Information and Participation in Social Programs

David Coady, César Martinelli and Susan W. Parker*

May 2010

Abstract

Participation in social programs, like that in clubs and other social organizations, is the result of a process in which an agent first learns about the requirements, benefits, and the likelihood of acceptance, applies for membership, and finally is accepted or rejected. We propose a model of this participation process, and analyze empirically the process using data from a social program in Mexico. Our analysis shows that decisions at each stage of the process are responsive to expectations about the decisions and outcomes at the following stages, and that knowledge about the program has a large impact on participation outcomes. *JEL* I38, D83

Keywords: program participation process, take up, information acquisition, targeting, undercoverage, leakage

*Coady: International Monetary Fund, 700 19th Street NW, Washington, DC 20431 <dcoady@imf.org>. Martinelli: CIE-ITAM, Camino Santa Teresa 930, 10700 Mexico DF, Mexico <martinel@itam.mx>. Parker: CIDE, Carretera Mexico-Toluca No. 3655, 01210 Mexico DF, Mexico <susan.parker@cide.edu>. We acknowledge financing from the Instituto Nacional de Salud's (INSP) ongoing evaluation of *Oportunidades* and from Asociación Mexicana de Cultura, A.C. We thank Harold Alderman, Carola Alvarez, Jean-Yves Duclos, Paul Gertler, Mauricio Hernandez, John Maluccio, Ferdinando Regalia and several seminar audiences for comments and discussion. We also thank Iliana Yaschine, Bernardo Hernandez and Citlalli Hernandez for helpful clarifications. The authors alone are responsible for any remaining errors.

1 Introduction

Social programs around the world often rely on the voluntary participation of those deemed deserving. Available evidence, however, shows an enormous variation in the "take-up" rate, i.e. the rate of participation by eligible individuals in social programs.[1] As a result, participation in such programs has attracted a good deal of attention from the economics literature since the early work by Ashenfelter (1983), Moffitt (1983), and Blundell, Fry and Walker (1988).

Most of the literature on participation focuses on the impact of application costs, and psychological costs related to stigma, on participation outcomes for eligible individuals. Heckman and Smith (2004), henceforth denoted HS, have broadened the scope of this literature by considering participation in social programs as the outcome of a sequential process. They propose a statistical decomposition of the impact of different variables on the stages of this process, including awareness, application, acceptance, and enrollment, and apply this framework to analyze participation into JTPA, a job training program in the US.

In this paper, we present a decision-theoretic model of participation in social programs that recognizes this sequential nature of the participation process, and analyze empirically the participation process in a conditional cash transfer program in Mexico. In our model, the first stage of the participation process corresponds to the agent's decision to invest some time and effort in learning about how to apply to the program, given the agent's prior expectations about benefits from the program and the likelihood of being accepted. The second stage corresponds to the agent's decision to apply to the program, having learned in the previous stage the cost of application, and given the agent's expectations about benefits from the program and the likelihood of being accepted. The third stage corresponds to the decision by program officers about whether or not to enroll the agent into the program.

Our model captures two key features of participation. The first is the sequential nature of the decision process: an agent needs to obtain information before actually applying, and needs to apply before being assessed for

[1] Currie (2006) reports take-up rates from below 10% to more than 90% in the US, and from below 50% to close to 100% in the UK. Remler and Glied (2003) report take-up rates of US medical assistance programs varying from 43% to 99%.

eligibility. The second key feature is the interdependence between stages: at each stage, the agent's decision is responsive to the agent's expectations about the decisions and outcomes in the following stages. In the spirit of rational expectations, we assume that the agent has unbiased beliefs about the decisions and outcomes in the following stages. This assumption ties the estimation of each stage to that of the subsequent stages.[2]

We use the model to analyze empirically the participation process in *Oportunidades,* a prominent social safety-net program in Mexico that combines means-testing with self-selection by households. The survey data we use contain detailed information on the different stages of the participation process as well as on the socioeconomic household characteristics used to determine eligibility and the level of transfers a household would receive if deemed eligible. The absence of such detailed information on the different stages of the process and on the characteristics of eligible and ineligible households has been problematic in previous work.

Unlike in HS, our data allow us to estimate separately the potential participant's decision to apply and the decision by program officials to enroll or not the applicant. Since we have detailed information on the official criteria for eligibility, we can check for enrollment mistakes, leading both to undercoverage of eligible households and to leakage to non-eligible households. Information on the benefit entitlements of participants allows us to explore the effect of expected benefits on the different stages of the participation process.

We estimate the stages of the participation process in reverse order. In particular, at the information and application stages we take into account the expected benefit for the potential participant of going into the next stage of the participation process. We also provide an alternative estimation that follows closely the methodology proposed by HS. In this alternative estimation, the same set of explanatory variables is used at every stage of the participation process, and expected benefits are omitted at the application and information acquisition stages, so coefficients reflect the net effect of costs and benefits.

[2] Lahiri et al. (2008) study disability insurance application behavior in the US in a sequential model in which individuals anticipate the eligibility probability and the expected discounted lifetime utility when applying and when not applying. They do not consider information to be a constraint for application.

We then present a statistical decomposition of the impact of different variables at the different stages of the participation process using both the HS methodology and the estimation based on our model. In both estimations, the information stage is the major source of variation in participation, accounting for more than half of the impact of almost every variable we consider. The second main source of variation in participation is enrollment, accounting for more than a quarter of the impact of most variables, with application coming as a distant third source of variation for most variables.

The estimation based on our model indicates that the stages of the participation process are indeed interdependent: whether a household becomes informed and whether it applies conditional on being informed are sensitive to the expected benefits. The marginal impact of monetary benefits on participation outcomes, however, is small. This suggests that increasing benefits will not do much for participation; this is not unreasonable since monetary benefits for participants are already quite high.

A general lesson arising from our work is that a narrow focus on application costs may not be the best approach to analyzing participation outcomes, and that indeed the enrollment stage and especially the information stage may be more important than the application stage in explaining participation outcomes in other social programs as well.[3] Another lesson, illustrated by our model, is that it is important to control for the effects of the expected benefit of going into the next stage of the participation process to make sure variation in participation due to, say, the information stage is not simply masking expectations about the application stage. Finally, our work points to the usefulness of collecting disaggregated data about the different stages of the participation process in other social programs, both in developed and in developing countries.[4]

[3] The importance of the information stage is consistent with the findings from HS and other authors working on US programs. Daponte et al. (1999), for instance, find that informing households about their eligibility and benefits increases participation in the Food Stamp program in the US. Aizer (2003, 2007) finds that outreach efforts in the form of community based application assistance and advertising campaigns improve take up of Medicaid among groups facing language barriers and immigration concerns.

[4] To our knowledge, the only previous analysis of the participation process in a developing country is by Micklewright et al. (2004), who investigate the determinants of participation of households in a social assistance program in Uzbekistan. Both the program design and data limitations prevent the authors from differentiating between the

The remainder of the paper is organized as follows. In section 2 we provide some background on our database. In section 3 we present our model of the participation process. In section 4 we describe our empirical results. In section 5 we gather some concluding remarks.

2 Evidence on Information and Participation

Oportunidades was introduced in the poorest urban localities in Mexico in 2002.[5] An advertising campaign was carried out to inform potential applicants that registration centers for the program would open during certain dates. The advertising campaign used TV and radio advertisements, flyers, posters in churches, schools, health clinics and market places, and loudspeaker announcements. Applicants who turned up at the registration centers were asked to provide information on their address and on their dwelling characteristics, such as whether the dwelling had access to running water, whether it had a dirt floor, the number of rooms in the dwelling, and household appliances and other durable goods available to the household. Eligibility into the program was determined using those characteristics and demographic information to compute a household poverty index. The weights attached to each characteristic in the household poverty index were previously determined using a poverty regression similar to those described by Ravallion (1996). The methodology was public (Reglas de Operación 2002) but not the specific weights.

Applicants initially found to be eligible received a household visit during the following weeks to verify the information given, after which a final classification on eligibility was made. Due to budget and capacity constraints at the level of program offices, offices were sometimes closed when certain quotas were reached and not every household initially found eligible was considered for a household visit. This led in all likelihood to errors of exclusion. Moreover, some households who were classified initially as eligible at

impact of fixed effects, benefit variations, and cost variations on outcomes.

[5] *Oportunidades* is a scaled-up version of the rural *Progresa* program. This program has become widely known in the economic literature because of the substantial resources devoted to its evaluation, and has been seen as a prototype for social safety-net reforms in other developing countries, especially in Latin America (see e.g. Parker, Rubalcava and Teruel 2007).

Table 1
Participation in Oportunidades by Eligibility Status[a]

Level of participation (in %)	Eligible households	Ineligible households
Did not know about the program	27.8	49.1
Knew about program but not where to apply	5.8	9.8
Knew where to apply but did not apply	5.9	9.8
Applied but not enrolled	10.0	11.5
Enrolled	50.4	19.8

[a]Observations: 10,515. Source: *ENCELURB*.

the registration center and found to be ineligible after the verification did in fact enroll in the program, leading to errors of inclusion.

Our dataset is the *ENCELURB* (Encuesta de Evaluación de los Hogares Urbanos 2002), the survey used to evaluate the performance of *Oportunidades* in urban areas. Shortly after enrollment but before beneficiary households began to receive Oportunidades transfers, a sample of residential blocks where the program operates was selected and all households in these selected blocks were visited (20,859). An initial screener survey found 4,649 Oportunidades households beneficiaries all of whom were included in the evaluation sample. Additionally, a subsample (5,776) of non beneficiary households was added to the evaluation sample. Among other information in the *ENCELURB* survey, all households were asked a series of questions relating to their knowledge, application and enrollment in the program *Oportunidades*.

The screener survey for the *ENCELURB* includes a module with questions needed to construct the household poverty index and thus the program eligibility of households in the evaluation sample.[6] Table 1 presents information on participation levels by eligible and ineligible households. Leakage (that is, participation by ineligibles as a fraction of total participation) is 28.2%, and undercoverage (that is nonparticipation by eligibles as a fraction of the eligible population) is 49.6%. Table 1 also illustrates that lack of knowledge about the program is a major barrier to participation, especially

[6]For those individuals applying to the program we have verified that this constructed index is nearly identical to the actual index from the verification visit.

Table 2
Monthly Cash Benefits of Oportunidades[a]

Grants	Nutrition grant	150		
	Education grants:	Grade	Boys	Girls
	Primary	3	100	100
		4	115	115
		5	150	150
		6	200	200
	Middle School	7	290	310
		8	310	340
		9	325	375
	High School	10	490	565
		11	525	600
		12	555	635
Maximum Transfer to Household	With High-School children	1550		
	Other households	915		
Average Transfer[b]		350		

[a]In Mexican pesos (2002); 11 pesos is approx. US$1. [b]Urban households (2003).

Table 3
Characteristics of Potential Participants[a]

	Eligible		Ineligible	
Household characteristics	Mean	Std. Dev.	Mean	Std. Dev.
Total monthly expenditure (pesos)	2314	2404	2899	3923
Per capita expenditure (pesos)	492	492	777	1317
Family size	5.19	2.20	4.23	1.79
Children from 0 to 5	0.97	0.98	0.51	0.71
Children from 6 to 11	1.27	1.13	0.68	0.84
Children from 12 to 17	0.73	0.97	0.63	0.88
Mother Characteristics	Mean	Std. Dev.	Mean	Std. Dev.
Age	36.7	13.1	38.5	13.7
Education (years)	4.03	3.20	4.91	3.40
Speaks indigenous language	0.13	0.34	0.06	0.24

[a]Observations: 9,944 eligible and 5,755 ineligible households. Source: *ENCELURB*.

for ineligible applicants.[7]

Cash benefits for participants in *Oportunidades* include a purely unconditional grant (termed "nutrition grant"), plus grants conditional on the school attendance of the children in the household, as described in Table 2. The program also includes free medical consultations and nutrition supplements. Since we can calculate the potential cash benefits a household can receive under the program, we can estimate the monetary incentive to participate for each potential applicant.

Table 3 describes average household characteristics for eligible and ineligible households. Ineligible households are better off than eligible households both in terms of total expenditure and in terms of per capita expenditure. They have smaller families, so in addition to being less likely to be enrolled into the program they have smaller benefits of participation. Benefits of participation, nonetheless, are substantial both for eligible and for ineligible households; the average monthly transfer is approximately 15% of the average monthly expenditure for eligible households and 12% for ineligible households.

3 A Model of the Participation Process

Whether or not a potential participant receives benefits from a targeted program depends on whether the participant decides to seek knowledge, apply, and is accepted. Thus, the participation outcome is the result of a "participation process" with three stages. The first two stages involve decisions by the potential participant. In each of these two stages, expectations about the next stages are crucial. Beliefs about the probability of being enrolled are important for the decision to apply, and beliefs about the likelihood of applying and getting enrolled into the program are important for the decision to seek information about the program. For this reason, we describe the participation process in reverse, starting with the probability of being enrolled for a potential participant who is already informed about the program and contemplating whether to apply.

[7] Coady and Parker (2009) study the participation rates across different socio-economic groups based on household consumption per capita.

3.1 Enrollment decisions and gains from participation

Eligibility for means-tested poverty-alleviation programs is usually determined on the basis of a score and a cutoff. In *Oportunidades*, the score is calculated using demographic information and other observable characteristics of the applicant's household, including the number of household members, the number of children below eleven in the household, an index of household overcrowding, the age and years of education of the household head, a set of dummies indicating whether the dwelling lacks a number of desirable characteristics (like a connection to running water, a paved floor, a refrigerator, etc.), and a set of regional dummies. Household h is eligible if $\gamma_e X_h \geq \rho$, where X_h is the vector for household h of the characteristics used in the score, γ_e is the vector of weights attached to these characteristics, and the cutoff ρ represents the "poverty line." In practice, enrollment is determined not only by eligibility according to program rules but also by rationing due to budget limitations at different program offices, discrimination at the program offices, and other considerations that can lead to undercoverage or leakage.

We introduce the possibility of enrollment errors by assuming that (i) the actual weights determining enrollment may be different from those set for eligibility; (ii) the variables determining enrollment may include variables other than the official criteria; and (iii) the actual cutoff for enrollment may be different from the one used for eligibility and may vary for different applicants. Here we have in mind the fact that the thresholds for different individuals reflect varying (regional specific) budget constraints and rationing. Formally, we assume that the actual cutoff for enrollment is distributed according to a logistic distribution with location parameter μ and scale parameter σ. Thus, the probability that h is enrolled is

$$F\left(\alpha_e + \beta_e X_h\right), \tag{1}$$

where F is the standard logistic distribution function, $\beta_e = \gamma_e/\sigma$ is the vector of (normalized) weights of household characteristics in the enrollment score, and $\alpha_e = -\mu/\sigma$ is a constant term. We can estimate equation (1) using the actual enrollment decisions by program officers.

The utility gain from participation depends on the pre-program household income Y_h and the (monetary) benefit of participation B_h, both in per capita terms. Assuming for simplicity that the household has a constant risk aversion utility function with risk parameter ρ, we get that the gain from participating is

$$G_{eh} = \begin{cases} (Y_h + B_h)^{1-\rho} - Y_h^{1-\rho} & \text{if } \rho \neq 1 \\ \ln(1 + B_h/Y_h) & \text{if } \rho = 1 \end{cases} .$$

We can calculate the potential benefits of participation using the program rules (see Table 2).[8] Note that monetary benefits enter nonlinearly in the expression for the utility gain from participation.

3.2 The application problem

We assume that households have beliefs about the expected utility gain from application given by

$$G_{ah} = F\left(\beta_e X_h\right) G_{eh}.$$

We also assume that the cost of application is a linear function of a vector of observable characteristics of the household X_{ah} and a random term η_{ah}. That is,

$$C_{ah} = \max(\gamma_a X_h + \eta_{ah}, 0).$$

For tractability, we assume that the terms η_{ah} are independently distributed across households according to a logistic distribution with location parameter 0 and scale parameter σ_a.[9] Though we use a linear expression for the cost of application, we take care in bounding the application cost from below by zero, i.e. we interpret a negative realization of $\gamma_a X_h + \eta_{ah}$ as meaning a zero cost of application or no disincentive to apply.

Using the preceding expressions, we have that the household will apply to the program if it is informed and the gains from application exceed the

[8] We are sidestepping for simplicity the issue of the different horizon of benefits for different applicants, according to the age and school grade of their children. An explicit model of dynamic decisionmaking, considering all future schooling choices (as in Todd and Wolpin 2006) would take us far from our focus on the early decisions regarding participation into the program.

[9] The assumption of logistic distribution is in line with common practice in discrete choice analysis. The variance of a logistic distribution is equal to $\pi^2/3$ times the square of the scale parameter. Usually logistic and normal errors are indistinguishable empirically (see e.g. Train 2004).

costs; that is,

$$\beta_{ag} G_{ah} + \beta_{ax} X_h \geq \varepsilon_{ah}, \tag{2}$$

where $\beta_{ag} = 1/\sigma_a$, $\beta_{ax} = -\gamma_a/\sigma_a$, and $\varepsilon_{ah} = \max(\eta_{ah}/\sigma_a, -\beta_{ax} X_h)$. Note that ε_{ah} is a random term with a density identical to the standard logistic density for $\varepsilon_{ah} \geq -\beta_{ax} X_{ah}$.

We can estimate equation (2) using a previous estimation of equation (1) and the decisions to apply or not by informed households. It is simple to check that the likelihood function associated with equation (2) above is the same whether we assume that ε_{ah} has a standard logistic distribution or that ε_{ah} has a density identical to the standard logistic density for $\varepsilon_{ah} \geq -\beta_{ax} X_h$ and a point mass at $\varepsilon_{ah} = -\beta_{ax} X_h$, as long as $\beta_{ag} > 0$.

From the previous expressions, the net expected utility gain from application is

$$G_{ah} \text{ if } \varepsilon_{ah} \leq \beta_{ax} X_h, \text{ and}$$

$$G_{ah} + (\beta_{ax}/\beta_{ag}) X_h - \varepsilon_{ah}/\beta_{ag} \text{ if } \beta_{ax} X_h \leq \varepsilon_{ah} \leq \beta_{ag} G_{ah} + \beta_{ax} X_h,$$

with the household declining to apply otherwise.

3.3 The information acquisition problem

We model awareness about the program as coming for free or being the result of voluntary information acquisition from the part of potential participants. We assume that, in seeking information about the program, individuals attempt to anticipate how likely they are to apply to the program and to end up being enrolled into it. After acquiring information, individuals may have a better idea about whether it is convenient to apply to the program, which we model as learning the realization of the random term in the application cost.

Since acquiring information allows a household to apply, and households ignore the realization ε_{ah} before acquiring information, the value of information is

$$G_{kh} = G_{ah} F(\beta_{ax} X_h) + (1/\beta_{ag}) \int_{\beta_{ax} X_h}^{\beta_{ag} G_{ah} + \beta_{ax} X_h} (\beta_{ag} G_{ah} + \beta_{ax} X_h - y) f(y)\, dy,$$

where F is the standard logistic distribution function and f is the standard logistic density function. Gathering terms and integrating by parts, we obtain

$$\begin{aligned} G_{kh} &= G_{ah}F(\beta_{ag}G_{ah} + \beta_{ax}X_h) \\ &\quad +(\beta_{ax}/\beta_{ag})X_{ah}\left(F(\beta_{ag}G_{ah} + \beta_{ax}X_h) - F(\beta_{ax}X_h)\right) \\ &\quad -(B_h + (\beta_{ax}/\beta_{ag})X_{ah})F(\beta_{ag}G_{ah} + \beta_{ax}X_h) \\ &\quad +(\beta_{ax}/\beta_{ag})X_{ah}F(\beta_{ax}X_h) \\ &\quad +(1/\beta_{ag})\ln(1 + \exp(\beta_{ag}G_{ah} + \beta_{ax}X_h)) \\ &\quad -(1/\beta_{ag})\ln(1 + \exp(\beta_{ax}X_{ah})). \end{aligned}$$

Cancelling terms in the expression above we get

$$G_{kh} = (1/\beta_{ag})\ln\left(\frac{1 + \exp(\beta_{ag}G_{ah} + \beta_{ax}X_h)}{1 + \exp(\beta_{ax}X_h)}\right).$$

We assume that the cost of information is a linear function of a vector of observable characteristics of the household, that is,

$$C_{kh} = \max(\gamma_k X_h + \eta_{kh}, 0),$$

where the terms η_{kh} are independently distributed across households according to a logistic distribution with location parameter 0 and scale parameter σ_k, and are also independent of the terms η_{ah}. As in the case of the application cost, we take care in bounding the information cost from below by zero. Thus, we allow for households receiving information about the program without spending any effort.

From the previous expressions, a household will look for information about the program if

$$\beta_{kg}G_{kh} + \beta_{kx}X_h \geq \varepsilon_{kh}, \tag{3}$$

where $\beta_{kg} = 1/\sigma_k$, $\beta_{kx} = -\gamma_k/\sigma_k$, and $\varepsilon_{kh} = \max(\eta_{kh}/\sigma_k, -\beta_{kx}X_h)$. Note that ε_{kh} is a random term with a density identical to the standard logistic density for $\varepsilon_{kh} \geq -\beta_{kx}X_h$. We can estimate equation (3) using a previous estimation of equation (2) and the household reports about being informed or not about the program.

4 Empirical Analysis

4.1 Determinants of enrollment

We estimate equation (1) using the sample of households in our dataset that reported applying to the program. We include as explanatory variables: (1) household's characteristics: age, education and disability status of the mother, whether the mother speaks an indigenous language and whether she works outside home in the year previous to the survey,[10] the percentage of eligible households in the block, participation in other social programs and organizations, and distance to the nearest registration center, (2) household demographics: number of children, adult women and adult men by age intervals, and (3) dummies for household belongings. The official criteria for eligibility are household belongings and a set of regional dummies. We exclude the regional dummies contemplated by the official criteria, which are not public. We include instead dummies for the 170 neighborhoods in the sample, attempting to capture fixed effects at the neighborhood level due to rationing and other correlated shocks.

The results are reported in Table 4. For comparison purposes, official criteria are detailed in Table 5. Most of the important official criteria are also important and significant in practice, according to the estimation. An exception is not having a gas water heater. It is likely affected by location, which may explain its lack of significance since we include neighborhood dummies.

On the other hand, speaking an indigenous language (which has no official weight) appears as significant and important in practice. The latter means that we cannot reject the possibility that there is discrimination at the program office level in favor of indigenous applicants. Other variables without official weight that have a positive impact on enrollment and may tell a story of rationing or discrimination at the margin are participation in organizations and owning a radio. The range of organizations mentioned in the survey are cooperatives, rotating credit associations, political organiza-

[10] We consider the characteristics of the mother rather than the household head as we are interested in detecting discrimination at the program office level, and in 95% of the cases the applicant is in fact the mother (Martinelli and Parker 2007). This is not surprising since cash benefits under *Oportunidades* are paid directly to the mother.

Table 4
Determinants of Enrollment[a]

Household characteristic	Estimated coefficient	Marginal effect
1. Applicants and location		
Age of mother	.02649	.00399
	(.01851)	(.00279)
Square age	-.00037*	-.00005*
	(.00020)	(.00003)
Years of education	-.00132	-.00019
	(.01438)	(.00217)
Speaks indig language	.32463**	.04897**
	(.14221)	(.02143)
Works outside home	-.19212**	-.02953**
	(.08778)	(.01373)
Disabled	.01688	.00256
	(.30446)	(.04641)
Eligible households in block (%)	-.38172	-.05759
	(.46205)	(.06969)
Participation in social programs	.13887	.02063
	(.09264)	(.01356)
Participation in organizations	.17630*	.02582*
	(.10005)	(.01423)
Distance to reg center (km)	-.02623	-.00395
	(.04499)	(.00679)
2. Demographics		
Children 0-5 years	.1495***	.02255***
	(.05624)	(.00847)
Children 6-11 years	.27680***	.04176***
	(.04590)	(.00687)
Children 12-17 years	.06858	.01034
	(.04985)	(.00752)
Women 18-39 years	-.15724**	-.02372**
	(.07706)	(.01162)
Women 40-59 years	-.13503	-.02037
	(.11573)	(.01746)

Table 4
(continues)

Household characteristic	Estimated coefficient	Marginal effect
2. Demographics (continues)		
Women 60 years or older	.51747***	.07807***
	(.17900)	(.02698)
Men 18-39 years	-.17959***	-.02709***
	(.06769)	(.01020)
Men 40-59 years	-.14767	-.02227
	(.10474)	(.01580)
Men 60 years or older	-.17962	-.02837
	(.15836)	(.02614)
3. Household belongings		
No vehicle (no car nor truck)	.78680***	.14684***
	(.27801)	(.06113)
No television	-.15862	-.02322
	(.11778)	(.01671)
No radio	-.20186**	-.02991**
	(.08866)	(.01290)
Own house	.05239	.00796
	(.09854)	(.01508)
Unpaved floor	.37713***	.05669***
	(.09231)	(.01381)
No refrigerator	.45169***	.07116***
	(.09313)	(.01531)
No gas heating	-.00429	-.00064
	(.11089)	(.01675)
No toilet	.84391***	.10681***
	(.17936)	(.01880)
Unconnected to running water	.41633***	.06649***
	(.12513)	(.02110)
Family size/rooms in the house	.10459***	.01578***
	(.02997)	(.00451)

[a]Observations: 4323. Source: *ENCELURB.*

Regression includes neighborhood fixed effects and control for missing information on distance. Standard errors are shown in parenthesis. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 5
Official Criteria for Enrollment

Household characteristic	Normalized weight (%)
Age of household head (years)	0.10
Household head without education	8.88
Household head with only primary education	4.70
Female household head	-0.45
Access to health facilities	11.12
Children 0-11 years	5.97
Children/working age adults	4.10
No vehicle (no car nor truck)	3.73
Unpaved floor	11.12
No refrigerator	11.86
No gas heating	17.81
No toilet connected to running water	5.15
No washing machine	2.96
Family size/rooms in the house	3.23

Administrative sources. Regional dummies are excluded.

tions, communal organizations for the provision of local public goods, and religious organizations.

4.2 Determinants of application

We estimate the determinants of application using: (1) the sample of households in our dataset that reported knowing where to go in order to apply to the program, and (2) the sample of households in our dataset that reported being aware about the existence of registration centers for the program. The difference between the two samples is very small; a large majority of households that reported being aware of the program also knew the location of the registration office (see Table 1). Thus, results using either sample are nearly identical and we report only those obtained from the first sample.

We use two different methodologies for estimation. First, we estimate equation (2) including as explanatory variables the expected benefit of application and all the explanatory variables from the estimation of equation (1).

We have assumed a risk parameter of one for the estimation of the expected benefit of application, but the results are not very sensitive to the choice of the risk parameter around one. Since we use the results from equation (1) to estimate the expected benefit of application, we have bootstrapped the standard errors. Second, following closely the methodology proposed by HS, we estimate the application decision using only the same explanatory variables from the estimation of equation (1), i.e., excluding the expected benefit variable.

The results are reported in Table 6. The expected benefit of application appears to have a large and significant impact on the application decision. For the other variables, results using either methodology are similar. Participation in other social programs has a large and significant positive impact on participation in the program; this suggests unobservable characteristics related to the cost or benefit of application that are common across social programs. Education has a negative and significant impact on application. This may be due to an income effect, or may reflect stigma.[11] Distance to registration center has a positive impact on application, which is puzzling since distance would be expected to increase the cost of applying.

The dummies for household belongings have a significant impact on the application decision; this may be due to an income effect or to expectations about the benefit of application that are not captured by the expected benefit term. Excluding the expected benefit term has a small positive impact on the coefficients for household belongings, which seems to favor the former explanation. As with household belongings, and possibly for similar reasons, the number of small children have a significant positive effect on the application decision.

[11] Consistently, another study finds that more educated applicants tend to omit reporting at the registration center that they lack concrete floor or a toilet, potentially excluding themselves from the program, which can be attributed to embarrassment (Martinelli and Parker 2009).

TABLE 6
DETERMINANTS OF APPLICATION[a]

	Our model		Heckman-Smith	
Household characteristic	Estimated coefficient	Marginal effect	Estimated coefficient	Marginal effect
Expected benefit	2.61569***	.23915***		
	(.55991)	(.05061)		
1. Applicants and location				
Age of mother	.01145	.00104	.00395	.00036
	(.02181)	(.00199)	(.02175)	(.00199)
Square age	-.00006	0	0	0
	(.00024)	(.00002)	(.00024)	(.00002)
Years of education	-.04903***	-.00448***	-.04980***	-.00456***
	(.01551)	(.00142)	(.01544)	(.00142)
Speaks indig language	.13176	.01204	.15658	.01435
	(.16306)	(.01490)	(.16238)	(.01487)
Works outside home	-.00312	-.00028	-.01240	-.00113
	(.09864)	(.00903)	(.09794)	(.00901)
Disabled	.31684	.03269	.31984	.03312
	(.30001)	(.03468)	(.29967)	(.03480)
Eligible households in block (%)	.19675	.01798	.19055	.01746
	(.51372)	(.04697)	(.51159)	(.04690)
Participation in social programs	.30245***	.02649***	.32773***	.02870***
	(.10782)	(.00904)	(.10744)	(.00898)
Participation in organizations	.14212	.01261	.11236	.01006
	(.11035)	(.00950)	(.10949)	(.00957)
Distance to reg center (km)	.11005**	.01006**	.11516**	.01055**
	(.05317)	(.00485)	(.05290)	(.00484)
2. Demographics				
Children 0-5 years	.13088**	.01196**	.08905	.00816
	(.06582)	(.00600)	(.06489)	(.00594)
Children 6-11 years	.15465***	.01413***	.19070***	.01748***
	(.05300)	(.00483)	(.05219)	(.00475)
Children 12-17 years	-.03445	-.00315	.13393**	.01222**
	(.06506)	(.00595)	(.05651)	(.00517)
Women 18-39 years	-.02730	-.00249	-.01215	-.00111
	(.08466)	(.00774)	(.08336)	(.00764)
Women 40-59 years	-.22921*	-.02095*	-.19311	-.01770
	(.12776)	(.01168)	(.12678)	(.01162)

Table 6
(continues)

Household characteristic	Our model: Estimated coefficient	Our model: Marginal effect	Heckman-Smith: Estimated coefficient	Heckman-Smith: Marginal effect
2. Demographics (continues)				
Women 60 years or older	-.04667	-.00426	-.02464	-.00225
	(.19565)	(.01789)	(.19369)	(.01776)
Men 18-39 years	-.17221**	-.01574**	-.17900**	-.01640**
	(.07560)	(.00691)	(.07465)	(.00683)
Men 40-59 years	-.30405***	-.02779***	-.30550***	-.02800***
	(.11643)	(.01064)	(.11519)	(.01055)
Men 60 years or older	.04377	.00400	.03300	.00305
	(.18532)	(.01694)	(.18425)	(.01689)
3. Household belongings				
No vehicle (no car nor truck)	.90641***	.11552***	1.05265***	.14124***
	(.22797)	(.03822)	(.22476)	(.04070)
No television	-.14702	-.01297	-.18243	-.01600
	(.14077)	(.01197)	(.13891)	(.01164)
No radio	-.17135*	-.01535*	-.21396**	-.01913**
	(.10205)	(.00897)	(.10115)	(.00883)
Own house	-.04302	-.00390	-.04923	-.00447
	(.11062)	(.00996	(.10975)	(.00989)
Unpaved floor	.39851***	.03609***	.43508***	.03944***
	(.10968)	(.00983)	(.10897)	(.00975)
No refrigerator	.21622**	.02023**	.28472***	.02691***
	(.10369)	(.00994)	(.10211)	(.00996)
No gas heating	.25489*	.02210*	.28430**	.02456**
	(.13418)	(.01100)	(.13305)	(.01079)
No toilet	.85465***	.06288***	.95479***	.06881***
	(.19869)	(.01171)	(.19661)	(.01108)
Unconnected to running water	.67147***	.06902***	.72151***	.07497***
	(.12283)	(.01422)	(.12096)	(.01424)
Family size/rooms in the house	.14600***	.01334***	.16805***	.01540***
	(.03548)	(.00322)	(.03495)	(.00317)

[a]Observations: 4953 (our model) and 5025 (Heckman-Smith). Source: *ENCELURB.* Regression includes neighborhood fixed effects and control for missing information on distance. Standard errors are shown in parenthesis. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

4.3 Determinants of information acquisition

We estimate the determinants of information using the whole sample of households in our dataset.[12] As in the previous section, we use two different methodologies for estimation. First, we estimate equation (3) including as explanatory variables the expected benefit of knowledge and all the explanatory variables from the estimation of equation (1). Since we use the results from equation (2) to estimate the expected benefit of knowledge, we have bootstrapped the standard errors. Second, following closely HS, we estimate the determinants of information or awareness about the program using only the same explanatory variables from the estimation of equation (1).

The results are reported in Table 7. Consistent with the model, the expected benefit of knowledge has an important and statistically significant effect. For the other variables, results using either methodology are nearly identical. Among the variables that have a significant and important positive effect on information are the percentage of eligible households in the block, participation in other social programs, participation in organizations, whether the mother speaks an indigenous language, and age of household head. In all these cases, the targeting of information and word-of-mouth communication may have been at work. In particular, advertising was targeted to poor blocks; note that the percentage of eligible households in the block does not have a significant effect in the other stages of the participation process but has a very strong effect on knowledge.

4.4 Decomposing the participation process

In this section we decompose the effect of several household characteristics over participation outcomes into the different stages of the participation process. We begin with the HS (2004) methodology. Let $\Pr(\text{par}|X_h)$ be the unconditional probability that a household with characteristics X_h participates in the program, $\Pr(\text{en}|\text{ap, in},X_h)$ be the probability that a household is enrolled in the program conditional on application and information, $\Pr(\text{ap}|\text{in},X_h)$ be the probability that a household applies to the program con-

[12] We use two definitions of informed household: (1) those who reported knowing where to go in order to apply, and (2) those who reported being aware of the existence of registration centers. Results are nearly identical; we report those obtained using (1).

Table 7
Determinants of Learning[a]

Household characteristic	Our model: Estimated coefficient	Our model: Marginal effect	Heckman-Smith: Estimated coefficient	Heckman-Smith: Marginal effect
Expected benefit	1.6891***	.40403***		
	(.49390)	(.11810)		
1. Applicants and location				
Age of mother	.05173***	.01237***	.04513***	.01110***
	(.01130)	(.00270)	(.01097)	(.00270)
Square age	-.00053***	-.00012***	-.00045***	-.00011***
	(.00012)	(.00003)	(.00012)	(.00003)
Years of education	-.01457*	-.00348*	-.01396*	-.00343*
	(.00855)	(.00205)	(.00829)	(.00204)
Speaks indig language	.27271***	.06523***	.28688***	.07057***
	(.09174)	(.02194)	(.09009)	(.02216)
Works outside home	.00890	.00212	.00558	.00137
	(.05655)	(.01352)	(.05455)	(.01342)
Head is disabled	.11232	.02714	.09519	.02353
	(.17872)	(.04359)	(.17519)	(.04351)
Eligible households in block (%)	3.1754***	.75956***	3.1461***	.77396***
	(.27411)	(.06556)	(.27008)	(.06642)
Participation in social programs	.67965***	.15511***	.67383***	.16016***
	(.06284)	(.01347)	(.06018)	(.01361)
Participation in organizations	.14792**	.03505**	.12508**	.03061**
	(.06409)	(.01504)	(.06249)	(.01521)
Distance to reg center (km)	-.04187	-.01001	-.04469*	-.01099*
	(.02604)	(.00623)	(.02585)	(.00636)
2. Demographics				
Children 0-5 years	.16750***	.04006***	.15250***	.03751***
	(.03601)	(.00861)	(.03431)	(.00844)
Children 6-11 years	.17805***	.04259***	.19107***	.04700***
	(.02974)	(.00711)	(.02829)	(.00696)
Children 12-17 years	.03405	.00814	.09995***	.02458***
	(.03632)	(.00869)	(.03042)	(.00748)
Women 18-39 years	-.04885	-.01168	-.03186	-.00783
	(.04741)	(.01134)	(.04527)	(.01114)
Women 40-59 years	.03492	.00835	.06866	.01689
	(.07339)	(.01756)	(.07088)	(.01744)

Table 7
(continues)

Household characteristic	Our model: Estimated coefficient	Our model: Marginal effect	Heckman-Smith: Estimated coefficient	Heckman-Smith: Marginal effect
2. Demographics (continues)				
Women 60 years or older	.02292	.00548	-.00361	-.00088
	(.10813)	(.02587)	(.10279)	(.02529)
Men 18-39 years	-.09967**	-.02384**	-.11347***	-.02791***
	(.04311)	(.01031)	(.04141)	(.01019)
Men 40-59 years	-.27616***	-.06605***	-.28470***	-.07003***
	(.06803)	(.01627)	(.06517)	(.01603)
Men 60 years or older	-.18985*	-.04541*	-.17542*	-.04315*
	(.10318)	(.02468)	(.09920)	(.02441)
3. Household belongings				
No vehicle (no car nor truck)	.56822***	.14014***	.68388***	.16921***
	(.12948)	(.03220)	(.12440)	(.02995)
No television	.07820	.01880	.06146	.01515
	(.07586)	(.01832)	(.07305)	(.01805)
No radio	-.08916	-.02125	-.07510	-.01884
	(.05652)	(.01343)	(.05423)	(.01329)
Own house	.06154	.01476	.04506	.01109
	(.06183)	(.01486)	(.05970)	(.01472)
Unpaved floor	.20623***	.04906***	.18965***	.04648***
	(.06161)	(.01456)	(.05901)	(.01440)
No refrigerator	.20407***	.04892***	.25634***	.06311***
	(.06042)	(.01451)	(.05757)	(.01417)
No gas heating	-.06439	-.01545	-.06705	-.01653
	(.07096)	(.01710)	(.06823)	(.01686)
No toilet	.42367***	.09744***	.47381***	.11287***
	(.10630)	(.02333)	(.10127)	(.02313)
Unconnected to running water	.46470***	.11228***	.50095***	.12363***
	(.07284)	(.01770)	(.06968)	(.01716)
Family size/rooms in the house	.10189***	.02437***	.10651***	.02620***
	(.01971)	(.00471)	(.01870)	(.00460)

[a]Observations: 8515 (our model) and 9331 (HS). Source: *ENCELURB.*
Regression includes neighborhood fixed effects and control for missing information on distance. Standard errors are shown in parenthesis. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

ditional on information, and $\Pr(\text{in}|X_h)$ be the unconditional probability that the household is informed. Using the chain rule, we have

$$\Pr(\text{par}|X_h) = \Pr(\text{en}|\text{ap, in,}X_h) \times \Pr(\text{ap}|\text{in,}X_h) \times \Pr(\text{in}|X_h).$$

The effect on participation of a change in a given observable variable x can be written as the sum of the (weighted) enrollment effect, application effect, and information effect. In particular, the enrollment effect is

$$\partial_x \Pr(\text{en}|\text{ap, in,}X_h) \times \Pr(\text{ap}|\text{in,}X_h) \times \Pr(\text{in}|X_h),$$

the application effect is

$$\Pr(\text{en}|\text{ap,in,}X_h) \times \partial_x \Pr(\text{ap}|\text{in,}X_h) \times \Pr(\text{in}|X_h),$$

and the information effect is

$$\Pr(\text{en}|\text{ap,in,}X_h) \times \Pr(\text{ap}|\text{in,}X_h) \times \partial_x \Pr(\text{in}|X_h).$$

In these expressions, $\partial_x \Pr(\text{en}|\text{ap, in,}X_h)$ is the marginal effect of the variable on enrollment, conditional on application and information, $\partial_x \Pr(\text{ap}|\text{in,}X_h)$ is the marginal effect of the variable on application, conditional on information, and $\partial_x \Pr(\text{in}|X_h)$ is the unconditional marginal effect of the variable on information.

In our model the enrollment effect is a similar expression

$$\partial_x \Pr(\text{en}|\text{ap,in,}X_h) \times \Pr(\text{ap}|\text{in,}X_h, B_h, Y_h) \times \Pr(\text{in}|X_h, B_h, Y_h).$$

Note, however, that we now use information about household benefits B_h and income Y_h.

The application effect in our model is more involved as it contains a term that depends on changes in the expected gain from application induced by changes in the probability of enrollment:

$$\begin{aligned}
&\partial_x \Pr(\text{ap}|\text{in,}X_h, B_h, Y_h) \times \Pr(\text{en}|\text{ap,in,}X_h) \times \Pr(\text{in}|X_h, B_h, Y_h) \\
&+\partial_G \Pr(\text{ap}|\text{in,}X_h, B_h, Y_h) \times \partial_x \Pr(\text{en}|\text{ap, in,}X_h) \times \ln(1 + B_h/Y_h) \\
&\times \Pr(\text{en}|\text{ap,in,}X_h) \times \Pr(\text{in}|X_h, B_h, Y_h),
\end{aligned}$$

where $\partial_G \Pr(\text{ap}|\text{in},X_h, B_h, Y_h)$ is the marginal effect on application of the gain from enrollment, conditional on information, and $\ln(1 + B_h/Y_h)$ is the utility gain from enrollment. In the expression above, the first term is the direct effect of variable x on application, and the second term is the indirect effect of variable x on application via its effect on enrollment. With respect to the second term, note that $\partial_x \Pr(\text{en}|\text{ap, in},X_h) \times \ln(1 + B_h/Y_h)$ is the change in the expected benefit of applying, and $\partial_G \Pr(\text{ap}|\text{in},X_h, B_h, Y_h)$ is the marginal effect of the expected benefit on the application decision. As in the case of the direct effect, we need to weight the indirect effect using $\Pr(\text{en}|\text{ap,in},X_h) \times \Pr(\text{in}|X_h, B_h, Y_h)$.

Finally, the information effect in our model is

$$\begin{aligned}
&\partial_x \Pr(\text{in}|X_h, B_h, Y_h) \times \Pr(\text{en}|\text{ap,in},X_h) \times \Pr(\text{ap}|\text{in},X_h, B_h, Y_h) \\
&+\partial_G \Pr(\text{in}|X_h, B_h, Y_h) \times \partial_x \Pr(\text{en}|\text{ap, in},X_h) \times \ln(1 + B_h/Y_h) \\
&\times \Pr(\text{en}|\text{ap,in},X_h) \times \Pr(\text{ap}|\text{in},X_h, B_h, Y_h)^2 \\
&+\partial_G \Pr(\text{in}|X_h, B_h, Y_h) \times \frac{\partial_x \Pr(\text{ap}|\text{in},X_h, B_h, Y_h)}{\partial_G \Pr(\text{ap}|\text{in},X_h, B_h, Y_h)} \\
&\times(\Pr(\text{ap}|\text{in},X_h, B_h, Y_h) - F(\beta_{ax}X_h|\text{in}) \\
&\times \Pr(\text{en}|\text{ap,in},X_h) \times \Pr(\text{ap}|\text{in},X_h, B_h, Y_h),
\end{aligned}$$

where $\partial_G \Pr(\text{in}|X_h, B_h, Y_h)$ is the unconditional marginal effect on information of the gain from application, and $F(\beta_{ax}X_h|\text{in})$ is the probability that application is costless (so is not affected by marginal changes in benefits) and is equal to the logistic distribution function $F(z) = 1/(1 + \exp(-z))$ evaluated at $\beta_{ax}X_h$ for an informed household.

In the expression above, the first term is the direct effect of variable x on information, the second term is the indirect effect of variable x on information via its effect on enrollment, and the third term is the indirect effect of variable x on information via its effect on application. As before, we need to weight indirect effects using $\Pr(\text{en}|\text{ap,in},X_h) \times \Pr(\text{ap}|\text{in},X_h, B_h, Y_h)$. Note that $\partial_G \Pr(\text{in}|X_h, B_h, Y_h)$ is the marginal effect of the expected benefit on the information decision. In the second term, $\Pr(\text{ap}|\text{in},X_h, B_h, Y_h) \times \partial_x \Pr(\text{en}|\text{ap, in},X_h) \times \ln(1 + B_h/Y_h)$ is the change in the expected benefit of information due to a change in enrollment. In the third term,

$$\frac{\partial_x \Pr(\text{ap}|\text{in},X_h, B_h, Y_h)}{\partial_G \Pr(\text{ap}|\text{in},X_h, B_h, Y_h)} \times (\Pr(\text{ap}|\text{in},X_h, B_h, Y_h) - F(\beta_{ax}X_h|\text{in})$$

is the change in the expected benefit of information due to a change in application, and is equal to the marginal effect of variable x on the expected gain from application, multiplied by the probability that application is costly.

In our model, by assumption, a change in benefits has no impact on enrollment. The marginal impacts of a change in monetary benefits on application and information are, respectively,

$$\Pr(\text{en}|\text{ap,in,}X_h) \times \partial_G \Pr(\text{ap}|\text{in,}X_h, B_h, Y_h) \times (Y_h + B_h)^{-1} \times \Pr(\text{in}|X_h)$$

and

$$\Pr(\text{en}|\text{ap,in,}X_h) \times \Pr(\text{ap}|\text{in,}X_h, B_h, Y_h)^2 \times \partial_G \Pr(\text{in}|X_h, B_h, Y_h) \times (Y_h + B_h)^{-1}.$$

Table 8 reports a decomposition of the effect of several household characteristics and demographic variables according to the two methodologies. The results for both methodologies are similar. Quantitatively, the main source of variation for most variables is the information term, explaining about a half or more of the variation in every case. The second source of variation for most variables is enrollment, with application coming last in all cases except for education and participation in other social programs.

Most of the effect of participation in organizations comes from the information term; the effect on application is not significant. The effect of participation in other social programs rests heavily on the information term. The effect of the percentage of eligible households in the block (not shown in the table) rests even more heavily on the information term. The effect of the mother speaking an indigenous language rests on both the information term and the enrollment term. An exception to the previous pattern is the effect of education. In this case the application term accounts for nearly half of the overall negative effect. As discussed above, this may be due to stigma or to the opportunity cost of time.

The number of teenagers is the only variable in which the two decompositions differ sharply. In particular, in our decomposition the application term is negative (and not significant), while in the HS methodology it is positive (and significant). This suggests that the effect of more teenagers on participation may be due to expected benefits.

Table 8

Weighted Effects of Changes in Characteristics on Probability of Participation

	Overall effect	Weighted Enrollment Term	Percent of Overall	Weighted Application Term	Percent of Overall	Weighted Information Term	Percent of Overall
Our model							
+100 pesos in benefits	.01770			.00613	34.46	.01166	65.54
One more year of education	-.00527	-.00011	2.27	-.00249	47.20	-.00266	50.46
Mother speaks indig language	.08733	.02931	33.56	.00823	9.43	.04880	55.88
Participation in social programs	.13830	.01233	8.92	.01534	11.09	.11021	79.69
Participation in organizations	.05028	.01545	30.74	.00781	15.55	.02648	52.68
One more child 0-5	.05103	.01350	26.45	.00732	14.41	.02972	58.25
One more child 6-11	.06778	.02499	36.88	.00916	13.52	.03278	48.37
One more child 12-17	.01108	.00619	55.85	-.00142	-12.79	.00610	55.06
Heckman-Smith							
One more year of education	-.00503	-.00011	2.24	-.00251	49.98	-.00237	47.20
Mother speaks indig language	.08701	.02912	33.47	.00782	9.00	.04892	56.23
Participation in social programs	.13955	.01225	8.78	.01571	11.26	.11099	79.54
Participation in organizations	.04264	.01534	35.98	.00547	12.84	.02121	49.75
One more child 0-5	.04443	.01341	30.18	.00448	10.10	.02599	58.52
One more child 6-11	.06796	.02480	36.49	.00958	14.10	.03258	47.94
One more child 12-17	.03018	.00614	20.37	.00669	22.18	.01704	56.48

Finally, the effect of monetary benefits on participation arises mainly from the effect on information and is quantitatively small. Raising monetary benefits in 100 pesos would increase participation in less than 2%; average monetary benefits were 350 pesos. This suggests that further increases in benefits will not have a large impact on participation, an implication that is not unrealistic taking into account that monetary benefits are already quite high compared to household pre-program expenditure (see Tables 2 and 3). It is worth emphasizing that this is an average marginal effect but that in principle it could vary across different socioeconomic groups. For example, increasing the level of benefits for poor households who correctly expect to get low benefits (e.g., elderly without children) may be an effective approach to increase participation among this group.

5 Concluding Remarks

In this paper we combine a sequential decision model of participation in social programs with a unique database, containing detailed information about the stages of participation in *Oportunidades*, a flagship Mexican social program that incorporated an element of self-selection when introduced in urban localities. The model is geared at capturing the effect at each stage of expectations about the following stages. We decompose the effect of different variables on the stages of the participation process–information acquisition, application, and enrollment–following a methodology based on the model as well as a methodology proposed in a seminal article by HS. Results are very similar under both methodologies. In both cases, the main source of the impact of most variables we consider on participation is the information stage followed by the enrollment stage. The estimation based on our model also indicates that the effect of expected benefits is significant at the application and information stages, but variation due to monetary benefits is not quantitatively very important.

Variation in participation outcomes due to the impact of variables other than the official criteria on the enrollment stage is interesting from a policy viewpoint because the official rules for eligibility were very precise, and may have been due to occasional rationing. It points to the importance of administrative decisions, perhaps taken at the office level, in addition to the official rules. Variation on participation outcomes due to the information stage is also very interesting from a policy viewpoint. A quantitatively important and significant determinant of awareness about the program is the percentage of eligible households in the block, a variable that has an insignificant effect on the other stages. This provides some evidence that targeting of the advertising campaign carried out before *Oportunidades* was introduced in urban localities may have worked effectively.

We can think of two different ways to increase participation by eligible households: (1) increase monetary benefits and (2) decrease their costs of participation. With respect to (1), our results indicate a small impact, at least on average. With respect to (2), our results indicate that the main impact on participation costs comes from the availability of information.

These empirical results raise the question of the importance of the determinants of information and of the determinants of enrollment other than the official criteria in other social programs as well. A disaggregated view of the participation process like the one developed in this paper seems a promising avenue to answer that question and more generally to deepen our knowledge of what determines participation patterns in social programs.

References

[1] Aizer, A. (2003), "Low Take-Up in Medicaid: Does Outreach Matter and for Whom?," *American Economic Review Papers and Proceedings* 93: 238-241.

[2] Aizer, A. (2007), "Public Health Insurance, Program Take-up and Child Health," *Review of Economics and Statistics* 89: 400–415.

[3] Ashenfelter, O. (1983), "Determining Participation in Income-Tested Social Programs," *Journal of the American Statistical Association* 78: 517-525.

[4] Besley, T. and S. Coate (1992), "Workfare versus Welfare: Incentive Arguments for Work Requirements in Poverty-Alleviation Programs," *American Economic Review* 82: 249-261.

[5] Blundell, R., V. Fry and I. Walker (1988), "Modelling the Take-Up of Means-Tested Benefits: The Case of Housing Benefit in the United Kingdom," *Economic Journal* 98: 58-74.

[6] Coady, D. and S.W. Parker (2009), "Targeting Performance under Self-selection and Administrative Targeting Methods," *Economic Development and Cultural Change* 57: 559-587.

[7] Currie, J. (2006), "The Take-Up of Social Benefits," in A. Auerbach, D. Card and J. Quigley (eds), *Public Policy and the Income Distribution*, New York: Russell Sage.

[8] Daponte, B., S. Sanders and L. Taylor (1999), "Why Do Low Income Households Not Use Food Stamps? Evidence from an Experiment," *Journal of Human Resources* 34: 612-628.

[9] Heckman, J., and J. Smith (2004), "The Determinants of Participation in a Social Program: Evidence from a Prototypical Job Training Program," *Journal of Labor Economics* 22: 243-298.

[10] Lahiri, K., J. Song, and B. Wixon (2008), "A Model of Social Security Disability Insurance Using Matched SIPP/Administrative Data," *Journal of Econometrics* 145: 4-20.

[11] Martinelli, C. and S.W. Parker (2009), "Deception and Misreporting in a Social Program," *Journal of the European Economic Association* 7: 886-908 .

[12] Micklewright, J., A. Coudouel and S. Marnie (2004), "Targeting and Self-Targeting in a New Social Assistance Scheme," Discussion Paper No. 1112, Institute for the Study of Labour (IZA), Bonn, Germany.

[13] Moffitt, R. (1983), "An Economic Model of Welfare Stigma," *American Economic Review* 73: 1023-1035.

[14] Parker, S.W., L. Rubalcava and G. Teruel (2007), "Evaluating Conditional Schooling and Health Programs," in T. P. Schultz and J. Strauss (eds.), *Handbook of Development Economics, Volume 4*, Amsterdam: Elsevier.

[15] Ravallion, M. (1996), "Issues in Measuring and Modelling Poverty," *Economic Journal* 106: 1328-1343.

[16] Reglas de Operación del Programa Oportunidades de Desarrollo del Capital Humano para el Ejercicio Fiscal 2002, *Diario Oficial de la Federación*, May 8, 2002.

[17] Remler, D. and S. Glied (2003), "What Other Programs Can Teach Us: Increasing Participation in Health Insurance Programs," *American Journal of Public Health* 93: 67-74.

[18] Todd, P. and K. Wolpin (2006), "Assessing the Impact of a School Subsidy Program in Mexico: Using a Social Experiment to Validate a Dynamic Behavioral Model of Child Schooling and Fertility," *American Economic Review* 96: 1384-1417.

[19] Train, K. (2003), *Discrete Choice Methods with Simulation*, Cambridge, UK: Cambridge University Press.