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Estimating the Effect of Policy Changes on Participation in Social Programs[1]

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Abstract

In this paper, we extend the previous research on participation in social programs by using a switching probit model, which allows average take-up rates, as well as the change in take-up due to a policy change, to depend on demographic factors. The standard model assumes that the take-up rate is constant, and does not attempt to measure the change in take-up from a policy experiment. Further, our approach avoids the problems of positive participation probabilities for ineligible individuals, and of the possibility for participation probabilities of individuals lying outside the unit interval, unlike the previous literature. Using data from the SIPP and exploiting the exogenous policy changes in the Medicaid environment that took place in late 1980's and early 1990's, we first estimate the average take-up response of the general population as well as that for different demographic groups. We then measure how different demographic groups respond to a simple policy experiment. Our results suggest that there is a significant variation among the different demographic groups in average take-up rates and in their reaction to a policy change. For example, the response of minorities is about 70 percent higher to a policy change than whites. Differences in the response to the policy change are also dramatic if we separate families according to number of earners in the family and family structure.

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1. Introduction

Research on participation in social programs constitutes a significant research area in public economics, health economics and labor economics (Cutler and Gruber (1996), Shore-Sheppard (2000), Ham and Shore-Sheppard (2003), Bitler et al (2003) etc.). By far the most common way of modeling such participation is to first specify a linear probability model for eligibility in the program. One then estimates a linear probability model for participation where a dummy variable for eligibility is an endogenous explanatory variable in the participation equation. One criticism econometricians have of this model is that the linear probability model is unsatisfactory since predicted probabilities can lie outside the unit interval, and a bivariate probit simultaneous equation model is more appropriate. In this paper we argue that this common approach has two important additional problems and these problems are not addressed by moving to the bivariate probit simultaneous equation model. First, the commonly used model has the disadvantage that it allows for a positive probability of participation even if an individual is ineligible for the program while the estimated probability should be zero. Secondly, it assumes that all demographic groups react to eligibility with the same probability of participating the program.[2] Researchers can avoid these problems by considering a switching model, which can also be used to estimate the potential impacts of further policy changes concerning social program eligibility on program participation. Readers may be tempted to argue that the common approach is preferred on computational grounds, but since the switching approach is readily available in programs such as STATA or LIMDEP, we do not find this argument compelling.

In this paper we outline the switching approach. We then show how the predicted probabilities from our estimated model can be used to calculate two parameters of interest: for a particular demographic group, what is (i) the average take up rate and (ii) the change in participation for a given policy change concerning eligibility. The commonly used approach calculates the average take-up rate for the groups affected by variation in the Medicaid laws.

[2] Of course researchers can avoid this latter problem by interacting eligibility with different characteristics, but this has not been done in the literature; moreover the first problem remains. Some may argue that researchers are implicitly allowing for difference across groups by estimating a random coefficients model. However we would argue that this is an example of where one would actually want to know the value of the coefficient for different groups, rather than treating them as interchangeable, and thus the interaction strategy would be preferable. See Hsiao (2003)

We compare our average take up rates against those from the commonly used model and then conduct a simple policy experiment concerning an expansion in Medicaid eligibility for a widely studied problem: How will changes in Medicaid eligibility for children affect the participation of children in public health insurance? We find that there are very large differences in the two parameters of interest for different demographic groups, motivating our suggested approach on practical, as well as theoretical, grounds.

The late 1980's and early 1990's were an era of significant changes in the legislative environment towards Medicaid. For the first time the link between eligibility for Aid to Families with Dependent Children (AFDC) and eligibility for Medicaid was weakened for low-income children and pregnant women at the federal level. Children and pregnant women coming from low-income families, regardless of the family structure, became eligible for Medicaid even if they were not income-eligible for AFDC, as income thresholds for Medicaid eligibility were set at levels far above the AFDC levels. With these changes in the eligibility criteria, about 30 percent of the kids aged 0-18 became eligible for public health insurance by 1996, and only about one half of these children were from the traditional welfare families (Selden, Banthin, and Cohen 1998)[3]. These expansions of Medicaid eligibility for children outside the traditional welfare population raises the issue of how these newly eligible families respond to policy changes in terms of Medicaid participation and how does it affect their coverage by private insurance (crowding out). For both of these issues it seems especially important to allow the reaction to differ across demographic groups since over time the policy change is making higher income families eligible. In this paper we focus on the participation in Medicaid issue, but our approach is equally applicable to crowding out, and we will consider crowding out in a future draft of the paper.

In the last decade a number of studies have examined these questions. All of those studies used the form or timing of the expansions, and the fact that some groups were affected by the policy changes while others were not, to disentangle the effects of Medicaid expansions on the health insurance coverage of individuals. Although the identification strategies of the previous papers are similar in this very fundamental aspect, the methods used and the estimates obtained differ considerably. Some of the most important studies in this

[3] In this paper, we focus on the insurance coverage of the children while excluding from that of pregnant women.

literature treat Medicaid eligibility as endogenous in an instrumental variable procedure where the instrument varies only due to the legislative amendments over the sample period[4]. They then use linear probability models to compute the parameters of interest. Although this method is simple and coefficients obtained are easy to interpret, it suffers from the problems we discussed above[5].

In this paper we revisit the issues of Medicaid participation in response to the eligibility expansions that took place during the corresponding time period. We extend the previous literature by using a more flexible, and theoretically appropriate, switching probit model. This model allows us to estimate average participation rates for different demographic sub-groups. It also allows us to estimate the effect of a Medicaid expansion on program participation. We use model specifications similar to what researchers used in the previous literature to make our take-up estimates comparable to theirs.

According to our results the average take-up rate is 0.20. However, for one and two earner families this falls to .118 – this is a group most likely to be affected by the expansions and thus corresponds to the IV estimates from the linear probability model. We estimate the take-up response of the general population to a plausible Medicaid expansion at about 20 percent, but this response varies across demographic groups dramatically. For example, minorities respond about 60 percent stronger to the expansion than whites. Furthermore, female-headed families respond twice as strongly as male-headed and two-parent families. There is also significant variation in response if we separate families according to the number of earners in the household: it changes from 0.0627 for families with more than two earners to 0.5397 for families with no earner in the household.

The plan of the paper is as follows. In the next section we explain how one can apply switching probit model into the social program participation context. We then show how it can be used to estimate average take-up rates for different groups. Finally, we use predicted probabilities of eligibility, and of eligibility and participation, to estimate the response to an expansion in the coverage of the program. In Section 3 we provide some background

[4] We will discuss this instrument in more detail in section 3.3.

[5] Others make use of a direct control group, which is comprised of a group of people assumed to be unaffected by eligibility expansions, and comparing health insurance trends of this group with the targeted population. While being a clever approach, this approach is very sensitive to the comparison group chosen, and the demographic groups that have been used in the literature are hard to justify as a proper control group.

information about the social program of interest in this study, namely Medicaid, and previous studies that estimate the take-up response attributable to eligibility expansions. After discussing our data briefly in Section 4, we present our results in section 5. Section 6 concludes our paper.

2. Methods

2.1. Estimation Strategy

2.1.a Standard Approach

The standard evaluation of a policy change in this literature estimates a 'linear probability model' version of the following econometric model. The index function for participation is given by

$$Part_i^* = X_i\beta + \gamma elig_i + u_i, \tag{1}$$

where X_i is a vector of demographic variables, $elig_i$ is a dummy variable coded 1 if an individual is eligible for a program and zero otherwise and u_i is an error term. An individual participates ($part_i = 1$) if $Part_i^* > 0$. The index function for eligibility is given by

$$Elig_i^* = Z_i\delta + e_i, \tag{2}$$

where $Z_i = (X_i, z_i)$ and z_i is a variable that affects eligibility but not participation conditional on eligibility. An individual is eligible ($elig_i = 1$) if $Elig_i^* > 0$. Given the literature on limited dependent variables, it is standard to assume (u_i, e_i) are iid N(0,V).

This model has the problem that the probability of participation conditional on not being eligible for a ***randomly chosen*** individual[6] is

$$\Pr(part_i = 1 | elig_i = 0) = \Phi(X_i\beta) > 0. \quad (3)$$

Secondly, in this model, the change in participation due to moving from ineligible population to eligible population for a ***randomly chosen*** individual is given by

$$\Pr(part_i = 1 | elig_i = 1) - \Pr(part_i = 1 | elig_i = 0) = \Phi(X_i\beta + \gamma) - \Phi(X_i\beta) \ . \quad (4)$$

Since the linear probability model linearizes (4) for every individual, the change in the probability of participating from becoming eligible is a constant equal to γ.

Before concluding this section, we note an important problem with the bivariate probit version of the standard model. The log likelihood for this model is

$$L = \sum_{i=1}^{N} \log \Phi_2(q_{1i}(X_i\beta + \gamma elig_i), q_{2i}Z_i\delta, q_{i1}q_{i2}\rho) \ , \quad (5)$$

where $\Phi_2(.,.)$ is the cumulative bivariate normal distribution function, $q_{1i} = 2part_i - 1$ and $q_{2i} = 2elig_i - 1$. If there are no misclassification errors, i.e. there is no one classified as ineligible who is seen to participate, this likelihood is maximized by letting the constant in the participation equation go to a large negative number approaching minus infinity and letting the coefficient on eligibility go to minus this large negative number plus a constant. In other words, the likelihood function for simultaneous equation probit model is unbounded if there is no misclassification. We find this to be a troubling aspect of the standard bivariate probit model. While this problem does not arise in the linear probability model, it does make the

[6] This is to be compared with the conditional probability of a person who is actually ineligible which equals $\Pr(part_i = 1 | elig_i = 0) = \frac{\Phi_2(X_i\beta, -Z_i\delta, -\rho)}{\Phi_1(-Z_i\delta)}$.

interpretation of the linear probability model as an approximation to the bivariate probit model quite problematic.

2.1.b An Alternative Approach

To avoid these problems we use a switching model[7]. The index function for eligibility is still

$$Elig_i^* = Z_i\delta + e_i \tag{2)'$$

and $elig_i = 1$ if $Elig_i^* > 0$. However we specify that the probability of participation given noneligibility is zero. Further, for ***a randomly chosen*** individual, the index function for participation given eligibility is given by

$$Part_i^* = X_i\mu + \varepsilon_i, \tag{6}$$

where $(\varepsilon_i, e_i) \sim iidN(0,\tilde{V})$ and $\tilde{V} = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$.

This is a switching model, e.g. Quandt (1958), (1960), and (1972), Heckman (1979), which has been applied in the bivariate probit case by van de Ven and van Praag (1981). The appropriate log likelihood is

$$\begin{aligned} L = &\sum\nolimits_{Elig=1,Part=1} \log\Phi_2(X_i\mu, Z_i\delta, \tilde{\rho}) \\ &+ \sum\nolimits_{Elig=1,Part=0} \log\Phi_2(-X_i\mu, Z_i\delta, -\tilde{\rho}) \qquad (7) \\ &- \sum\nolimits_{Elig=0} \log\Phi_1(-Z_i\delta), \end{aligned}$$

where $\Phi_2(.,.)$ is the cumulative bivariate normal distribution function and $\Phi_1(.)$ is the standard cumulative normal distribution function.

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[7] This is also referred to as the bivariate probit model with sample selection in the literature.

2.2 Calculating Average Take-up Rates

For the entire sample, we define the average take up rate as

$$ATR = \frac{1}{N}\sum_{1=1}^{N} \hat{P}_i^{TU} \ \ where\ \hat{P}_i^{TU} = 1 - \Phi_1(-X_i\hat{\mu})\ . \tag{8}$$

That is we simply predict the participation for each (randomly chosen) person with characteristics X_i from the estimates for (6) and then take the average over the whole sample. We can also calculate this average take-up rate for different groups. For example, Cutler and Gruber (1995) and Ham and Shore-Sheppard (2005) estimate this average take-up rate for Medicaid for people who became eligible during the Medicaid expansions. To mimic them, we calculate the average take-up rate for one and two earner families. However, using our approach one can calculate the average take-up rate for many other groups.

2.3. Calculating the Take-up Response to a Policy Change

The strategy we follow in calculating the take-up responses of individuals exploits the exogenous variation of instrument due to legislative changes in the sample period. First, we calculate, for the program rules in effect during our sample period, the joint probability of being eligible and participating in our sample and take the sample averages. Second, we calculate the marginal probability of being eligible for each observation and take averages. Third, we recalculate our policy instrument (described below) by increasing it 10% for each observation in our sample. Fourth, we repeat steps one and two above while holding regression variables other than our policy instrument constant. The ratio of (i) the change in average joint probability of being eligible and participating to (ii) the change in average probability of being eligible gives our parameter of interest. We now we explain our strategy in more detail.

2.3.a Current Policy Estimates

Define $(\hat{\mu}, \hat{\delta}, \hat{\rho})$ are the estimated parameters, and that $X_i\hat{\mu}$ and $Z_i\hat{\delta}$ are estimated participation and eligibility index functions, respectively, for the (counterfactual) current policy. The sample average of the predicted joint probability of being eligible and participating is given by

$$P_1 = \frac{1}{N}\sum_{i=1}^{N}\Phi_2(X_i\hat{\mu}, Z_i\hat{\delta}, \hat{\rho})\,. \tag{9}$$

Furthermore, the sample average of the predicted marginal probability of being eligible is given by

$$E_1 = \frac{1}{N}\sum_{i=1}^{N}\Phi_1(Z_i\hat{\delta})\,. \tag{10}$$

2.3.b Eligibility and Participation under a Policy Experiment

To compute the marginal probability of eligibility, and the joint probability of eligibility and participation in our simple policy experiment, we increase our policy instrument 10% for each observation in our sample and repeat the process explained in the previous section while holding regression variables other than our policy instrument constant. These predicted probabilities then can be written as

$$P_2 = \frac{1}{N}\sum_{i=1}^{N}\Phi_2(X_i\hat{\mu}, \tilde{Z}_i\hat{\delta}, \hat{\rho}) \tag{11}$$

and

$$E_2 = \frac{1}{N}\sum_{i=1}^{N}\Phi_1(\tilde{Z}_i\hat{\delta})\,, \tag{12}$$

where $\tilde{Z}$ denotes the explanatory variables when the Medicaid variables have been set to their actual (non-counterfactual) values.

2.3.c The Effect of a Policy Change

Since we are interested in the participation behavior of the individuals who change their eligibility status due to variation in the legislation environment towards Medicaid our estimation of the take-up rate response will be

$$\Delta Tu = \frac{P_1 - P_2}{E_1 - E_2}. \qquad (13)$$

To compute the participation responses of different demographic groups (for example, according to race, education, family structure etc.), we simply repeat the process for each group that we are interested in.[8]

3. Medicaid Expansions and Previous Literature

3.1. Background

Medicaid was first established as a public health insurance program for welfare recipients and low-income aged and disabled individuals. Since its creation by the Social Security Amendments of 1965, however, it has been transformed to be an important in-kind transfer for the most of the low-income families regardless of welfare status, disability status and age[9]. Although this transformation had begun before the late 1980's by allowing states to expand their eligibility criterions over the traditional Medicaid population (with state options such as Ribicoff Option, AFDC-UP and Medically Needy Programs), the Omnibus Budget Reconciliation Acts (OBRAs) of 1986 and 1987 caused more radical changes. These allowed states to cover pregnant women and infants with family income up to 185 percent of the poverty threshold, and young children up to 100 percent of the poverty threshold, independent of family structure. Further, federally mandated expansions followed with OBRA's of 1989 and 1990. By 1992, states were required to cover all pregnant women and children aged 6 or younger with family income up to 133 percent of the poverty line and given the option to

[8] We can use simple delta method to calculate the standard errors for our parameters of interest. For details, see Appendix 2. This can be done in STATA.

[9] See Gruber (2000) for an excellent review of Medicaid's historical evolution.

increase their eligibility threshold up to 185 percent of the poverty line. Furthermore, states were also required to cover all children born after September 30, 1983 with family income up to 100 percent of the poverty limit. Hence, the link between Medicaid eligibility and AFDC eligibility greatly diminished for young children and pregnant women in low-income families. In this paper, we exclusively focus on the Medicaid coverage of children since previous studies have found that participation response of the pregnant women is not statistically significant (see, for example, Cutler and Gruber, 1996).

Before the expansions in the Medicaid program, families who were enrolled for cash receipt (welfare) were also automatically enrolled for Medicaid. With expansions weakening the link between two programs in late 1980s and early 1990s, among the 30 percent of kids aged between 0 and18 who were eligible for Medicaid in 1996, only about one half were coming from the traditional welfare families (Selden, Banthin, and Cohen 1998). This remarkable separation of two eligibility criterions raises an important policy question: To what extend did eligibility lead to public health insurance coverage for targeted population of children? In the next section we will look at previous studies, which investigate this question.

3.2. Previous Literature on the Expansions and Their Impact on Medicaid Coverage

In the last decade, substantial amount of information have accumulated on the impact of Medicaid eligibility expansions on both public and private insurance coverage of targeted population. Since our concern is take-up response of Medicaid rather than crowding out, we will focus on the estimates of take-up while visiting the previous studies[10]. An important study was Cutler and Gruber’s (1996) seminal paper. In this paper the authors use an instrumental variables (IV) approach and treated eligibility as endogenous. The latter is likely to be true since parental wages, which in turn determine the eligibility, are likely to be correlated with benefits, and benefits are unobserved and thus part of the error term for the reasons discussed below. To overcome this problem they make use of an instrument that only varies with legislative environment towards Medicaid to identify their models. Using March Current Population Survey (CPS) data on children from 1988 to 1993, they use two-stage least squares to estimate the effect of imputed Medicaid eligibility on insurance status,

[10] As noted above we will use our approach to measure crowding out in future drafts.

controlling for demographics and state and year effects.[11] They estimate that a ten percentage-point in Medicaid eligibility increased Medicaid coverage by 2.35 percent, implying an average take-up rate of 23.5 percent for those affected by the expansions.

Shore-Sheppard (2000) regresses the change in Medicaid coverage rate on the change in eligibility rates aggregating the individual data to the region income cells using CPS data from 1988, 1989, 1994, and 1995 and treating eligibility as endogenous. To attempt to control for the possibility that shocks to coverage may be correlated with expansions, she uses single men ages 20-45 as a comparison group. Her estimates of the average take-up rates for those affected by the expansions are 0.281 when single men are not included in the analysis as direct comparison group and 0.237 when this control group is included.

Ham and Shore-Sheppard (2003) use data from Survey of Income and Program Participation (SIPP) covering the period from October 1985 to August 1995 to replicate Cutler and Gruber (1996) analysis and found smaller average take-up rate of 0.118 for those affected by the expansions. They attributed some of the differences in their results to different samples and recall periods in the data sets used. Ham and Shore-Sheppard also extend the literature in the several directions; by examining whether having eligible siblings affects the probability a child is enrolled in Medicaid; by examining the effect of time spent as eligible on the taking-up Medicaid; and by estimating a simple dynamic model of insurance choice. According to their estimates, children with a larger fraction of their siblings eligible are more likely to be enrolled, but the increase in the estimated take-up is small. Furthermore, they also found that children are more likely to be enrolled after having spent some time eligible. Finally, when they account for dynamics, they find that the estimated long-run impact of eligibility on take-up that is larger than the effect estimated from the static model, while the short run impact of expanded Medicaid eligibility is smaller.

3.3. The Endogeneity of Medicaid Eligibility and Creating the Policy Instrument

As some of previous studies note[12], the Medicaid eligibility is likely to be endogenous. There are several reasons for that. First of all, unobservables affecting eligibility are likely to be correlated with unobservable individual and family characteristics that determine take-up.

[11] We will explain their instrument in detail when we discuss our estimation strategy.

Second, eligibility may proxy family income if income, which is also likely to be endogenous, is not included as an independent variable.

As a solution to the problematic nature of the eligibility variable, Cutler and Gruber (1996) suggested an instrument that is correlated with individual eligibility for Medicaid, but not otherwise correlated with the demand for insurance. They create this instrument, which is essentially an index of the expansiveness of Medicaid eligibility for each age group in each state and year, by nationally selecting a random sample of 300 children of each age from CPS, imputing the eligibility to this sample according to rules in each state, and finally calculating the fraction of eligible kids in each state-year-age group.[13] By its nature, the instrument, therefore, varies only with the legislative environment towards Medicaid for that state-year-age group and is not correlated with the demand for insurance.[14]

Ham and Shore-Sheppard (2003) slightly modified this instrument in their study. They use all sample observations of children of a given age in a SIPP wave except for those from the state for which the instrument (FRACELIG) is calculated. By using a larger sample, they created an instrument, which is theoretically superior to the version using random sample[15]. This instrument is also independent of any family characteristics and only depends on the age of a child, state of residence and time. We follow their strategy to calculate the (Cutler-Gruber) policy instrument and use exogenous changes in state rules, time and age-eligibility to identify the model.

4. Data

In this paper we use data from the Survey of Income and Program Participation (SIPP). SIPP is a nationally representative longitudinal household survey, which is specifically designed to collect detailed income and program participation information of randomly chosen individuals from the U.S population. It has a tri-annual feature such that recall period between each interview is four months for every individual. For the time period covered in this paper (from October 1985 to August 1995), the length of the panels varies

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[12] See Currie and Gruber (1996a, 1996b), Cutler and Gruber (1996), Shore-Sheppard (1997, 2000), and Ham and Shore-Sheppard (2003).

[13] Their methodology follows Currie and Gruber (1996a, 1996b)

[14] Of course it is true under the assumption that changes in a state's Medicaid eligibility standards are not correlated with changes in the availability of private insurance or changes in a state's macroeconomic conditions.

from 24 months for the 1988 panel to 40 months for the 1992 panel[16]. Although the sample universe is the entire U.S, the Census Bureau does not separately identify state of residence for residents of nine low population states. Since state of residence information is critical for us to impute Medicaid eligibility, we had to drop all of the individuals whose state of residence information is not identified. We also restrict our sample to children living in original households who are younger than 16 years old at the first time they are observed. Furthermore, we drop children who are observed only once, children who leave the sample and then return and children who move between states during the sample period for comparability with earlier studies. (In total, these observations constitute less than 8 percent of the sample.)

Although the four-month period increases the probability of accurate reporting, particularly relative to the fifteen-month recall period of the March Current Population Survey,[17] the SIPP suffers from the problem of "seam bias". Census Bureau researchers have shown that there are a disproportionate number of transitions between the last month of the wave and the first month of the next wave (see, e.g., Young 1989, Marquis and Moore 1990). Because of this seam bias problem, we estimate our models using only the fourth month of the each wave, dropping the first three months. While this approach has the disadvantage of that information on the timing of transitions reported to occur between months other than at the seam is lost, the advantage is that the data in the fourth month of each wave are the most likely to be accurate since it is closest to the time of interview.

We impute eligibility in four steps. First, we construct the family unit relevant for Medicaid program participation and determine family income. Second, we assign family-specific poverty thresholds based on the size of the family and the year. Since Medicaid eligibility results from AFDC eligibility, we then use information on the family income and family structure, along with the AFDC parameters in effect in the state and year, to impute

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[15] While their measure is to be preferred in theory, in practice Ham and Shore-Sheppard found that the instrument values are not affected significantly with this changes in the calculation.

[16] In total we used 7 panels from 1986 to 1993. The 1989 panel is not used because it was ended after only three waves.

[17] Bennefield (1996) finds that health insurance coverage in the early 1990s is measured more accurately in the SIPP than in the CPS, due in part to the shorter recall period.

eligibility for AFDC.[18] Finally, we assign Medicaid eligibility if any of the following conditions hold: the child is in an AFDC-eligible family; the child is income eligible for AFDC and either lives in a state with a " Ribicoff program" or lives in a state with an AFDC-UP program and has an unemployed parent; or the child's family income as a percent of the relevant poverty line is below the Medicaid expansion income eligibility cutoff in effect for that age child in his or her state of residence at that time.

In Table 1 we present the sample means for the variables used in our regressions.[19] The insurance variables are private insurance and Medicaid, where we define private coverage to include CHAMPUS (military) coverage. A child may report both private and public coverage, although this is relatively uncommon (only 1.8 percent of the total months). Consistent with national trends, Medicaid coverage of eligible is higher in our sample in later panels. Furthermore, starting with the 1990 panel, which covers the period of 1990-1992, there is a significant increase in our policy instrument (FRACELIG) capturing eligibility expansions at the federal level occurring during this time period. In addition to the variables in the Table 1, we also use state, year and age dummies for each child in our index functions to control for the possible state-specific, age-specific and year-specific unobservables that could influence participating in Medicaid. Finally, since we use longitudinal data, we cluster the standard errors to control for dependency between person-specific observations.

5. Results

5.1 Parameter Estimates

Table 2 shows our parameter estimates for the switching probit model. Since these are probit coefficients, their values do not directly have a meaningful interpretation as those produced by a linear probability model.[20] By looking at their signs, however, one can obtain

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[18] Families must pass two income tests to receive AFDC, the "gross test", which requires that a family's gross income be less than 1.85 times the state's need standard, and the "net test", which requires that a family's income after disregards be less than the state's payment standard. In determining AFDC eligibility, families are permitted to disregard actual childcare expenses up to a maximum. Since we do not know actual child care expenses, we assume that families can deduct the full disregard for all children under age 6, and no disregards for older children. This assumption overstates the amount of the disregard for families that use informal or low cost care.

[19] These sample means have not been weighted, so they should not be considered to be representative of the nation.

[20] In future drafts we will show the effect of the independent variable on the probability of the respective event occurring to obtain measures that are directly interpretable.

some important information about the participation behavior of children. According to our estimates, white children are both less likely to be eligible for and participate Medicaid compare to minorities. This result is expected since, on average, white children come from more affluent families and the percentage of them who have dependent coverage through their parents' employment health insurance is higher in our sample for all years. Further, families with a female head or with no earners are more likely to be eligible for, and to participate in, Medicaid compared to other demographic groups. Finally, education and the age of family head, as well as the size of the health insurance unit, negatively affect both Medicaid eligibility and participation. An important difference between the switching model and previous work is that we allow demographic to affect the change in take-up rate. To test the assumption that take-up rate is constant across groups, we test the null hypothesis $H_0 : \tilde{\mu} = 0$ against $H_1 : \tilde{\mu} \neq 0$ where $\tilde{\mu}$ is the vector of coefficients for all variables except the constant in the participation equation (6). We reject this null hypothesis at the 1 percent significance level.

5.2 Calculating Average Take-up Rates

We calculate the average take-up rate for the entire sample and different demographic groups. For example, the average for the sample is 0.20, while the average rate for minority families is 0.39 and the average rate for white families is 0.16.[21] The average rates for zero earner, one earner, two earner, and more than two earner families are 0.72, 0.17, 0.06, and 0.02 respectively.

We argue that our approach is flexible enough to mimic the results of previous studies based on the linear probability model. Ham and Shore-Sheppard (2003) estimate the take-up response of newly eligible families due to eligibility expansions of late 1980s and early 1990s as 0.118 from the same data that we use. Since the newly eligible families were the ones without any kind of automatic participation through welfare, this number can be taken as the take-up rate of the non-welfare families who became eligible due to policy expansions separating Medicaid eligibility from welfare eligibility. These are individuals can be approximated by (i) the two-parent families or male-headed families and (ii) families with one

[21] In future drafts we will use the delta method to calculate standard errors for the average take-up rate.

or two earners. For the families with one or two earners, the average unconditional probability of participation is about 0.118, which is exactly the Ham and Shore-Sheppard's estimate. For the two-parent or male-headed families, the corresponding probability is 0.104, which is smaller than, but not far from, Ham and Shore-Sheppard's estimate. Thus our approach can mimic previous results and provide average take-up rates for other groups.

5.3 Results from a Policy Experiment

In this section we calculate the response of different groups to a 10% increase in FRACELIG for each person using (13) for the whole population as well as of different demographic groups in the Table 3. Column (1) demonstrates the eligibility rates for each group before the policy experiment, i.e. given the actual rules. Column (2) shows the eligibility rates after the policy experiment. Column (3) represents the average joint probability of participation and eligibility before the experiment, while column (4) shows the rate after the policy experiment. Column five shows our estimated take-up response for the aggregate population, as well as for different demographic groups, when we change our policy instrument, i.e. raise FRACELIG by 10%. We compute different take-up responses according to race, education, number of earners in the family, and family structure.

Our take-up response to the policy changes is 0.1970 for the general population. This means that 10 percentage point increase in the total number of eligible children leads to about 2 percentage point in the total number of the covered kids. When we calculate change in take-up for different groups, we find important variations among them. For example, while we compute the take-up response for whites as 0.1743, it is 0.2977 for minorities, implying about a 70 percent higher take-up response for minorities. The take-up responses according to family structure are 0.1393 for two-parent families and 0.3987 for female-headed families. Furthermore, when we calculate take-up responses according to the number of earners in the family, we obtain values varying between 0.0641 for the families with more than two earners and 0.5378 for families with no earners. Finally, we found that take-up response is is 0.2618 for family heads who are high school dropouts, 0.2085 for high school graduates and 0.1868 for family heads with some college education.

There are several possible reasons for this variation in take-up response. One reason is the difference in private health insurance coverage of children coming from different demographic groups. In our estimates, children of families who are from groups that are less likely to have a private coverage through employment have higher take-up rates as expected[22]. Another reason for different take-up rates might be that participation cost might be different for different demographic groups. Although there is no monetary cost of participating Medicaid it is possible that, other costs might outweigh the benefits of enrolling their kids for the public health insurance coverage. One of the costs suggested in the literature is the cost of stigma (Moffitt 1983). The idea is that stigma associated with transfer programs can create an additional cost for individuals preventing them to participate even if they are eligible for a program. While being reasonable in theoretical grounds, in practice, Stuber et al (2000) found that stigma measures they used were insignificantly related to take-up of Medicaid. Another cost is associated with difficulty of administrative procedures (such as filling up lengthy forms answering extensive questions about personal history etc.)[23]. Stuber et al (2000) actually obtained some empirical evidence for this cost. According to their estimates, those who perceived the applications as long and complicated were 1.8 times less likely to take-up Medicaid and those who felt that application hours were inconvenient were 1.7 times less likely. Finally, varying take-up responses might be the result of possible informational asymmetries between different demographic groups about their Medicaid eligibility status. For example, if familiarity with eligibility rules differs between whites and minorities (maybe due to living in different neighborhood environment or differing in familiarity with other means-tested transfer programs) this could lead to variation in take-up rates between them.

6. Conclusions

In this paper we suggest a flexible methodology to estimate (i) the average take-up rate and (ii) the take-up response of a social program attributable to a policy change in eligibility. Our approach allows demographics to play a much bigger role in take-up rates and responses. It does not suffer from the criticisms directed to previous studies that use linear probability model such as the problems of positive participation probabilities for ineligible individuals and of the possibility for participation probabilities of individuals lying outside the unit interval.

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[22] See Table 1A in Appendix 1.

Using data from Medicaid and exploiting the exogenous policy changes that took place in late 1980's and early 1990's, we estimate average take-up rates and the take-up response of different demographic groups according to race, family structure, education and number of earners in the family. Our results suggest that there are significant variations across different demographic groups in taking-up Medicaid and responding to policy changes. For example, Minorities have a 70 per cent higher response to out policy change. Moreover, the take-up responses across family structures range from 0.1393 for two parent families to 0.3987 for female-headed families. Further, when we calculate take-up responses according to the number of earners in the family, we obtain values varying between 0.0641 for the families with more than two earners and 0.5378 for families with no earners.

[23] See Craig (1991) for an extensive review of literature about economic and psychological costs related to the participation of social programs

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Table 1- The Means of Variables Used in Estimation

	1986	1987	1988	1990	1991	1992	1993
Medicaid	0.1195	0.1158	0.1138	0.1619	0.1669	0.1810	0.2001
Private Insurance	0.7330	0.7522	0.7490	0.7098	0.7255	0.7101	0.6943
Imputed Eligibility	0.1871	0.1755	0.1792	0.2757	0.2953	0.3125	0.3341
Size of HIU	4.2196	4.1603	4.1827	4.1586	4.2161	4.1722	4.2207
White	0.8280	0.8301	0.8248	0.7817	0.8152	0.8047	0.8109
Male	0.5084	0.5154	0.5090	0.5120	0.5129	0.5201	0.5148
Two Parents	0.7585	0.7678	0.7677	0.7104	0.7439	0.7277	0.7335
Male Head Only	0.0220	0.0234	0.0186	0.0267	0.0289	0.0262	0.0212
No Earners	0.1402	0.1310	0.1235	0.1593	0.1539	0.1561	0.1619
One Earner	0.4109	0.4163	0.4188	0.4234	0.4204	0.4132	0.4065
Two Earners	0.3819	0.3901	0.3991	0.3677	0.3774	0.3816	0.3844
Age of Highest Earner	36.5616	36.5630	36.5754	36.7479	36.9833	36.9764	37.1813
Education of Highest Earner	12.6777	12.6933	12.8479	12.7389	12.9187	12.9542	12.9497
FRACELIG	0.1959	0.1861	0.1921	0.2823	0.3022	0.3208	0.3375
Years Covered	86-88	87-89	88-89	90-92	91-93	92-95	93-95
Number of Observations	44016	45691	40895	99446	66991	108572	101967

Table 2- Switching Probit Estimates for Medicaid Eligibility and Participation

	Participation	Eligibility
Size of Household	0.1508	0.2739
	(0.0063)	(0.0049)
White	-0.3378	-0.2837
	(0.0185)	(0.0133)
Male	0.0055	-0.0145
	(0.0153)	(0.0104)
Two parents	-0.8578	-0.8488
	(0.0212)	(0.0156)
Male head only	-0.7628	-0.2355
	(0.0443)	(0.0293)
No earners	1.9092	2.4210
	(0.0689)	(0.0321)
One earner	0.7761	0.9698
	(0.0650)	(0.0289)
Two earners	0.4208	0.1173
	(0.0639)	(0.0285)
Higher earner's age	-0.0176	-0.0320
	(0.0011)	(0.0008)
Higher earner's education	-0.0739	-0.1474
	(0.0033)	(0.0020)
FRACELIG	-	0.4661
		(0.0060)

Notes: All regressions include year, age, and state dummies. Standard errors have been corrected for repeated observations within individuals.

Table 3- Predicted Probabilities and the Response to the Policy Change[24]

	$\Pr(Elig^*_{BPE} > 0)$	$\Pr(Elig^*_{APE} > 0)$	$\Pr(Elig^*_{BPE} > 0, Part^*_{BPE} > 0)$	$\Pr(Elig^*_{APE} > 0, Part^*_{APE} > 0)$	Take-up Response[25]
All population	0.2733	0.2985	0.1395	0.1445	0.1970
	(0.0024)	(0.0024)	(0.0014)	(0.0015)	(****)
Race					
White	0.2298	0.2552	0.1007	0.1052	0.1743
	(0.0020)	(0.0021)	(0.0013)	(0.0015)	(****)
Non-White	0.4573	0.4815	0.3036	0.3108	0.2977
	(0.0063)	(0.0066)	(0.0025)	(0.0027)	(****)
Education					
High School Drop-out	0.5436	0.5669	0.3364	0.3425	0.2618
	(0.0068)	(0.0071)	(0.0024)	(0.0026)	(****)
High School Graduate	0.2891	0.3174	0.1395	0.1454	0.2085
	(0.0023)	(0.0024)	(0.0017)	(0.0018)	(****)
Some College	0.2073	0.2346	0.0886	0.0937	0.1868
	(0.0016)	(0.0018)	(0.0014)	(0.0016)	(****)
Family Structure					
Female Head	0.5914	0. 6147	0.4181	0.4274	0.3987
	(0.0075)	(0.0079)	(0.0029)	(0.0031)	(****)
Male Head	0.3182	0.3459	0.1032	0.1074	0.1514
	(0.0089)	(0.0096)	(0.0046)	(0.0049)	(****)
Two parents	0.1689	0.1946	0.0506	0.0542	0.1393
	(0.0014)	(0.0079)	(0.0011)	(0.0013)	(****)
Number of Earners					
No earner	0.8338	0.8530	0.6483	0.6566	0.5378
	(0.0124)	(0.0128)	(0.0033)	(0.0033)	(****)
One earner	0.2836	0.3197	0.0879	0.0948	0.1908
	(0.0021)	(0.0023)	(0.0021)	(0.0023)	(****)
Two earners	0.0700	0.0894	0.0122	0.0144	0.0954
	(0.0007)	(0.0009)	(0.0006)	(0.0008)	(****)
More than two earners	0.0402	0.0488	0.0049	0.0055	0.0641
	(0.0011)	(0.0018)	(0.0005)	(0.0006)	(****)

[24] BPE and APE in the subscripts stand for before policy expansion and after policy expansion respectively.
[25] Standard errors available next draft.

Appendix 1

Table 1A- Probit Estimates of Children's Private Health Insurance Coverage

	Private Health Insurance Coverage
Size of Household	-0.1246
	(0.0043)
White	0.2939
	(0.0129)
Male	0.0076
	(0.0101)
Two parents	0.4951
	(0.0142)
Male head only	0.1937
	(0.0289)
No earners	-1.8258
	(0.0253)
One earner	-0.6102
	(0.0227)
Two earners	-0.1522
	(0.0218)
Higher earner's age	0.0162
	(0.0008)
Higher earner's education	0.1566
	(0.0020)

Notes: All regressions include year, age, and state dummies. Standard errors have been corrected for repeated observations within individuals.

Appendix 2

Calculating standard errors for average probabilities and the change in take-up rate is straightforward using the delta method. For example, we can calculate the variance for average joint probability of participation and eligibility, which is a bivariate cumulative distribution function, as follows.

The bivariate normal cumulative distribution function can be written as

$$\Phi_2(\beta x_{1i}, \gamma x_{2i}, \rho) = \int_{-\infty}^{\beta x_{1i}} \int_{-\infty}^{\gamma x_{2i}} \phi_2(\varepsilon_{1i}, \varepsilon_{2i}, \rho) d\varepsilon_{2i} d\varepsilon_{1i}$$

where $\phi_2(.,.,.)$ is bivariate normal density function, x_{1i} is the vector of variables in the first equation and x_{2i} is the vector of variables in the second equation , and β and γ are the vectors of coefficients in the first and second equation respectively.

Our parameter of interest, for which we are supposed to calculate the variance, is

$$g(\theta) = \frac{1}{N}\sum_{i=1}^{N} \Phi_2(\beta x_{1i}, \gamma x_{2i}, \rho)$$

Then, variance for $g(\theta)$ can be written as follows

$$\operatorname{var} g(\theta) = \begin{bmatrix} \frac{1}{N}\sum_{i=1}^{N}\frac{\partial \Phi_2}{\partial \beta} & \frac{1}{N}\sum_{i=1}^{N}\frac{\partial \Phi_2}{\partial \gamma} & \frac{1}{N}\sum_{i=1}^{N}\frac{\partial \Phi_2}{\partial \rho} \end{bmatrix} \begin{bmatrix} \operatorname{var}(\beta) & \operatorname{cov}(\beta,\gamma) & \operatorname{cov}(\beta,\rho) \\ \operatorname{cov}(\beta,\gamma) & \operatorname{var}(\gamma) & \operatorname{cov}(\gamma,\rho) \\ \operatorname{cov}(\beta,\rho) & \operatorname{cov}(\gamma,\rho) & \operatorname{var}(\rho) \end{bmatrix} \begin{bmatrix} \frac{1}{N}\sum_{i=1}^{N}\frac{\partial \Phi_2}{\partial \beta} \\ \frac{1}{N}\sum_{i=1}^{N}\frac{\partial \Phi_2}{\partial \gamma} \\ \frac{1}{N}\sum_{i=1}^{N}\frac{\partial \Phi_2}{\partial \rho} \end{bmatrix}$$

By using same method, we can also calculate the variances for other parameters of interest we report on the Table 3.