \varepsilon_i \quad \text{where} \quad k_i = \begin{cases} 1 & \text{if} \quad k_i^* \le 0 \\ 2 & \text{if} \quad \kappa \ge k_i^* > 0 \\ 3 & \text{if} \quad k_i^* > \kappa \end{cases} \tag{14}$$

$$y_i^* = W_i'\gamma + \nu_i \quad \text{where} \quad y_i = \begin{cases} 0 & \text{if} \quad y_i^* \le 0 \\ 1 & \text{if} \quad y_i^* > 0 \end{cases} \tag{15}$$

$$\begin{pmatrix} \varepsilon_i \\ \nu_i \end{pmatrix} \sim \text{i.i.d. } N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right) \tag{16}$$

Equation (14), which determines latent class membership, is an ordered probit model that now depends on a variable y_i in addition to the observables Z_i. Equation (15) specifies a probit model in which the binary variable y_i depends on a separate vector W_i of observable covariates, which may differ from X_i and Z_i. We assume that the error terms ε_i and ν_i in (16) are independent of the covariates Z_i and W_i. If the correlation coefficient ρ in (16) is non-zero, then the variable y_i is endogenous.

Let $\theta = (\alpha, \delta, \kappa, \gamma, \rho)$ and $s_i = 2y_i - 1$. Let $\Phi_2(\cdot,\cdot,\rho)$ denote the unit bivariate normal cumulative distribution function with correlation coefficient ρ. We have:

$$\pi_1(Z_i, W_i, y_i, \theta) = \frac{\Phi_2(-Z_i'\alpha - \delta y_i,\ s_i W_i'\gamma,\ -s_i\rho)}{\Phi(s_i W_i'\gamma)} \tag{17}$$

$$\pi_2(Z_i, W_i, y_i, \theta) = \frac{\left(\Phi_2(\kappa - Z_i'\alpha - \delta y_i,\ s_i W_i'\gamma,\ -s_i\rho) - \Phi_2(-Z_i'\alpha - \delta y_i,\ s_i W_i'\gamma,\ -s_i\rho)\right)}{\Phi(s_i W_i'\gamma)}$$

$$\pi_3\left(Z_i, W_i, y_i, \theta\right) = \frac{\Phi_2\left(Z_i'\alpha + \delta y_i - \kappa,\ s_i W_i'\gamma,\ -s_i\rho\right)}{\Phi\left(s_i W_i'\gamma\right)}$$

In (17), each expression $\pi_k\left(Z_i, W_i, y_i, \theta\right)$ represents the corresponding probability that pregnant woman i belongs to latent class k given the observed values of Z_i, W_i *and* y_i. These latent class probabilities likewise satisfy $\sum_{k=1}^{3}\pi_k\left(Z_i, W_i, y_i, \theta\right) = 1$ for all $i = 1, \ldots, M$.

With the inclusion of the endogenous variable y_i, the log likelihood function becomes

$$\text{(18)} \qquad \tilde{L}\left(n, X, Z, W, y \mid \beta, \theta\right) = \sum_{i=1}^{M}\ln\left[\sum_{k=1}^{3}\pi_k\left(Z_i, W_i, y_i, \theta\right) f_k\left(n; X_i, \beta\right)\right] + \sum_{i=1}^{M}\ln\Phi\left(s_i W_i'\gamma\right)$$

where the additional term on the right-hand side corresponds to the likelihood contribution of the probit model for y_i in (15). Once again, the EM algorithm can be employed to maximize the log likelihood in (18). Suppose that we have parameter estimates $\left(\beta^{(t)}, \theta^{(t)}\right)$ at a specific iteration t. For each woman $i = 1, \ldots, M$, we once again compute the posterior probability that woman i belongs to class k as

$$\text{(19)} \qquad p_{ik}^{(t)} = \frac{f_k\left(n; X_i, \beta_k^{(t)}\right)\pi_k\left(Z_i, W_i, y_i, \theta^{(t)}\right)}{\sum_{j=1}^{3} f_j\left(n; X_i, \beta_j^{(t)}\right)\pi_j\left(Z_i, W_i, y_i, \theta^{(t)}\right)} \text{ for } k = 1,2,3$$

Given $\left(\beta^{(t)}, \theta^{(t)}\right)$, the expected value of the extended log likelihood is

$$\text{(20)} \qquad Q\left(\beta, \theta, \beta^{(t)}, \theta^{(t)}\right) = \sum_{k=1}^{3}\left[\sum_{i=1}^{M} p_{ik}^{(t)}\left(n_i X_i'\beta_k - \exp\left(X_i'\beta_k\right)\right)\right] - M\ln\left(n_i!\right) +$$

$$\sum_{k=1}^{3}\left[\sum_{i=1}^{M} p_{ik}^{(t)}\ln\pi_k\left(Z_i, W_i, y_i, \theta\right)\right] + \sum_{i=1}^{M}\ln\Phi\left(s_i W_i'\gamma\right)$$

Maximization with respect to the parameters $\beta = (\beta_1, \beta_2, \beta_3)$ and $\theta = (\alpha, \delta, \kappa, \gamma, \rho)$ is similarly obtained by setting the corresponding derivatives of (19) equal to zero. Note that (20) remains separable in β and θ, so that the first-order conditions for β in (7) still apply. Moreover, parameter γ, which appears only in the last term of (20), need not be estimated iteratively.

2.6. Testing Alternative Models

With one exception to be described below, our alternative models of the number of prenatal visits are successively nested. Thus, the basic model with fixed mixing probabilities (8) is nested within the ordered probit model of mixing probabilities (12). The former model is equivalent to the latter under the restriction that $\theta = 0$. Likewise, the model (12) is nested within the ordered probit model of mixing probabilities with an endogenous variable (17). The former is equivalent to the latter under the restriction that $\rho = 0$. Thus, the standard likelihood ratio tests can be employed to distinguish between models.

We can extend the nesting concept to other alternative models not explicitly considered above. Consider the model (17) with only two latent classes, rather than three. This would correspond to a simple probit model of mixing probabilities with an endogenous variable. Such a model would likewise be nested within the model (17), and would be equivalent to the restriction that $\kappa = 0$. Alternatively, consider a simple count-data model in which the number of prenatal visits n_i is Poisson distributed with mean $\lambda_1 = \exp(X_1' \beta_1)$. This model is nested within the basic latent class model with fixed probabilities (8), with the restriction $\theta_2 = \theta_3 = 0$.

Prior contributions to the latent class literature have considered a multinomial logit specification for the mixing probabilities $\pi_k(Z_i,\theta)$ (Nagin and Land 1993; Roeder, Lynch et al. 1999; Clark, Elité et al. 2005; Bago d'Uva and Jones 2008). In that case, equation (12) is replaced by

$$(21) \qquad \pi_k(Z_i,\theta) = \frac{\exp(Z_i'\alpha_k)}{\sum_{j=1}^{3}\exp(Z_i'\alpha_j)} \text{ for } k = 1,2,3$$

where $\theta = (\alpha_1, \alpha_2, \alpha_3)$. This model, which can also be estimated by the EM algorithm, is not nested within our ordered probit models. In our empirical analysis, we employed the Akaike Information Criterion (AIC) (Aikake 1974) and the Bayesian Information Criterion (BIC) (Schwarz 1978) to compare (21) with our alternative models. The former criterion corresponds to $2N - 2L^*$, where L^* is the maximized value of the log likelihood function L in (2) or $\tilde{L}$ in (18) and N is the total number of parameters in (β,θ). The latter criterion corresponds to $N \ln M - 2L^*$, where M, as noted above, is the sample size.

2.7. Computation of Treatment Effects

In our empirical work, we focus on two treatment effects: (1) the direct effect of Seguro Popular; and (2) the indirect effect of public policies intended to increase participation in Seguro Popular. In the terminology of (Heckman and Vytlacil 2007), the former corresponds to the "treatment effect on the treated," while the latter represents the "policy relevant treatment effect," where a public policy that may alter the probability of treatment. In both cases, the endpoint is the predicted number of prenatal visits in our sample population.

To that end, we explicitly identify Seguro Popular with the binary endogenous variable y_i. We permit y_i to be a covariate the model of the conditional distribution of the number of prenatal visits n_i, given that pregnant woman i belongs to latent class k. Thus, equation (5) is generalized to:

(22) $$f_k\left(n_i;X_i,\beta\right)=\frac{\lambda_{ik}^{n}\exp\left(-\lambda_{ik}\right)}{n!}$$, where $\lambda_{ik}=\exp\left(X_i'\beta_k+\zeta_k y_i\right)$, for $k=1,2,3$

and where $\beta=\left(\beta_1,\beta_2,\beta_3,\zeta_1,\zeta_2,\zeta_3\right)$. The explicit inclusion of y_i in (22) does not alter the fact that the expected log likelihood function is separable in the parameters β and θ.

Let $E\left[n_i|y\right]$ denote the mean number of prenatal visits of pregnant woman i, conditional upon the presence or absence of Seguro Popular, that is, conditional upon y. For each $k=1,2,3$, we abbreviate $\lambda_{ik}\left(y\right)=\exp\left(X_i'\beta_k+\zeta_k y\right)$ and $\pi_{ik}\left(y\right)=\pi_k\left(Z_i,W_i,y,\theta\right)$, where $\pi_k\left(\ \right)$ is defined in (17). Then $E\left[n_i|y\right]=\sum_{k=1}^{3}\pi_{ik}\left(y\right)\lambda_{ik}\left(y\right)$. The direct effect of Seguro Popular (that is, the effect of a change in y from 0 to 1) on the mean number of prenatal visits of pregnant woman i is:

(23) $$\Delta E\left[n_i\right]=E\left[n_i|1\right]-E\left[n_i|0\right]=\sum_{k=1}^{3}\left(\pi_{ik}\left(1\right)\lambda_{ik}\left(1\right)-\pi_{ik}\left(0\right)\lambda_{ik}\left(0\right)\right)$$

which can be decomposed into:

(24) $$\Delta E\left[n_i\right]=\sum_{k=1}^{3}\pi_{ik}\left(1\right)\left(\lambda_{ik}\left(1\right)-\lambda_{ik}\left(0\right)\right)+\sum_{k=1}^{3}\left(\pi_{ik}\left(1\right)-\pi_{ik}\left(0\right)\right)\lambda_{ik}\left(0\right)$$

The first summation captures the effect of Seguro Popular on the mean number of visits within each latent class, while the second term captures the effect of Seguro Popular on the probabilities of latent class membership. Noting that $\lambda_{ik}(1)=\left(\exp\left(\zeta_k\right)-1\right)\lambda_{ik}(0)$ for $k=1,2,3$, we can derive a computationally simpler form for (24) as:

$$(25)\qquad \Delta E\left[n_i\right]=\sum_{k=1}^{3}\lambda_{ik}(0)\left[\pi_{ik}(1)\exp\left(\zeta_k\right)-\pi_{ik}(0)\right]$$

We calculate the population mean and median values of $\Delta E\left[n_i\right]$.

We next compute the indirect effect of a change in a policy variable intended to increase participation in Seguro Popular. For this purpose, we focus on a specific continuous covariate w_h that is a component of the vector W but not a component of the vectors X or Z. We define:

$$(26)\qquad \tilde{\pi}_{i1}(y)=\Phi\left(\frac{-Z_i'\alpha-\delta y+\rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)$$

$$\tilde{\pi}_{i2}(y)=\Phi\left(\frac{\kappa-Z_i'\alpha-\delta y+\rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)-\Phi\left(\frac{-Z_i'\alpha-\delta y+\rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)$$

$$\tilde{\pi}_{i3}(y)=\Phi\left(\frac{Z_i'\alpha+\delta y-\kappa+\rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)$$

where $\tilde{\pi}_{ik}(y)=\pi_{ik}(y)$ when $\rho=0$. In the Appendix, we show that the marginal effect of a change in w_h is

$$(27)\qquad \frac{\partial E\left[n_i\right]}{\partial w_h}=\gamma_h\,\varphi\left(W_i'\gamma\right)\sum_{k=1}^{3}\left[\lambda_{ik}(1)\tilde{\pi}_{ik}(1)-\lambda_{ik}(0)\tilde{\pi}_{ik}(0)\right]$$

where γ_h is the component of γ corresponding to w_h. The first term $\left[\gamma_h\,\varphi\left(W_i'\gamma\right)\right]$ represents the effect of a marginal change in w_h on the probability that pregnant woman i participates in Seguro Popular, while the summation represents the effect on the mean number of visits. When $\rho = 0$, the marginal effect of a change in w_h on the mean number of prenatal visits collapses to:

$$(28) \qquad \frac{\partial E[n_i]}{\partial w_h} = [\gamma_h \, \varphi(W_i'\gamma)] \, \Delta E[n_i]$$

We calculate the population mean and median of the quantity $\frac{\partial E[n_i]}{\partial w_h}$.

3. BACKGROUND AND DATA

3.1. Seguro Popular and Prenatal Health Services in Mexico

Beginning in the mid-1990s, Mexico introduced a series of public policies designed to improve the health of its poorest and most vulnerable populations: the Program to Expand Coverage ("Programa de Ampliación de Cobertura") in 1995, Oportunidades (initially named "PROGRESA") in 1997, and the Fair Start in Life program ("Arranque Parejo en la Vida") in 2001 (Frenk, Gonzalez-Pier et al. 2006). There is evidence that these programs improved access to health care and health outcomes, particularly in the area of maternal and reproductive health. Evaluations of Oportunidades, in particular, have demonstrated an increase in prenatal visits among pregnant women beneficiaries (Gertler 2000).

Despite these initiatives, half of Mexico's population remained uninsured at the start of 2001. At that time, a pregnant woman faced essentially three choices for her prenatal and obstetric care. First, if a family member were employed in a specific sector of the formal economy, such as petroleum (PEMEX), she could take advantage of the prevailing system of social security ("Seguridad Social"), which offered a modern network of high-quality primary and secondary maternal health care services, mostly in urban areas. Second, if she were ineligible for social security but eligible for a state-run program, she could seek prenatal and obstetric care at government-sponsored facilities, including those of the Department of Health ("Secretaría de Salud"). Such facilities were often poorly staffed and widely regarded as having variable quality. Third, she could seek medical care in the private sector, paying out of pocket. While many urban women with adequate incomes paid a private obstetrician, poorer women and those in rural areas frequently sought low-priced care from informal providers, including midwives and traditional healers. Some of these women had no prenatal care prior to labor and delivery.

Seguro Popular ("People's Insurance") was introduced in 2001 with a two-fold purpose: to provide insurance coverage to the nation's most vulnerable populations; and to increase the quality of health care services provided in the public sector (Gakidou, Lozano et al. 2006; King, Gakidou et al. 2009; Sosa-Rubí, Galárraga et al. 2009). Initially launched as a pilot project in five states and gradually rolled out in the rest of the country, Seguro Popular had been incorporated by 2005 into all of Mexico's 32 states.

On the demand side, SP served as a voluntary insurance program for uninsured households, with well-defined eligibility rules, benefit packages and premiums scaled to income. The eligibility rules favored the poorest households in rural areas, including those who were also eligible for the Oportunidades program, and precluded households with access to insurance through the system of social security. On the supply side, the federal government allocated funds to state health departments to upgrade public health care facilities to meet minimum quality standards. Federal transfers to states were directly related to the number of SP-enrolled households, so that the states had an incentive to enroll households in the program.

In a prior study of survey-based observational data, we found that Seguro Popular enhanced access of pregnant women to obstetrical care for labor and delivery (Sosa-Rubí, et al 2009). Another observational study has found that SP enhanced access to treatment for hypertension in those areas with adequate physician supply (Bleich, Cutler et al. 2007). A recent experimental study, in which randomization was performed at the level of the locality, demonstrated reductions in out-of-pocket "catastrophic" health spending, but no significant effects on utilization, medication spending, or health outcomes (King, Gakidou et al. 2009). The latter negative findings may have been due to the relatively short, 10-month duration of the experimental intervention (Victora and Peters 2009).

3.2. The 2006 ENSANUT Survey Data

We analyzed data from the 2006 National Health and Nutrition Survey (Encuesta Nacional de Salud y Nutrición, or "ENSANUT"), a nationally representative cross-section survey of 48,304 households containing 206,700 individuals, conducted in all 32 states of Mexico during November 2005 – May 2006 (Instituto Nacional de Salud Pública 2006). We complemented the survey responses with data on the characteristics of the localities in which respondents lived, as derived from 2005 census data (Instituto Nacional de Estadística y Geografía (INEGI) 2005). We focused on a sample of 4,381 females aged 14–49 years, who reported giving birth during 2002–2005, and who provided responses concerning the number of prenatal visits as well as the explanatory variables to be delineated below.

Table 1 shows the summary statistics for all variables used in our econometric analyses. We have classified the explanatory variables into individual, household and locality characteristics. At the individual level, we included variables reflecting the woman's age, educational attainment, language spoken, work status, reproductive history, and past history of conditions that commonly complicate pregnancy. To address possibly nonlinearity in the relationship between age and prenatal care, we included age squared as an explanatory variable (not shown in Table 1). We classified educational attainment into three levels: primary school or no education; second school; and high school or greater. The first level served as the reference category. Although we could not ascertain the respondent's work status during her pregnancy, nonetheless we included an explanatory variable reflecting the respondent's work status during the two weeks prior to the ENSANUT survey.

At the household level, we included variables reflecting the presence of young children, an index of household wealth, and indicator variables for household enrolment in Oportunidades, Seguro Popular, or Seguridad Social (social security). The asset index, in particular, was based upon household infrastructure, building materials, and ownership of certain durable assets, such as a refrigerator, television, telephone, oven and stove (McKenzie 2004).

At the locality level, we included variables reflecting rural location and level of social deprivation. The latter indicator, also known as the locality's index of socioeconomic marginality ("índice de marginación") is based on such factors as the rate of illiteracy, the proportions of dwellings with a dirt floor, with overcrowding, without running water, sewer drainage, or electricity, and the proportion of the population under the poverty (CONAPO 2005).

We also included a locality-level variable for the percentage penetration of Seguro Popular among the eligible population (Instituto Nacional de Estadística y Geografía (INEGI) 2005). SP penetration depended in large part on the investments made by each state to upgrade the infrastructure and staffing of local health care facilities in compliance with federal requirements. Local penetration also depended on individual states' efforts to inform households of their eligibility and recruit them into the program. We therefore treated local SP penetration as an exogenous instrumental variable that influenced the probability that a pregnant woman would enroll in Seguro Popular, but did not affect her probability membership in a particular latent class or her utilization of prenatal care conditional on class membership. Thus, local SP penetration appeared as an exogenous variable in the vector W_i of covariates in equation (15) but not in the vector Z_i of covariates in equation (14) or the vector X_i of covariates in equation (5).

Other investigators have used similar individual-, household- and local-level covariates to explain prenatal care utilization in developing countries (Wong, Popkin et al. 1987; Pebley, Goldman et al. 1996; Celik and Hotchkiss 2000; Magadi, Madise et al. 2000; Chen, Liu et al. 2003; Sepehri, Sarma et al. 2008).

4. RESULTS

4.1. Principal Estimation Results

Table II shows the estimates derived from our principal specification, as given in equations (5) and (14)–(16). The first two columns of estimates show the results of the model of latent class determination, where the column entitled "Ordered Probit" refers to equation (14) and the column entitled "Probit SP Enrollment" refers to equation (15). At the bottom of the first column, the parameter κ refers to the threshold parameter in the ordered probit equation (14), while the parameter ρ refers to the correlation coefficient of the error terms in equation (16). The last three columns of Table II show the parameters of the three conditional Poisson models of prenatal care utilization, as specified in equation (5).

At the bottom of each of the last three columns of Table II, we report the estimated population mean values of the probabilities $\pi_k\left(Z_i, W_i, y_i, \theta\right)$ for $k = 1,2,3$, as defined in equation (17), as well as the estimated population mean values of the rate parameters $\lambda_{ik} = \exp\left(X_i'\beta_k\right)$ for $k = 1,2,3$, as defined in equation (5). Thus, the average probability of belonging to the first latent class was $\pi_1 = 0.0514$, while members of that class had a mean of 0.5242 visits. The average probability of belonging to the second class was $\pi_2 = 0.8814$, where the mean was 7.3302 visits. The average probability of belonging to the third class was $\pi_3 = 0.0672$, where the mean was 16.8447 visits. We interpret the first latent class as representing those pregnant women with little or no access to prenatal care, who made very few visits, if any. The second latent class represents the large majority of pregnant women, who on average sought care about once every five weeks during a 40-week pregnancy. Finally, we interpret the third latent class as representing those women with complications of pregnancy that were recognized prior to labor, and thus required an average of one prenatal visit every 2.4 weeks.

In the ordered probit specification in equation (14), a positive value of the parameter δ implies that an increase in the endogenous variable y_i will shift the distribution of latent class variables to the right. That is, an increase in y_i will tend to move pregnant woman i from latent class $k = 1$ to latent class $k = 2$, and from class $k = 2$ to class $k = 3$. Under our interpretation of the three latent classes, the rightward shift from the first class to the second represents an improvement in access to prenatal care. The rightward shift from the second to the third class represents the recognition of preexisting complications of pregnancy prior to labor and delivery. In the first column of Table II, the endogenous variable Seguro Popular in fact had a significant positive coefficient.

A positive value of a particular component of the parameter vector α, as specified in equation (14), similarly implies that an increase the corresponding component of Z_i will shift the distribution of latent class variables to the right. Among the observed covariates with a significant positive coefficient in the same column were: educational attainment, household wealth, enrollment in the Oportunidades program, and a history of prior health conditions (diabetes, hypertension, urinary tract infections) that could complicate pregnancy. The negative coefficient for the number of pregnancy losses suggests that this variable serves as a proxy for reduced access to care in prior pregnancies rather than as an indicator of current pregnancy risk.

In Table II, the estimated correlation coefficient of the error terms in the model of latent class determination (that is, ρ, as specified in equation 16) is –0.22, and the estimate is significantly different from zero $(P = 0.025)$. Put differently, those unobserved factors that increase participation in SP are correlated with those unobserved factors that prevent women from recognizing complications prior to labor (latent class 3) and relegate them to the low-access group (latent class 1). The finding of a negative correlation coefficient is consistent with our prior work on Seguro Popular (Sosa-Rubí, Galárraga et al. 2009). A negative correlation coefficient has been seen in other observational studies in developing countries (Waters 1999), although the evidence overall remains mixed (Harmon and Nolan 2001; Trujillo 2003; Jowett, Deolalikar et al. 2004).

In the second column of estimates in Table II, we find that indicators of lower educational attainment, lower family wealth, and participation in the Oportunidades program are predictors of participation in Seguro Popular. We dropped Seguridad Social from the covariates in this equation, since it was perfectly correlated with nonparticipation in SP, inasmuch as women enrolled in Seguridad Social are ineligible for SP. Finally, the percentage penetration of SP in the local area is a strong predictor of individual participation. This finding supports the validity of local SP penetration as an instrumental variable.

In the group of columns in Table II under the heading "Poisson Models of Prenatal Visits," the estimates for latent class 1 reveal significant positive coefficients for age, high school education, number of prior pregnancy losses, and the index of household wealth. Living in a rural locality or in a locality with a high index of social deprivation reduces the number of prenatal visits within in this group. Enrollment in Seguro Popular markedly increases the number of visits within this latent class. Being a beneficiary of social security (Seguridad Social) or the Oportunidades program also increases prenatal attendance, but the effect of enrollment in Oportunidades is reduced in those localities with high levels of deprivation, as evidenced by the negative interaction term.

The utilization estimates for latent class 2 in Table II show significant positive coefficients for number of prior pregnancy losses, our index of household wealth, and a history of diabetes, hypertension or urinary tract infections. Enrollment in social security or Oportunidades also increases attendance, and the interaction with the index of deprivation in the locality is again negative. Seguro Popular, however, does not have a significant effect on prenatal visits in the second latent class.

The estimates for the third latent class in the rightmost column of Table II require more scrutiny, as the signs of many of the significant coefficients are unexpectedly negative. This reversal of sign is seen for such variables as age, secondary and high school education, number of prior pregnancy losses, the index of household wealth, and enrollment in social security or Oportunidades. Many of the same variables have a significant positive sign in the ordered probit equation that determines latent class composition. Thus, if a woman becomes a beneficiary of Oportunidades, she tends to move out of the second and into the third latent class or, under our interpretation, her doctor or midwife recognizes a previously undetected complication of pregnancy. We assume that those inframarginal women who are already in the third latent class have the most serious complications of pregnancy. If so, then a marginal rightward shift in the distribution tends to *decrease* the average severity of complications in third latent class, thus resulting in a *negative* association between Oportunidades and prenatal attendance.

Figure 1 compares the predicted distribution with the empirical distribution of prenatal visits in the sample population of 4,381 pregnant women. The predicted distribution is displayed as three partially superimposed vertical bar graphs, each corresponding to a separate latent class. For each class $k = 1,2,3$, the vertical bars represent the predicted unconditional distribution of prenatal visits, that is, $\pi_k f_k(n)$ as a function of n. In Figure 2, the empirical distribution is compared to the predicted distribution of prenatal visits for the three latent classes combined, that is, $\sum_{k=1}^{3} \pi_k f_k(n)$ as a function of n.

Figures 1 and 2 show a generally good fit between the empirical and predicted distribution of visits. A total of 3.22 percent of women had no prenatal visits, while the predicted proportion was 3.04 percent, nearly all of which represented the contribution of the first latent class. A total of 1.12 percent of women had 1 prenatal visit, while the predicted proportion was 1.13 percent, consisting of 0.66 percent in class 1 and 0.47 percent in class 2. At nine visits, there is a marked deviation between the observed frequency (23.90%) and the predicted frequency (9.97%). This deviation may be due respondents' tendency to report one visit per month, or 9 per pregnancy. Similar deviations between observed and predicted frequencies are seen at 15 visits (3.38% versus 1.01%) and 20 visits (1.28% versus 0.27%), which may also be due to rounding by respondents. As a consequence of these deviations, a chi-squared test rejects the hypothesis that the observed and predicted distributions are indistinguishable $(P < 0.001)$.

4.2. Comparison of Alternative Models

Table III displays the results of our comparison of alternative models. Model A, in the first row, corresponds to our principal specification. By contrast, in Model B, we retain three latent classes and the ordered probit model of latent class membership, but assume that SP is an exogenous variable. Equivalently, the correlation coefficient ρ of error terms in equation (16) is assumed to equal zero. In Model C, we restrict our analysis to two latent classes, retaining a probit equation for class membership with SP as an endogenous variable. Equivalently, the threshold parameter κ in equation (14) is assumed to equal zero, while the parameter ρ in equation (16) remains unrestricted. In Model D, we replace the ordered probit specification with a multinomial logit model of latent class membership with SP as an exogenous variable, as specified in equation (21). Model E entails fixed mixing probabilities, as specified in equation (8). Finally, we include Model F, which represents a naïve Poisson model with no latent classes.

As noted above, all of our alternative models except Model D are nested within our principal Model A. Based upon the standard log likelihood ratio test, all of these models are rejected in favor of Model A. Thus, the test statistic computed as twice difference in log likelihood between Models A and B, which is distributed as χ^2 with 1 degree of freedom, is equal to 5.04. Hence, we reject Model B at the significance level $P = 0.0248$. Similarly, the test statistic computed as twice the difference in log likelihood between Models A and E, which is distributed as χ^2 with 17 degrees of freedom, is equal to 93.65. Hence, we rejected Model E at the significance level $P < 10^{-6}$. Finally, while the multinomial logit Model D is not nested in our principal Model A, we find that Model A is superior by both the AIC and BIC criteria.

Appendix Tables I, II, and III, respectively, display the coefficient estimates of Models B, C, and D. In Model B, when the endogeneity of Seguro Popular is ignored, its effect in the ordered probit equation for latent class membership was reduced by more than half. In Model C, when only two latent classes were assumed, the population mean numbers of visits were 1.4 and 7.7, respectively. The two-class model thus failed to identify the subpopulation of women who, under our interpretation, had recognized complications of pregnancy. In Model D, which does not account for the potential endogeneity Seguro Popular, the coefficient of SP was not significant either in the equation for class 2 versus class 1 membership, or in the equation for class 3 versus class 1 membership. In both Models B and D, we continued to observed significant negative parameter estimates for such variables as education, prior pregnancy losses, household wealth, and social security enrollment in the conditional Poisson utilization model for latent class 3. Thus, the negative coefficients for these variables in our principal model, as shown in the rightmost column of Table II, do not appear to be an artifact of the ordered probit specification or the treatment of SP as endogenous.

In the ordered probit Model A, any explanatory variable such as SP that shifts pregnant women in class 1 rightward to class 2 must also shift pregnant women in class 2 rightward to class 3. The alternative multinomial logit Model D, by contrast, does not impose such a restriction. In that model, an explanatory variable such as SP could, at least in principle, shift pregnant women in class 1 rightward to class 2 and, at the same time, shift pregnant women in class 3 leftward to class 2. To test whether the ordering restriction imposed by our principal Model A has a significant effect on the predicted probabilities of class membership, we compared the predicted values of the latent class probabilities for Model A with the corresponding predicted values of the latent class probabilities for Model D.

To simplify the notation, let $\pi_{ik}^{A} = \pi_k\left(Z_i, W_i, y_i, \theta\right)$ denote the probability that pregnant woman $i = 1, \ldots M$ belongs to latent class $k = 1, 2, 3$, as predicted from equation (17) based the parameter estimates for θ in Model A. Similarly, let $\pi_{ik}^{D} = \pi_k\left(Z_i, \theta\right)$

denote the corresponding probability predicted from equation (21) based on the parameter estimates for θ in Model D. Let $\pi_i^A = \left(\pi_{i1}^A, \pi_{i2}^A, \pi_{i3}^A\right)$ and $\pi_i^D = \left(\pi_{i1}^D, \pi_{i2}^D, \pi_{i3}^D\right)$ denote the corresponding vectors. We computed the Euclidean distance $\Delta_i = \left\| \pi_i^A - \pi_i^D \right\|$ for each pregnant woman $i = 1, \ldots M$ in our sample, where the distance Δ_i ranges from 0 to a maximum possible value of $\sqrt{2}$. In our sample of $M = 4,381$ pregnant women, the median value of Δ_i was 0.012, while 4,155 women (94.8 percent) had values of $\Delta_i < 0.5$.

Since each of the vectors π_i^A and π_i^D is contained within the two-dimensional simplex $S = \left\{ \left(\pi_1, \pi_2, \pi_3\right) \middle| \pi_1 + \pi_2 + \pi_3 = 1 \right\}$, we can plot them within a triangular planar region. The use of such triangular plots in economics dates back at least to McKenzie's analysis of factor prices in world trade (McKenzie 1955). (See also Leamer's use of "endowment triangles" in a three-factor general equilibrium model (Leamer 1987).) Figure 3 contains a pair of triangular plots, the upper panel displaying the values of π_i^A, and the lower panel displaying the corresponding plot of the values of π_i^D. In both of the panels in Figure 3, the three vertices of the triangle refer to the respective corners of the simplex, that is, $(1,0,0)$, $(0,1,0)$, and $(0,1,0)$. The three sides correspond to the lines where one of the three components of the vector $\left(\pi_1, \pi_2, \pi_3\right)$ is zero. In each graph, the gray points represent the 4,155 women with a value of $\Delta_i < 0.5$, while the black solid points represent the remaining 226 women with a value of $\Delta_i \geq 0.5$.

If the unordered multinomial logit Model D did not adhere to the ordering imposed by our principal Model A, then we would expect to see a large number of points situated along or close to the bottom margin of the triangle in the bottom panel of Figure 3, where $\pi_1 > 0$ and $\pi_3 > 0$, but $\pi_2 \approx 0$. In fact, nearly all the points lie very close to the left and right sides of the triangle. Put differently, the vast majority of women were found either to have some probability of belonging to latent classes 1 and 2 or some probability of belonging to latent classes 2 and 3, a finding that supports the validity of the ordered probit specification.

4.3. Estimation of Treatment Effects

Table III also shows the estimated treatment effects for our principal model and each of our alternative models. In all cases, we have computed both the population mean and median effects on the predicted number of prenatal visits. The pair of columns under the heading "Effect of Seguro Popular" refers to the direct effect of SP on the number of prenatal visits, that is, the "treatment effect on the treated," as defined in equation (23). The pair of columns under the heading "Marginal Effect of SP Penetration" refers to the indirect effect of a 10-percent increase in SP penetration on the number of prenatal visits, that is, the "policy relevant treatment effect," as defined in equation (27). In the latter case, we interpret the penetration of SP as a policy indicator of local, state and federal efforts to enroll eligible households into the program.

For both the direct effect of SP and the indirect effect of SP penetration, the distribution of estimated individual treatment effects was asymmetric and skewed to the right. Thus, the mean treatment effects were consistently larger than the corresponding median effects. For both types of treatment effects, our principal Model A predicted a much larger impact than the alternative models. Under Model A, the effect of the treatment on the treated corresponded to mean increase of 1.65 prenatal visits. Failure to take account of the endogeneity of SP in Model B reduced the estimated mean direct effect of SP to 1.31 visits, that is, by approximately 21 percent.

As shown in equation (24) above, the direct effect of SP in Model A could be decomposed into a change in the mean number of visits within latent classes (the first term $\sum_{k=1}^{3}\pi_{ik}(1)\left(\lambda_{ik}(1)-\lambda_{ik}(0)\right)$ in equation 24) and a shift in the distribution of latent classes (the second term $\sum_{k=1}^{3}\left(\pi_{ik}(1)-\pi_{ik}(0)\right)\lambda_{ik}(0)$ in equation 24). These components were, respectively, 0.976 visits (or 59% of the effect) and 0.675 visits (or 41% of the effect). The first component was dominated by the effect of SP on the number of prenatal visits among women who remained in latent class 1 (that is, by $\left(\pi_{i1}(1)-\pi_{i1}(0)\right)\lambda_{i1}(0)$ in equation 24), while the second effect was dominated by the movement of pregnant women into latent class 3 (that is, by $\left(\pi_{i3}(1)-\pi_{i3}(0)\right)\lambda_{i3}(0)$ in equation 24). Under our interpretation of the latent classes, the direct treatment effect of SP derived predominantly from a combination of two impacts: increased prenatal attendance among pregnant women with little or no access to care, and increased recognition of pregnancy complications prior to labor.

5. DISCUSSION AND CONCLUSIONS

In this observational study of a cross-sectional survey database, we found that Seguro Popular increased access to prenatal care for Mexican women who gave birth during 2002–2005. Specifically, enrollment in SP was associated with a mean increase in 1.65 prenatal visits during pregnancy (Table III). Approximately 59 percent of this treatment effect was the result of increased prenatal care among women in the first latent class, that is, women who had with little or no access to care. The remaining 41 percent of the treatment effect was the result of a shift in membership from the second to the third latent class, which we interpret as increased recognition of complications of pregnancy prior to labor and delivery.

These estimates represent the effect of the treatment (that is, Seguro Popular) on the treated (pregnant women whose households enrolled in SP). In an attempt to assess the effect of a policy-relevant treatment, we also studied the effect of an absolute increase of 10-percentage points in local penetration of Seguro Popular, that is, the proportion of eligible women enrolled in SP in the local area. We view local penetration as an intermediate measure of efforts by state health departments to upgrade health facilities to meet federal standards and then enroll eligible households. We estimated that a 10-percent increase in local penetration would result in a mean increase of 0.139 prenatal visits (Table III). Based upon published budgetary and coverage data (Comisión Nacional de Protección Social en Salud 2007; Comisión Nacional de Protección Social en Salud 2007), we estimate that a 10-percent increase in local penetration required a governmental investment of approximately USD 526 in the year 2006.[**] However, full

[**] In 2006, the federal government transferred 4.608 billion pesos to the states as part of the Seguro Popular program (Comisión Nacional de Protección Social en Salud 2007). The number of affiliated households at the close of 2005 was 3.556 million (Comisión Nacional de Protección Social en Salud 2007). Given these data and the prevailing exchange rate of 10.25 pesos per USD, we estimate that in 2006, the federal government allocated to each state an average of USD 126 per affiliated household. There were 11.898 million eligible households in a total of 285,823 localities in Mexico (Comisión Nacional de Protección Social en Salud 2007), or an average of 41.6 eligible households per locality. An increase in 10% in the penetration of SP thus required enrolling an average of 4.16 households, which comes to USD 526.

evaluation of such a marginal investment would require us to assess all of the potential benefits of Seguro Popular, and not simply the increment in prenatal visits.

Our analysis adds to the small but growing number of studies that model the probability of latent class membership as a function of observed covariates (Nagin and Land 1993; Roeder, Lynch et al. 1999; Greene and Hensher 2003; Clark, Elité et al. 2005; Bago d'Uva 2006; Clark and Etile 2006; Bago d'Uva and Jones 2008; Greene, Harris et al. 2008). Our research is distinguishable from prior work in that we explicitly address the problem of endogeneity in modeling latent class membership. We thus attempt to confront a serious drawback in the application of latent class models to observational data on health care utilization. We find, in fact, that failure to account for the endogeneity of Seguro Popular results in a significant underestimate of the impact of this public policy program on the utilization of prenatal care (Table III). Moreover, we show how the EM algorithm can substantially reduce the computational burden of such models. Specifically, at each stage of the iterative algorithm, the parameters of the model of latent class membership can be estimated separately from the parameters of the model of health care utilization.

Our study has several limitations. First, we used an ordered probit specification to model latent class membership. The assumption of joint normally distributed errors, inherent in the probit specification, simplified the task of incorporating endogeneity into the model of latent class membership, but the ordering imposed by our model may have been too restrictive. It is reassuring that the unrestricted multinomial logit specification gave nearly the same probability distribution of class membership (Figure 3).

Second, our conditional utilization model for the third latent class yielded unexpected negative coefficients for such covariates as the woman's education, the household's assets, and household enrollment in social security (Table II). These covariates were also found to shift the distribution of latent class membership to the right. That is, higher educational or household wealth attainment permits a woman to recognize a previously undetected complication of pregnancy, thus moving her at the margin from the second to the third latent class. If the inframarginal women already in the third latent class had the most serious complications requiring the largest number of prenatal visits, then a marginal rightward shift in the distribution would tend to decrease the average severity of complications in third latent class. This would result in a negative association between education or household wealth and prenatal attendance. The negative coefficients for the third latent class do not appear to be an artifact of our ordered probit model of class membership, as they are likewise observed in other less restricted models (Appendix Tables I and III).

Third, we have not pursued a number of potentially important analytical strategies for assessing the impact of Seguro Popular on prenatal care. In particular, we did not estimate two-part models (Pohlmeier and Ulrich 1995; Chen, Liu et al. 2003; Sepehri, Sarma et al. 2008). To be sure, we found that pregnant women in our first latent class had a mean of 0.52 prenatal visits (Table II and Figure 1), and our predicted distribution of the number of visits accurately captured the observed mode at zero visits (Figure 2). Nonetheless, we have made no formal tests of the accuracy of a two-part model against our latent class model. Moreover, our conditional utilization models relied upon the Poisson distribution. We did not test alternative specifications for the number of prenatal visits, such as the negative binomial distribution (Chen, Liu et al. 2003; Sepehri, Sarma et al. 2008). Further research is required to determine whether a finite latent class model in which class membership depends on observed covariates better captures the heterogeneity that is implicit in the negative binomial distribution. Finally, our sole measure of prenatal care was the number of visits. We did not address the timing of the first visit (Harris 1982; Wong, Popkin et al. 1987; Magadi, Madise et al. 2000), the type of provider (Pebley, Goldman et al. 1996), or the content of care (Wong, Popkin et al. 1987) in the present study.

Table I: Descriptive Statistics

Variable	**Mean**	**S. D.**	**Min.**	**Max.**
Dependent Variable				
Number of Prenatal Visits	7.596	3.777	0	38
Individual Characteristics of Women				
Age	28.618	6.885	14	49
Educational attainment: primary school or no education ¶ §	0.418	0.493		
Educational attainment: secondary school	0.348	0.476		
Educational attainment: high school, professional or university	0.234	0.423		
Working during year prior to interview ¶	0.211	0.408		
Number of pregnancy losses ‡	0.307	0.695	0	7
Parity (number of births)	3.001	1.922	1	19
Speaks indigenous language ¶	0.061	0.240		
Reported diabetes, high blood pressure, or urinary infection ¶	0.298	0.457		
Household Characteristics				
Presence of children < 7 years old ¶	0.924	0.265		
Asset index	–0.116	0.849	–2.02	1.57
Beneficiary of Oportunidades program ¶	0.363	0.481		
Enrolled in Seguridad Social ¶	0.300	0.458		
Enrolled in Seguro Popular ¶	0.194	0.395		
Locality Characteristics				
Rural ¶	0.288	0.453		
Deprivation index	3.987	1.175	2	5
Penetration of Seguro Popular (percent)	12.216	17.604	0	96.24

¶ Binary variable. § Reference category. ‡ Number of pregnancies less parity.

Table II: Estimation Results for Principal Model

Variable	Latent Class Composition		Poisson Models of Prenatal Visits		
	Ordered Probit	Probit SP Enrollment	Class 1	Class 2	Class 3
Age (years)	–0.0167	0.0298	§ **0.2936**	0.0010	* **–0.0379**
	0.0244	0.0248	0.0645	0.0060	0.0187
Age Squared	0.0002	–0.0005	§ **–0.0051**	0.0000	* **0.0008**
	0.0004	0.0004	0.0011	0.0001	0.0003
Education: Sec. Schoo1	§ **0.4440**	0.0588	0.0209	–0.0076	§ **–0.2082**
	0.0660	0.0581	0.1216	0.0144	0.0611
Education: H.S., Prof., Univ.	§ **1.1156**	§ **–0.2186**	§ **1.3889**	* **0.0459**	§ **–0.4209**
	0.0809	0.8000	0.1361	0.0179	0.0586
Working during prior year	–0.0437	–0.0596	§ **0.6008**	–0.0181	* **–0.0764**
	0.0601	0.0648	0.1297	0.0151	0.0368
Number of Pregnancy losses	§ **–0.3226**	–0.0077	§ **0.7313**	§ **0.0310**	§ **–0.2683**
	0.0335	0.0366	0.0415	0.0095	0.0507
Number of Births	–0.0149	–0.0167	§ **–0.2473**	§ **–0.0175**	§ **–0.0588**
	0.0155	0.0153	0.0338	0.0039	0.0130
Speaks indigenous language	–0.1558	–0.1333	–0.4704	–0.0134	† **0.1707**
	0.1056	0.1035	0.2956	0.0269	0.0950
Reported diabetes, HTN or UTI	§ **0.2234**	0.0154	–0.0394	§ **0.0372**	0.0410
	0.0545	0.0552	0.0844	0.0132	0.0336
Household with children < 7 yrs	§ **0.3482**	–0.0128	§ **–1.9475**	–0.0087	§ **–0.3924**
	0.0942	0.0935	0.1318	0.0223	0.0844
Asset index	§ **0.2443**	† **–0.0611**	§ **0.9749**	§ **0.0368**	§ **–0.1489**
	0.0370	0.0361	0.0842	0.0088	0.0275
Oportunidades beneficiary	§ **0.5608**	§ **0.5677**	§ **3.4470**	§ **0.1790**	† **–0.3326**
	0.2111	0.1873	0.6080	0.0484	0.1883
Seguridad Social Enrollment	§ **0.6160**		§ **0.4975**	§ **0.0451**	§ **–0.2664**
	0.0625		0.1835	0.0143	0.0369
Seguro Popular Enrollment	* **0.3907**		§ **2.7420**	0.0253	–0.0174
	0.1654		0.1469	0.0164	0.0633
Household in rural locality	0.0289	0.0694	§ **–2.2471**	–0.0158	* **–0.1687**
	0.0912	0.0769	0.3006	0.0210	0.0854
Deprivation Index	* **0.0494**	–0.0096	§ **–0.1990**	§ **0.0175**	–0.0036
	0.0273	0.0298	0.0548	0.0065	0.0199
Deprivation Index × Oportunidades	–0.0434	–0.0303	§ **–1.0048**	§ **–0.0418**	–0.0170
	0.0499	0.0455	0.1801	0.0117	0.0441
Penetration of Seguro Popular		§ **0.0306**			
		0.0014			
Constant	§ **1.0627**	§ **–1.8999**	* **–1.8749**	§ **1.8861**	§ **4.2995**
	0.3869	0.3944	0.9321	0.0937	0.3057
κ	§ **3.7998**				
	0.0724				
ρ	* **–0.2261**				
	0.1006				
π			**0.0514**	**0.8814**	**0.0672**
λ			**0.5242**	**7.3301**	**16.8445**

Notes to Table II: Each cell contains the estimated coefficient, with the asymptotic standard error immediately below. All significant coefficients are in boldface.

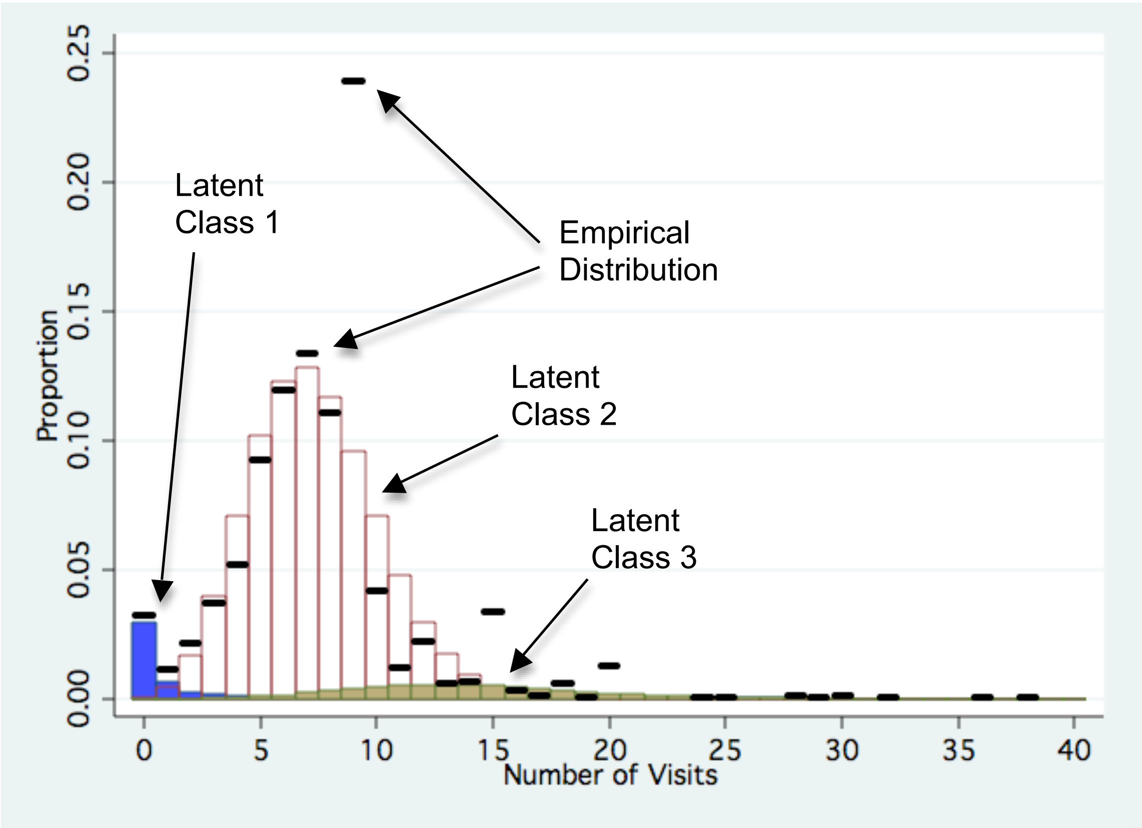
§ = Significant at P < 0.01; * = Significant at P < 0.05; † = Significant at P < 0.10. The next-to-last row, corresponding to the symbol π, shows the estimated population mean values of the probabilities π_k for $k = 1,2,3$, as defined in equation (17). The last row, corresponding to the symbol λ, shows the estimated population mean values of the rate parameters $\lambda_{ik} = \exp\left(X_i'\beta_k\right)$ for $k = 1,2,3$, as defined in equation (5).

Table III. Comparison of Alternative Models

Model	Number of Latent Classes	Model for Mixing Probabilities	Endogenous Seguro Popular	Log Likelihood	Effect of Seguro Popular		Marginal Effect of SP Penetration	
					Mean	Median	Mean	Median
A	3	Ord. Probit	Yes	–12,700.10	1.651	0.822	0.139	0.068
B	3	Ord. Probit	No	–12,702.61	1.312	0.347	0.066	0.022
C	2	Probit	Yes	–12,971.49	0.448	0.454	0.032	0.027
D	3	Mult. Logit	No	–12,702.49	0.597	0.284	0.036	0.018
E	3	Fixed	No	–12,793.75	0.610	0.497	0.034	0.028
F	None	None	No	–13,534.49	0.490	0.480	0.029	0.025

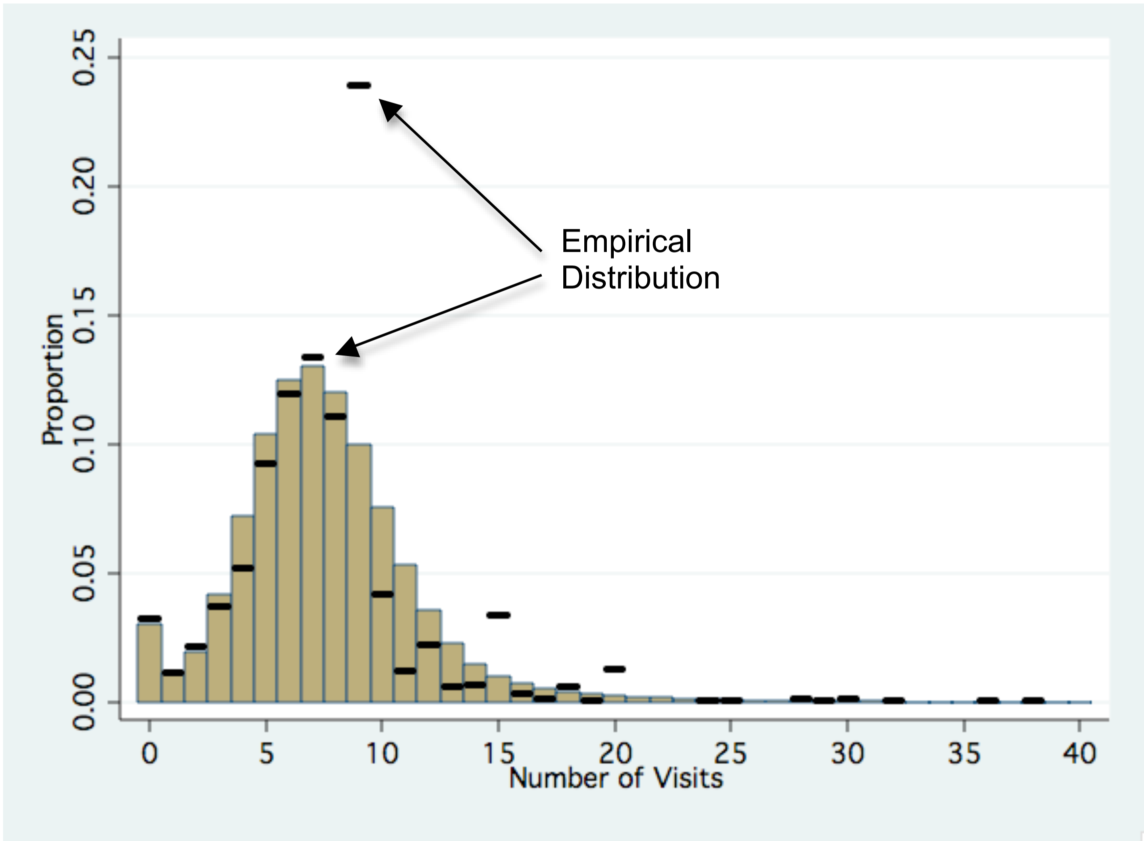
Note to Table III. Effect of Seguro Popular is equal to the effect of a discrete change on the expected number of prenatal visits, that is, $\Delta E\left[n_i\right]$. The marginal effect of Seguro Popular Penetration is equal to the effect of a 10-percent change on the expected number of prenatal visits, that is, $10 \times \frac{\partial E\left[n_i\right]}{\partial w_h}$. Model A had $N = 94$ parameters, while Model D had $N = 110$ unknown parameters. Both Model A and Model D had $M = 4{,}381$ observations. The AIC for Models A and D were, respectively, 25,588.20 and 25,625.22. The BIC for Models A and D were, respectively, 26,188.39 and 26,327.57.

Figure 1. Empirical Distribution of Prenatal Visits Compared to Predicted Distributions of Prenatal Visits in Each of Three Latent Classes



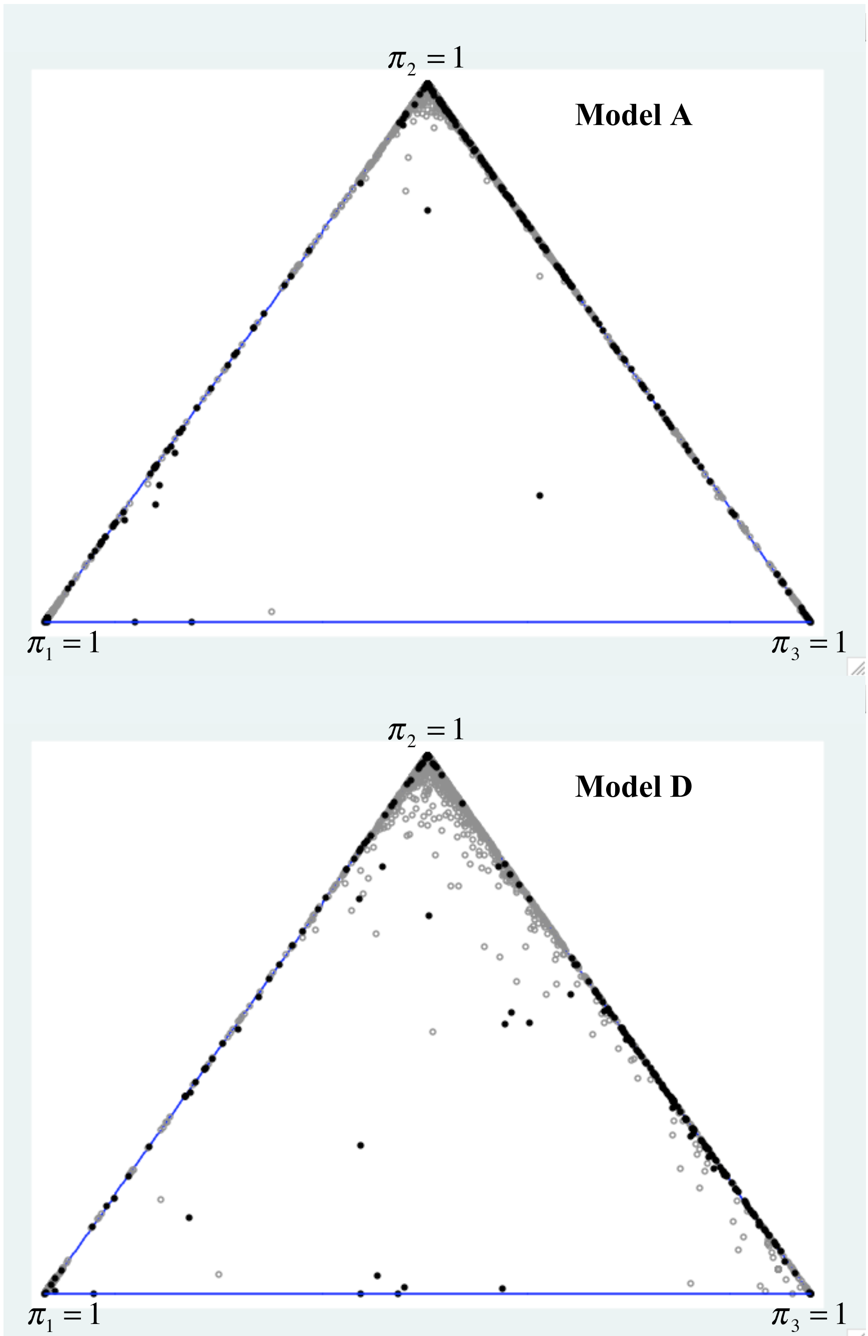
Note to Figure 1. The solid horizontal bars represent the empirical distribution of prenatal visits. The vertical bars represent the predicted unconditional distribution of prenatal visits in each of the three classes, that is, $\pi_k f_k(n)$ as a function of n for each class $k = 1,2,3$.

Figure 2. Empirical Distribution of Prenatal Visits Compared to Predicted Distributions of Prenatal Visits for the Three Latent Classes Combined



Note to Figure 2. The solid horizontal bars represent the empirical distribution of prenatal visits. The vertical bars represent the predicted distribution of prenatal visits for the three latent classes combined, that is, $\sum_{k=1}^{3} \pi_k f_k(n)$ as a function of n.

Figure 3. Comparison of the Predicted Distribution of Latent Class Probabilities in Model A (Ordered Probit with Endogenous SP) and Model D (Multinomial Logit with Exogenous SP)



Note to Figure 3. For Model A (upper panel) and Model D (lower panel), respectively, each triangular simplex plot shows the predicted distributions of $\left(\pi_{i1}^{A}, \pi_{i2}^{A}, \pi_{i3}^{A}\right)$ and

$\left(\pi_{i1}^{D},\pi_{i2}^{D},\pi_{i3}^{D}\right)$, respectively, for each pregnant woman $i = 1,\ldots M$. Specifically, $\pi_{ik}^{A} = \pi_{k}\left(Z_i, W_i, y_i, \theta\right)$ denotes the probability that pregnant woman i belongs to latent class $k = 1,2,3$, as predicted from equation (17) based the parameter estimates for θ in Model A, while $\pi_{ik}^{D} = \pi_{k}\left(Z_i, \theta\right)$ denote the corresponding probability predicted from equation (21) based on the parameter estimates for θ in Model D. The open gray circles represent those 4,155 women (94.8 percent) for whom the Euclidean distance $\Delta_i = \left\|\pi_i^A - \pi_i^D\right\|$, while the black filled circles represent the remaining 226 women (5.2 percent) for whom $\Delta_i \geq 0.5$. In both panels of Figure 3, the three vertices of the triangle refer to the respective corners of the simplex, that is, $(1,0,0)$, $(0,1,0)$, and $(0,1,0)$. The three sides correspond to the lines where one of the three components of the vector $\left(\pi_1, \pi_2, \pi_3\right)$ is zero.

APPENDIX: COMPUTATION OF MARGINAL EFFECTS

Denote the probability that pregnant woman i belongs to latent class k *and* is enrolled in SP by $\pi_i(k,1)$, while the probability that she belongs to latent class k *and* is not enrolled in SP is $\pi_i(k,0)$. We have:

(A1)
$$\begin{aligned}
\pi_i(1,1) &= \Phi_2\left(-Z_i'\alpha-\delta,\ W_i'\gamma,\ -\rho\right)\\
\pi_i(2,1) &= \Phi_2\left(\kappa-Z_i'\alpha-\delta,\ W_i'\gamma,\ -\rho\right)-\Phi_2\left(-Z_i'\alpha-\delta,\ W_i'\gamma,\ -\rho\right)\\
\pi_i(3,1) &= \Phi_2\left(Z_i'\alpha+\delta-\kappa,\ W_i'\gamma,\ -\rho\right)\\
\pi_i(1,0) &= \Phi_2\left(-Z_i'\alpha_i,\ -W_i'\gamma,\rho\right)\\
\pi_i(2,0) &= \Phi_2\left(\kappa-Z_i'\alpha_i,\ -W_i'\gamma,\ \rho\right)-\Phi_2\left(-Z_i'\alpha_i,\ -W_i'\gamma,\ \rho\right)\\
\pi_i(3,0) &= \Phi_2\left(Z_i'\alpha-\kappa,\ -W_i'\gamma,\rho\right)
\end{aligned}$$

The expected number of prenatal visits is $E[n_i]=\sum_{k=1}^{3}\sum_{y=0}^{1}\lambda_{ik}(y)\,\pi_i(k,y)$. Taking the partial derivative of each term in (A1) with respect to w_h:

(A2)
$$\frac{\partial\pi_i(1,1)}{\partial w_h}=\Phi\left(\frac{-Z_i'\alpha-\delta+\rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)\gamma_h\,\varphi\left(W_i'\gamma\right)$$

$$\frac{\partial\pi_i(2,1)}{\partial w_h}=\left[\Phi\left(\frac{\kappa-Z_i'\alpha-\delta+\rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)-\Phi\left(\frac{-Z_i'\alpha-\delta+\rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)\right]\gamma_h\,\varphi\left(W_i'\gamma\right)$$

$$\frac{\partial\pi_i(3,1)}{\partial w_h}=\Phi\left(\frac{Z_i'\alpha+\delta-\kappa+\rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)\gamma_h\,\varphi\left(W_i'\gamma\right)$$

$$\frac{\partial\pi_i(1,0)}{\partial w_h}=-\Phi\left(\frac{-Z_i'\alpha+\rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)\gamma_h\,\varphi\left(W_i'\gamma\right)$$

$$\frac{\partial\pi_i(2,0)}{\partial w_h}=-\left[\Phi\left(\frac{\kappa-Z_i'\alpha+\rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)-\Phi\left(\frac{-Z_i'\alpha+\rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)\right]\gamma_h\,\varphi\left(W_i'\gamma\right)$$

$$\frac{\partial \pi_i(3,0)}{\partial w_h} = -\Phi\left(\frac{Z_i'\alpha - \kappa + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)\gamma_h\,\varphi(W_i'\gamma)$$

where γ_h is the component of γ corresponding to w_h. We can now collect terms to compute the marginal effect of a change in w_h. Since $\frac{\partial E[n_i]}{\partial w_h} = \sum_{k=1}^{3}\sum_{y=0}^{1}\lambda_{ik}(y)\frac{\partial \pi_i(k,y)}{\partial w_h}$,

we have $\frac{\partial E[n_i]}{\partial w_h} = \gamma_h\,\varphi(W_i'\gamma)\,M$, where

(A3) $$M = \lambda_{i1}(1)\,\Phi\left(\frac{-Z_i'\alpha - \delta + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)$$

$$+\lambda_{i2}(1)\left[\Phi\left(\frac{\kappa - Z_i'\alpha - \delta + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right) - \Phi\left(\frac{-Z_i'\alpha - \delta + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)\right]$$

$$+\lambda_{i3}(1)\,\Phi\left(\frac{Z_i'\alpha + \delta - \kappa + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)$$

$$-\lambda_{i1}(0)\,\Phi\left(\frac{-Z_i'\alpha + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)$$

$$-\lambda_{i2}(0)\left[\Phi\left(\frac{\kappa - Z_i'\alpha + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right) - \Phi\left(\frac{-Z_i'\alpha + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)\right]$$

$$-\lambda_{i3}(0)\,\Phi\left(\frac{Z_i'\alpha - \kappa + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)$$

We make the following notational simplifications:

(A4) $$\tilde{\pi}_{i1}(y) = \Phi\left(\frac{-Z_i'\alpha - \delta y + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)$$

$$\tilde{\pi}_{i2}(y) = \Phi\left(\frac{\kappa - Z_i'\alpha - \delta y + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right) - \Phi\left(\frac{-Z_i'\alpha - \delta y + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)$$

$$\tilde{\pi}_{i3}(y) = \Phi\left(\frac{Z_i'\alpha + \delta y - \kappa + \rho W_i'\gamma}{\sqrt{1-\rho^2}}\right)$$

Then the marginal effect of a change in w_h becomes:

(A5) $$\frac{\partial E[n_i]}{\partial w_h} = \gamma_h \varphi(W_i'\gamma) \sum_{k=1}^{3} \left[\lambda_{ik}(1)\tilde{\pi}_{ik}(1) - \lambda_{ik}(0)\tilde{\pi}_{ik}(0)\right]$$

This is the expression in equation (27) in the main text.

Appendix Table I: Estimation Results for Model B. Ordered Probit without Endogeneity of Seguro Popular

Variable	**Latent Class Composition**		**Poisson Models of Prenatal Visits**		
	Ordered Probit	**Probit SP Enrollment**	**Class 1**	**Class 2**	**Class 3**
Age (years)	–0.0186	0.0314	§ **0.9202**	0.0020	* **–0.0467**
	0.0247	0.0250	0.1049	0.0060	0.0183
Age Squared	0.0002	–0.0005	§ **–0.0163**	0.0000	§ **0.0009**
	0.0004	0.0004	0.0018	0.0001	0.0003
Education: Sec. Schoo1	§ **0.3604**	0.0586	* **0.3670**	0.0144	* **–0.1324**
	0.0658	0.0582	0.1515	0.0143	0.0594
Education: H.S., Prof., Univ.	§ **1.1066**	§ **–0.2132**	§ **3.6067**	† **0.0353**	§ **–0.4237**
	0.0804	0.0800	0.1993	0.0180	0.0566
Working during prior year	–0.0707	–0.0573	0.2929	–0.0157	–0.0055
	0.0605	0.0648	0.1872	0.0151	0.0361
Number of Pregnancy losses	§ **–0.3133**	–0.0135	§ **0.8308**	§ **0.0318**	§ **–0.2269**
	0.0035	0.0370	0.0434	0.0094	0.0485
Number of Births	† **–0.0266**	–0.0162	§ **–0.1402**	§ **–0.0197**	§ **–0.0410**
	0.0156	0.0153	0.0249	0.0040	0.0219
Speaks indigenous language	–0.1234	–0.1344	† **–0.8325**	–0.0163	0.0746
	0.1053	0.1037	0.4524	0.0269	0.0902
Reported diabetes, HTN or UTI	§ **0.1790**	0.0193	–0.0065	§ **0.0406**	† **0.0605**
	0.0547	0.0552	0.0912	0.0132	0.0335
Household with children < 7 yrs	† **0.1637**	–0.0106	§ **–1.2760**	–0.0013	–0.1135
	0.0948	0.0936	0.1512	0.0224	0.0717
Asset index	§ **0.2309**	† **–0.0610**	§ **0.5482**	§ **0.0400**	**–0.1053**
	0.0372	0.0361	0.0853	0.0088	0.0269
Oportunidades beneficiary	0.2961	§ **0.5710**	§ **7.3881**	§ **0.1920**	0.0722
	0.2080	0.1875	0.8753	0.0485	0.1872
Seguridad Social Enrollment	§ **0.5950**		§ **–1.0129**	§ **0.0456**	§ **–0.1841**
	0.0622		0.2583	0.0143	0.0362
Seguro Popular Enrollment	* **0.1464**		§ **2.8067**	† **0.0278**	–0.0864
	0.0714		0.2583	0.0164	0.0598
Household in rural locality	* **0.1885**	0.0717	§ **–3.6899**	–0.0190	§ **–0.2938**
	0.0916	0.0770	0.3310	0.0210	0.0914
Deprivation Index	–0.0149	–0.0091	§ **0.9300**	§ **0.0201**	* **0.0427**
	0.0272	0.0298	0.1324	0.0066	0.0177
Deprivation Index × Oportunidades	–0.0277	–0.0316	§ **–1.3174**	§ **–0.0435**	–0.0630
	0.0501	0.0456	0.1944	0.0118	0.0442
Penetration of Seguro Popular		§ **0.0306**			
		0.0014			
Constant	§ **1.7180**	**–1.9251**	§ **–17.0221**	§ **1.8482**	§ **3.7708**
	0.3919	0.3965	1.7667	0.0934	0.2914
κ	§ **3.8182**				
	0.0653				
π			**0.0470**	**0.8837**	**0.0693**
λ			**0.2648**	**7.2956**	**15.9169**

Appendix Table II: Estimation Results for Model C. Two-Class Probit Model with Endogeneity of Seguro Popular

Variable	Latent Class Composition		Poisson Models of Prenatal Visits	
	Two-Class Probit	Probit SP Enrollment	Class 1	Class 2
Age (years)	* **0.0587** 0.0276	0.0284 0.0249	§ **–0.1489** 0.0275	–0.0043 0.0057
Age Squared	† **-0.0009** 0.0005	–0.0005 0.0004	§ **0.0024** 0.0005	0.0001 0.0001
Education: Sec. Schoo1	–0.0958 0.0724	0.0577 0.0582	§ **2.7915** 0.1788	0.0000 0.0139
Education: H.S., Prof., Univ.	§ **–0.4647** 0.0850	§ **–0.2121** 0.0798	§ **2.6820** 0.1806	§ **0.1126** 0.0167
Working during prior year	–0.0544 0.0698	–0.0626 0.0648	§ **0.1844** 0.0565	–0.0273 0.0142
Number of Pregnancy losses	0.0241 0.0431	–0.0132 0.0368	* **–0.1355** 0.0536	§ **0.0708** 0.0075
Number of Births	* **–0.0441** 0.0172	–0.0157 0.0153	§ **–0.3907** 0.0261	§ **–0.0233** 0.0038
Speaks indigenous language	–0.0051 0.1162	–0.1322 0.1034	§ **–2.4756** 0.4458	0.0132 0.0257
Reported diabetes, HTN or UTI	–0.0753 0.0629	0.0231 0.0551	–0.0259 0.0514	§ **0.0616** 0.0124
Household with children < 7 yrs	–0.1073 0.1150	–0.0150 0.0933	–0.0882 0.1023	–0.0024 0.0214
Asset index	§ **0.3847** 0.0411	† **–0.0632** 0.0361	§ **0.2504** 0.0386	§ **0.0490** 0.0085
Oportunidades beneficiary	0.2654 0.2606	§ **0.5680** 0.1872	§ **–0.2317** 0.3313	§ **0.2593** 0.0471
Seguridad Social Enrollment	0.1139 0.0692		**1.5353** 0.0656	0.0069 0.0135
Seguro Popular Enrollment	§ **0.6554** 0.1889		§ **0.9600** 0.0787	0.0070 0.0159
Household in rural locality	–0.0352 0.1058	0.0696 0.0771	§ **–0.4267** 0.1282	–0.0118 0.0206
Deprivation Index	§ **–0.0894** 0.0336	–0.0085 0.0297	§ **–0.4399** 0.0292	§ **0.0440** 0.0063
Deprivation Index × Oportunidades	–0.0156 0.0602	–0.0317 0.0455	§ **0.6640** 0.0804	§ **–0.0651** 0.0114
Penetration of Seguro Popular		§ **0.0307** 0.0014		
Constant	* **1.1238** 0.4405	§ **–1.8791** 0.3960	§ **3.6121** 0.4626	§ **1.9070** 0.0898
ρ	§ **-0.3470** 0.1216			
π			**0.0791**	**0.9209**
λ			**1.4142**	**7.7161**

Appendix Table III: Estimation Results for Model D. Multinomial Logit without Endogeneity of Seguro Popular

Variable	**Latent Class Composition**		**Poisson Models of Prenatal Visits**		
	Class 2 vs. Class 1	**Class 3 vs. Class 1**	**Class 1**	**Class 2**	**Class 3**
Age (years)	0.1011	§ **–0.2970**	§ **0.1550**	0.0101	0.0057
	0.0668	0.0921	0.0483	0.0061	0.0165
Age Squared	–0.0015	§ **0.0042**	§ **–0.0034**	–0.0001	0.0000
	0.0012	0.0016	0.0009	0.0001	0.0003
Education: Sec. Schoo1	0.2222	* **0.6847**	§ **3.5824**	0.0136	§ **–0.2254**
	0.1802	0.3109	0.2802	0.0142	0.0614
Education: H.S., Prof., Univ.	–0.2607	§ **2.5981**	§ **4.5403**	0.0232	§ **–0.4634**
	0.2281	0.3258	0.2883	0.0183	0.0554
Working during prior year	§ **–0.4764**	§ **0.7906**	§ **1.2096**	* **–0.0391**	§ **–0.2694**
	0.1733	0.2211	0.1006	0.0157	0.0329
Number of Pregnancy losses	–0.0937	§ **–1.0563**	–0.0135	§ **0.0905**	§ **–0.2591**
	0.0966	0.1993	0.0747	0.0076	0.0515
Number of Births	§ **–0.1518**	0.0547	0.0097	§ **–0.0285**	§ **–0.0795**
	0.0371	0.0584	0.0243	0.0040	0.0115
Speaks indigenous language	–0.3187	0.3092	§ **–3.4921**	–0.0191	**0.2381**
	0.2365	0.4275	0.8254	0.0270	0.0861
Reported diabetes, HTN or UTI	0.2600	§ **1.1928**	§ **–0.5727**	* **0.0337**	† **0.0575**
	0.1784	0.2251	0.1171	0.0132	0.0323
Household with children < 7 yrs	–0.4541	† **0.7540**	§ **1.1197**	–0.0050	§ **–0.5854**
	0.3114	0.4519	0.2697	0.0221	0.0691
Asset index	§ **0.7063**	§ **0.9707**	† **–0.1267**	§ **0.0519**	§ **–0.0660**
	0.1019	0.1444	0.0656	0.0089	0.0245
Oportunidades beneficiary	§ **1.8506**	§ **2.7797**	§ **–1.1722**	§ **0.1419**	§ **0.6765**
	0.6269	0.9873	0.4504	0.0481	0.2159
Seguridad Social Enrollment	§ **0.6582**	§ **1.9064**	§ **2.5407**	† **0.0282**	§ **–0.3055**
	0.2088	0.2534	0.1397	0.0144	0.0350
Seguro Popular Enrollment	0.3185	0.4479	§ **1.5068**	0.0210	–0.0840
	0.1980	0.3283	0.1217	0.0163	0.0653
Household in rural locality	–0.0483	§ **4.1447**	§ **–1.3418**	–0.0175	§ **–1.2927**
	0.2503	0.4605	0.1836	0.0212	0.1063
Deprivation Index	0.0113	§ **0.7537**	§ **–0.1449**	* **0.0131**	–0.0092
	0.0782	0.1262	0.0435	0.0065	0.0255
Deprivation Index × Oportunidades	† **–0.2787**	§ **–1.4830**	§ **0.7991**	* **–0.0301**	0.0710
	0.1496	0.2550	0.1133	0.0117	0.0575
Constant	† **2.1055**	–1.9629	§ **–6.0588**	§ **1.7796**	§ **3.9883**
	1.0756	1.5129	0.8611	0.0953	0.2796
π			**0.0484**	**0.8707**	**0.0810**
λ			**0.5231**	**7.3351**	**18.5979**

Note to Appendix Table III: Estimates for probit model of SP enrollment are identical to those in Appendix Table I, and therefore are not shown.

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