Information and Participation in Social Programs

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Participation in social programs, such as clubs and other social organizations, results from a process in which an agent learns about the requirements, benefits, and likelihood of acceptance related to a program, applies to be a participant, and, finally, is accepted or rejected. We propose a model of this participation process and provide an application of the model using data from a social program in Mexico. Our empirical analysis illustrates that decisions at each stage of the process are responsive to expectations about the decisions and outcomes at the subsequent stages and that knowledge about the program can have a significant impact on participation outcomes. JEL codes: I38, D83, program participation, take-up, information acquisition, targeting, undercoverage, leakage

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, that is, the rate of participation by eligible individuals in social programs.[1] As a result, participation in such programs has attracted considerable attention in 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, broadly defined to include the psychological costs related to stigma, on participation outcomes for eligible individuals. In particular, Duclos (1995), Pudney, Hancock, and Sutherland (2006), Pudney, Hernandez, and Hancock

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

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(2007), and Hernandez and Pudney (2007) consider the issue of estimating application costs in models of endogenous participation. Heckman and Smith (2004) extend this literature by considering participation in social programs to be the outcome of a sequential process and propose a statistical decomposition of the impact of different variables on the stages of this process. In this paper, we present a decision-theoretic model of participation in social programs that recognizes the sequential nature of the participation process and captures the interdependence between these stages. We use an empirical analysis of a cash transfer program in Mexico to highlight the roles of knowledge, expected benefits, and costs in the participation process.

In our model, the participation process is divided into three stages. The first stage of this process corresponds to the agent's acquisition of knowledge about the program. The second stage corresponds to the agent's decision to apply to the program after learning about and comparing the cost of application with his or her expectations about the program's benefits and the likelihood of being accepted. The third stage corresponds to the program officers' decision whether to enroll the agent into the program.

Our model captures two key features of participation. The first key feature is the sequential nature of the process: an agent first needs to obtain information before actually applying, and the agent must then apply before being assessed for 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 subsequent 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. The model thus provides a framework for studying the participation decisions-making process.

We conduct an empirical application of the model using data from 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 that we use contain detailed information on the different stages of the participation process as well as the socioeconomic household characteristics used to determine eligibility and the level of transfers a household would receive if deemed eligible. Information on the different stages of the process and the characteristics of eligible and ineligible households has not generally been available in previous work. Our data allow us to separately estimate the potential participant's decision to apply and the program officials' decision regarding whether to enroll the applicant. Because we have detailed information on the official criteria for eligibility, we can determine whether enrollment decisions are based exclusively on these criteria. Information on the benefit entitlements of participants allows us to explore the relationship between expected benefits and the different stages of the participation process.

In accord with the model presented, we estimate the stages of the participation process in reverse order. In particular, at the information acquisition and application stages, we consider the expected benefit for the potential participant of going through the next stages of the participation process. The estimation indicates that the stages of the participation process are interdependent: whether a household becomes informed and whether it applies conditional on being informed are sensitive to the expected benefits, that is, the probability of being accepted conditional on application multiplied by the utility benefit that one receives if enrolled in the program. This estimation is useful because it allows us to analyze the impact of changing program benefits on the different stages of participation.

Our results indicate that the marginal impact of monetary benefits on participation outcomes is small. This finding has important policy implications because it suggests that increasing benefits will not significantly increase participation. This conclusion is not unreasonable in the context of *Oportunidades* because monetary benefits for participants are already quite high. These results also suggest that policy should focus on addressing barriers to participation that stem from other determinants of applying and acquiring information.

A key policy issue involves disentangling the effect on outcomes of the different stages in the participation process. On the basis of our model, which follows the approach developed in Heckman and Smith (2004), we present a statistical decomposition of the impact of different variables at the different stages of the participation process. We find that the information stage is the major source of variation in participation, accounting for more than half of the impact of almost every variable that 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 a distant third source. Policies directed at increasing participation in *Oportunidades* should therefore focus more on these stages of the participation process. More generally, these findings reinforce the need for studies of program participation outcomes to take a disaggregated view of the participation process and, accordingly, to collect data to facilitate such an analysis (Heckman and Smith 2004). A general lesson arising from our work is that the enrollment stage and especially the information stage may be as important as the application stage in explaining participation outcomes in social programs. Because the outcomes of these stages are strongly affected by program design and implementation features, they can be heavily influenced by policy reform in these areas. Our work also points to the usefulness of collecting disaggregated data about the different stages of the participation process in other social programs, in both developed and developing countries, in order to better understand barriers to participation that limit the efficiency and effectiveness of such programs.

The remainder of this paper proceeds as follows. In section 2, we present our model of the participation process. In section 3, we provide some background on our database. In section 4, we describe our empirical results. In section 5, we summarize our findings and their policy implications.

A Model of the Participation Process

Whether a potential household participant receives benefits from a targeted program depends on whether the participant decides to seek knowledge and to apply and whether the applicant 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 stage are crucial. Beliefs about the probability of enrollment are important for the decision to apply, and beliefs about the likelihood of applying and enrolling in 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 a potential household participant's enrollment if that participant is informed about the program and contemplating whether to apply.

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 and socioeconomic characteristics of the applicant's household, including the number of household members, the number of children in the household younger than eleven, an index of household overcrowding, the age and years of education of the head of household, a set of dummies indicating whether the dwelling lacks a number of desirable characteristics (such as a connection to running water, a paved floor, or a refrigerator), 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 because of 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 differ 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 differ 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 (regionally 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

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

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 find that the gain from participating is

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

We can calculate the potential benefits of participation using the program rules to calculate the potential transfer income that can be received given the pre-program education levels of children in the household (Martinelli and Parker 2009). Note that monetary benefits enter nonlinearly in the expression for the utility gain from participation.

The modeling assumes that the household does not know the enrollment outcome in advance, even though the household knows the precise amount of the benefit. This assumption corresponds to the case of *Oportunidades*, in which the rules for benefits are clearly stated and publicized (see table 2), although the exact rules for enrollment are not public information.

The Application Problem

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

$$G_{ah} = F(\alpha_e + \beta_e X_h) G_{eh}.$$

We also assume that the cost of application is a linear function of a vector of observable characteristics of the household X_h 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.[2] The assumption that the cost of application is linear in household characteristics that are not binary is simply an approximation of first-order effects. Although we use a linear expression for the cost of application, we take care to bound the application cost from below by zero; that is,

2. 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 empirically indistinguishable (see, e.g., Train 2003).

we interpret a negative realization of $\gamma_a X_h + \eta_{ah}$ as a zero cost of application or no disincentive to apply.

Using the preceding expressions, we estimate that the household will apply to the program if it is informed and the gains from application exceed the 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 apply by informed households. It is simple to verify 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

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

with the household declining to apply otherwise.

The Information Acquisition Problem

We assume that awareness about the program is obtained for free or through voluntary information acquisition on the part of potential participants. Knowledge can be acquired passively (people hear about it from campaigns, from their friends and neighbors, and from their networks, including participation in other programs) or through the agent's decision to invest time and effort to learn how to apply to the program. In the latter case, the agent's prior expectations about benefits from the program and the likelihood of being accepted may play a role.

We assume that when individuals seek information about the program, they anticipate how likely they are to apply to the program and to ultimately enroll in 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 realizing the random term in the application cost.

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

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

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

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

Canceling terms in the expression above, we get

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

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 independent of the terms η_{ah}. As in the case of the application cost, we take care to bound the information cost from below by zero. Thus, we allow households to receive information about the program without expending effort.

From the previous expressions, a household will seek information about the program (3)

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

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 uninformed about the program.

Evidence on Information and Participation

We now turn to our empirical example. *Oportunidades* was introduced in the poorest urban localities in Mexico in 2002.[3] An advertising campaign was conducted to inform potential applicants that registration centers for the program would be 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 came to the registration centers were asked to provide information about their address and 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. We used these characteristics and demographic information to compute a household poverty index, which was used to determine an applicant's eligibility for enrollment in the program. The weights attached to each characteristic in the household poverty index were predetermined using a poverty regression similar to that described by Ravallion (1996). The methodology was public (Reglas de Operación 2002), but the specific weights were not.

Applicants initially found to be eligible received a household visit during subsequent weeks to verify the information provided, after which a final determination on eligibility was made. Because of 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 process likely led to errors of exclusion. Moreover, some households that were initially classified as eligible at the registration center and found to be ineligible after the verification did, in fact, enroll in the program, leading to errors of inclusion (Martinelli and Parker 2009).

Our dataset was 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 in the program's area of operation was selected, and all households in these selected blocks (20,859) were visited. An initial screening survey found 4,649 *Oportunidades* beneficiary households. All of these households were included in the evaluation sample. Additionally, a subsample (5,776) of nonbeneficiary 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 about, application to, and enrollment in *Oportunidades*.

3. *Oportunidades* is a scaled-up version of the rural *Progresa* program. This program has become widely known in the economics literature because of its careful evaluation and has been considered a prototype for social safety-net reforms in other developing countries, especially in Latin America (see, e.g., Schultz 2004; de Janvry et al. 2006; Parker, Rubalcava, and Teruel 2008). Our empirical analysis of enrollment in *Oportunidades* focuses on urban households; Leroy et al. (2008) compare urban and rural enrollment and discuss utilization of the different components of the program.

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, authors' calculations.

The screening survey for the ENCELURB included a module with questions to construct the household poverty index and the program eligibility of households in the evaluation sample.[4] Table 1 presents information on participation levels by eligible and ineligible households. Leakage (that is, participation by ineligible households as a fraction of total participation) was 28.2 percent, and undercoverage (that is, nonparticipation by eligible households as a fraction of the eligible population) was 49.6 percent. Table 1 also illustrates that a lack of knowledge about the program was a major barrier to participation, especially for ineligible applicants.[5,6]

Cash benefits for participants in *Oportunidades* include an unconditional grant (called a "nutrition grant") as well as grants that are 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. Because we can calculate the potential (maximum) cash benefits a household can receive under the program using the household's demographic composition and years of completed schooling of each pre-program child, we can estimate the monetary incentive to participate for each potential applicant.

Table 3 shows the average household characteristics for eligible and ineligible households. Ineligible households are better off than eligible households in terms of both total and per capita expenditure. Because ineligible households have smaller families, in addition to being less likely to enroll in the program, they have smaller benefits if they participate. Nonetheless, the benefits of participation are substantial for both eligible and ineligible households. The average monthly transfer is approximately 15 percent of the average monthly expenditure for eligible households and 12 percent for ineligible households.

4. For the subsample of households in the ENCELURB that applied for benefits according to administrative sources, we compared the program's calculated eligibility index to our index (based on the proxy means model and the characteristics in the ENCELURB survey). These two criteria for eligibility coincide in approximately 80 percent of the cases. Differences are likely due to different self-reports of household characteristics between the two visits.

5. In the survey, households that were recipients of the transfer were assumed to have applied, and households that applied were assumed to know about the program.

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

TABLE 2. Monthly Cash Benefits of *Oportunidades*[a]

Grants	Nutrition grant / Education grants:	Grade	Boys	Girls
	Nutrition grant		150	
	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		1,550	
	Other households		915	
Average transfer[b]			350	

[a]In Mexican pesos (2002); 11 pesos is approx. US $1. [b]Urban households (2002).
Source: Administrative sources, authors' elaboration.

TABLE 3. Characteristics of Potential Participants[a]

	Eligible		Ineligible	
	Mean	Std. Dev.	Mean	Std. Dev.
Household characteristics				
Total monthly expenditure (pesos)	2,314	2,404	2,899	3,923
Per capita expenditure (pesos)	492	492	777	1,317
Family size	5.19	2.20	4.23	1.79
Children from 0 to 5 years old	0.97	0.98	0.51	0.71
Children from 6 to 11 years old	1.27	1.13	0.68	0.84
Children from 12 to 17 years old	0.73	0.97	0.63	0.88
Mothers' characteristics				
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.

EMPIRICAL ANALYSIS

Consistent with the model developed above, our analysis of participation outcomes disaggregates the participation process into three stages: the knowledge acquisition decision by households, the application decision by households, and the enrollment decision by program officials. We estimate the model in reverse order beginning with the enrollment decision. Our estimates of the determinants of the outcomes at the final two stages (that is, application and enrollment) are based on selected samples. The sample of households that knew about the program is used to estimate the determinants of the application decision, and the sample of households that both knew about the program and subsequently applied is used to analyze the enrollment decision. Therefore, our estimates provide only unbiased estimates for the conditional samples.

All but one of the variables are included in all three stages. The exception is the expected benefit variable, which is excluded from the final enrollment equation because, in the case of *Oportunidades,* enrollment is administratively determined using categorical criteria that have been previously found to strongly correlate with poverty. The expected benefit variable is calculated as the product of the probability of proceeding through subsequent stages and the additional utility of the cash benefits received if the applicant is successfully enrolled. These benefits are exogenous to the household and are calculated using the schedule in table 2 above and capped accordingly.

Note that the potential cash benefits received depend not only on the demographic composition of the household but also on the pre-program schooling level of all children in the household. Because of high grade failure and early dropout levels, there is wide variation in the pre-program schooling attainment of children of a given age. Under the assumption that initial schooling does not correlate with unobserved knowledge and application costs, this wide variation provides potentially valuable information about the importance of identifying differences in the level of impact of program benefits.

The utility of the cash benefits is calculated using a constant risk aversion utility function with risk parameter 1. Because the marginal utility of income decreases with total income, the expected utility of benefits is a nonlinear function of cash benefits received. In addition to variation in pre-program schooling, this nonlinearity allows the separate identification of the impact of variation in benefits on knowledge acquisition and application outcomes. Because the results are insensitive to the choice of risk parameter around one, we only present results under this assumption. Furthermore, by including a large number of explanatory variables in addition to expected benefits, these variables may reflect the impact of unobserved characteristics that might correlate with the costs of participation.[7]

Determinants of Enrollment, Application, and Learning

We estimate equation (1) using the sample of households in our dataset that reported applying to the program. We include the following as explanatory variables: (i) household's characteristics, including age, education and disability status of the mother, whether the mother speaks an indigenous language,

7. Note that potential maximum benefits have been previously used as an instrument for actual benefits (see, e.g., Gertler, Martinez, and Rubio-Codina 2012 and Dubois, de Janvry, and Sadoulet 2011).

whether the mother worked outside of the home in the year prior to the survey, the percentage of eligible households in the block, participation in other social programs and organizations, and distance to the nearest registration center; (ii) household demographics, including the number of children, adult women and adult men by age intervals; and (iii) dummies for household belongings. The official criteria for eligibility are household belongings and a set of regional dummies. We exclude the regional dummies in the official criteria, which were not public. Instead, we include dummies for the 170 neighborhoods in the sample in an attempt to capture fixed effects at the neighborhood level due to rationing and other correlated shocks.[8]

The results are reported in the first column of table 4. For comparison purposes, official criteria are detailed in table 5 (normalized to total 100). Most of the important official criteria are also important and statistically significant in practice, according to the estimated enrollment equation. An exception is the lack of a gas water heater, which is likely affected by location. This influence may explain the lack of significance of this criterion because we include neighborhood dummies.

The statistically significant impact of variables other than the official criteria on enrollment is consistent with the use of unofficial criteria by program officials in selecting among applicant households. Although the program has explicit and precise eligibility criteria, many program offices were forced to ration program places because more applicants met the official eligibility criteria than the budget allocations allowed. Our results suggest that women who spoke an indigenous language, who were found to have a substantially higher probability of being poor, and who had participated in other social programs and in social and political organizations received priority. These decisions may also reflect early application by better-connected households before the process was because of a lack of funds. Women working outside the home (and who, presumably, have higher income) had a lower probability of being enrolled.

Next, we estimate the determinants of application using (1) the sample of households in our dataset that reported knowledge of where to go to apply to the program and (2) the sample of households in our dataset that reported awareness of the existence of registration centers for the program. The difference between the two samples was very small; a large majority of households that reported awareness of the program also knew the location of the registration office (see table 1). Thus, the results using either sample were nearly identical. We report only the results obtained from the first sample. We estimate equation (2) and include as explanatory variables the expected benefit of application and all of the explanatory variables from the estimation of equation (1). Note that households are implicitly assumed to use their own characteristics,

8. The applicant's characteristics, detailed in table 4, are those of the mother, who was the recipient of the transfer and the person actually approaching the registration center in the vast majority of cases.

TABLE 4. Determinants of Enrollment, Application, and Learning (Marginal Effects)[a]

Household characteristics	Enrollment	Application	Learning
Expected benefit		.23915***	.40403***
		(.05061)	(.11810)
1. Applicants and location			
Age of mother	.00399	.00104	.01237***
	(.00279)	(.00199)	(.00270)
Square age	−.00005*	0	−.00012***
	(.00003)	(.00002)	(.00003)
Years of education	−.00019	−.00448***	−00348*
	(.00217)	(.00142)	(.00205)
Speaks indigenous language	.04897**	.01204	.06523***
	(.02143)	(.01490)	(.02194)
Works outside home	−.02953**	−.00028	.00212
	(.01373)	−.00028	(.01352)
Disabled	.00256	.03269	.02714
	(.04641)	(.03468)	(.04359)
Eligible households in block (%)	−.05759	.01798	.75956***
	(.06969)	(.04697)	(.06556)
Participation in social programs	.02063	.02649***	.15511***
	(.01356)	(.00904)	(.01347)
Participation in organizations	.02582*	.01261	.03505**
	(.01423)	(.00950)	(.01504)
Distance to reg. center (km)	−.00395	.01006**	−.01001
	(.00679)	(.00485)	(.00623)
2. Demographics			
Children 0 to 5 years old	.02255***	.01196**	.04006***
	(.00847)	(.00600)	(.00861)
Children 6 to 11 years old	.04176***	.01413***	.04259***
	(.00687)	(.00483)	(.00711)
Children 12 to 17 years old	.01034	−.00315	.00814
	(.00752)	(.00595)	(.00869)
Women 18 to 39 years old	−.02372**	−.00249	−.01168
	(.01162)	(.00774)	(.01134)
Women 40-59 years old	−.02037	−.02095*	.00835
	(.01746)	(.01168)	(.01756)
Women 60 years or older	.07807***	−.00426	.00548
	(.02698)	(.01789)	(.02587)
Men 18 to 39 years old	−.02709***	−.01574**	−.02384**
	(.01020)	(.00691)	(.01031)
Men 40 to 59 years old	−.02227	−.02779***	−.06605***
	(.01580)	(.01064)	(.01627)
Men 60 years or older	−.02837	.00400	−.04541*
	(.02614)	(.01694)	(.02468)
3. Household belongings			
No vehicle (car or truck)	.14684***	.11552***	.14014***
	(.06113)	(.03822)	(.03220)
No television	−.02322	−.01297	.01880
	(.01671)	(.01197)	(.01832)

(Continued)

Table 4. Continued

Household characteristics	Enrollment	Application	Learning
No radio	−.02991**	−.01535*	−.02125
	(.01290)	(.00897)	(.01343)
Own house	.00796	−.00390	.01476
	(.01508)	(.00996)	(.01486)
Unpaved floor	.05669***	.03609***	.04906***
	(.01381)	(.00983)	(.01456)
No refrigerator	.07116***	.02023**	.04892***
	(.01531)	(.00994)	(.01451)
No gas heating	−.00064	.02210*	−.01545
	(.01675)	(.01100)	(.01710)
No toilet	.10681***	.06288***	.09744***
	(.01880)	(.01171)	(.02333)
Unconnected to running water	.06649***	.06902***	.11228***
	(.02110)	(.01422)	(.01770)
Family size/rooms in the house	.01578***	.01334***	.02437***
	(.00451)	(.00322)	(.00471)

[a]Observations: 4,323 (enrollment), 4,953 (application) and 8,515 (learning).

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

Table 5. Official Criteria for Enrollment

Household characteristics	Normalized weight
Age of household head (years)	0.11
Household head without education	9.84
Household head with only primary education	5.21
Female household head	−0.50
Access to health facilities	12.32
Children 0 to 11 years old	6.61
Children/working age adults	4.54
No vehicle (car or truck)	4.13
Unpaved floor	12.32
No refrigerator	13.14
No gas heating	19.73
No toilet connected to running water	5.70
No washing machine	3.28
Family size/rooms in the house	3.58

Source: Administrative sources. Regional dummies are excluded.

not only their estimate of their scores, in assessing their probability of enrollment if they apply to the program. Because we use the results from equation (1) to estimate the expected benefit of application, we have bootstrapped the standard errors.

The results are reported in the second column of table 4.[9] The key result is that the expected benefit of application has a significant impact on the application decision. Participation in other social programs has a large and significantly positive impact on participation in the program, suggesting unobservable characteristics related to the cost or benefit of application that are common across social programs. Education has a significantly negative impact on application, which may be due to an income effect or may reflect stigma.[10] Distance to the registration center has a positive impact on application, which is puzzling because distance would be expected to increase the cost of applying. Note that this study focuses on a sample of urban households; the importance of distance may be better identified in rural settings.

Finally, we estimate the determinants of information using the entire sample of households in our dataset. In particular, we estimate equation (3) with the expected benefit of knowledge and all of the explanatory variables from the estimation of equation (1) as explanatory variables. Because we use the results from equation (2) to estimate the expected benefit of knowledge, we have bootstrapped the standard errors. The results are reported in the last column of table 4. Consistent with the model, the expected benefit of knowledge of the program has a statistically significant effect. The other variables that have significant and important positive effects on information include the percentage of eligible households in the block, participation in other social programs, participation in organizations, whether the mother speaks an indigenous language, and the age of the household head. In all of these cases, targeted information and word-of-mouth communication may have played a role. In particular, the statistically significant positive coefficient associated with the percentage of eligible households in a block is consistent with the information strategy adopted by the program to target poor blocks. As a result, eligible households residing in blocks that are less poor had a substantially lower probability of knowing about the program.

Decomposing the Participation Process

In this section, we decompose the effect of several household characteristics on participation outcomes into the different stages of the participation process. We first explain the statistical decomposition proposed by Heckman and Smith (2004). Let $\Pr(\text{par}|X_h)$ be the unconditional probability that a household with characteristic X_h participates in the program, $\Pr(\text{en}|\text{ap}, \text{in}, X_h)$ 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 conditional on information, and $\Pr(\text{in}|X_h)$ be the unconditional

9. The marginal effect of benefits corresponds to a hundred pesos.

10. Martinelli and Parker (2009) also find that applicants who are more educated tend to omit reporting at the registration center that they lack a concrete floor or a toilet, potentially excluding themselves from the program; this omission may be attributed to embarrassment.

probability that the household is informed. Using the chain rule, we have

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

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

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

the application effect is

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

and the information effect is

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

In these expressions, ∂_x Pr(en|ap, in, X_h) is the marginal effect of the variable on enrollment conditional on application and information, ∂_x Pr(ap|in, X_h) is the marginal effect of the variable on application conditional on information, and ∂_x Pr(in|X_h) is the unconditional marginal effect of the variable on information.

In our model, the enrollment effect is a similar expression

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

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 because it contains a term that depends on changes in the expected gain from application induced by changes in the probability of enrollment:

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

where ∂_G Pr(ap|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 ∂_x Pr(en|ap, in, X_h) × ln(1 + B_h/Y_h) is the change in the expected benefit of applying, and ∂_G Pr(ap|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 weight the indirect effect using Pr(en|ap,in,X_h) × Pr(in|X_h,B_h,Y_h).

Finally, the information effect in our model is

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

where ∂_G Pr(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 it is not affected by marginal changes in benefits) and 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 the indirect effects using Pr(en|ap, in, X_h) × Pr(ap|in, X_h, B_h, Y_h). Note that ∂_G Pr(in|X_h,B_h,Y_h) is the marginal effect of the expected benefit on the information decision. In the second term, Pr(ap|in, X_h, B_h, Y_h) × ∂_x Pr(en|ap, in, X_h) × 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, (∂_x Pr(ap|in, X_h, B_h, Y_h) / ∂_G Pr(ap|in, X_h, B_h, Y_h)) × (Pr(ap|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,

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

and

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

Table 6 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. In both cases, the main source of the impact of most of the variables that we consider on participation is the

TABLE 6. 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 or more years of education	−.00527	−.00011	2.27	−.00249	47.20	−.00266	50.46
Mother speaks indigenous 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 or more children 0 to 5 years old	.05103	.01350	26.45	.00732	14.41	.02972	58.25
One or more children 6 to 11 years old	.06778	.02499	36.88	.00916	13.52	.03278	48.37
One or more children 12 to 17 years old	.01108	.00619	55.85	−.00142	-12.79	.00610	55.06
Heckman-Smith							
One or more years of education	−.00503	−.00011	2.24	−.00251	49.98	−.00237	47.20
Mother speaks indigenous 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 or more children 0 to 5 years old	.04443	.01341	30.18	.00448	10.10	.02599	58.52
One or more children 6 to 11 years old	.06796	.02480	36.49	.00958	14.10	.03258	47.94
One or more children 12 to 17 years old	.03018	.00614	20.37	.00669	22.18	.01704	56.48

Source: Authors' elaboration.

information stage, followed by the enrollment stage. There is, of course, no reason for the two decompositions to offer results similar to other databases because the decomposition that we offer attempts to capture both direct and indirect effects of the exogenous variables in the different stages of the participation process.

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 important.

Increasing monetary benefits by 100 pesos would increase the probability of participation by less than two percentage points; average monetary benefits were 350 pesos. This finding suggests that further increases in benefits, keeping the program design constant, will not have a large impact on participation. This implication is not unrealistic considering that monetary benefits are already quite high compared with household pre-program expenditure (see tables 2 and 3). It is worth emphasizing that this marginal effect is average, but in principle, it may vary across different socioeconomic groups. For example, increasing the level of benefits for poor households who correctly expect to receive low benefits (for example, elderly households without children) may be an effective approach to increase participation among this group.

Concluding Remarks

In this paper, we develop a sequential and interdependent decision model of participation in social programs and apply it to a unique data set that contains detailed information on the different stages of the participation process in *Oportunidades*, a flagship social program in Mexico. This program has become a prototype for a growing number of similar programs in developing countries. The model and empirical findings presented in this paper provide insight into the design, implementation, and evaluation of such programs and other programs that involve self-selection by potential beneficiaries.

A key component of the model is that it explicitly identifies three stages in the participation process (information acquisition, application, and enrollment) in which the decision by a potential beneficiary regarding participation in earlier stages is influenced by the expected outcomes at later stages and the expected benefit from participation. Our empirical analysis reveals a statistically significant positive impact of expected benefits on both the information acquisition and application decisions of households. The magnitude of the coefficients, however, suggests that the marginal impact of increasing benefits is relatively small; an extra 100 pesos increases the average probability of participation by less than two percent. To identify the stages in the participation process at which participation barriers are most prohibitive, we decomposed the contribution of each explanatory variable across the stages. We found that the information and enrollment stages explain most of the variation in outcomes.

The empirical results indicate how changes in program design and implementation could increase program participation among eligible households. The most important determinant of knowledge was the percentage of eligible households in a block. This result reflects the fact that the information campaign adopted by the program heavily concentrated its advertising in the poorest blocks. In programs where self-selection is a key component, it is therefore important to ensure that sufficient information about the program objectives and design are available to all households, regardless of location. In addition, for a given initial advertising intensity, allowing an ongoing registration process (as opposed to the relatively fixed, short registration interval used in *Oportunidades*) can facilitate a more gradual information diffusion process, such as diffusion by word-of-mouth communication.

The decomposition analysis identifies enrollment as the most important determinant of program participation after information acquisition. The use of other household characteristics in addition to official eligibility criteria to ration access to program places is consistent with the degree of demand from eligible households that often greatly exceeded planned office budgets, as reported by program offices. Rationing may have had unintended and possibly undesirable effects. A reallocation of benefits from those currently entitled to those who would have been entitled had rationing not been enforced may be socially desirable. Therefore, replacing the fixed budget approach with an entitlement approach that allows the budget to adjust to meet demand from eligible households would help to address low participation among eligible households. However, this alternative approach would require, at a minimum, a reallocation of budgets across blocks and is likely to require an increase in the budget.

Many social programs rely on self-selection as a way of saving on administrative resources by reducing the number of noneligible households that apply and the subsequent need to verify their household characteristics. Our empirical analysis highlights the trade-off in terms of undercoverage. Extensive information campaigns, ongoing registration, and flexible budgeting can help to reduce this trade-off. Although this strategy should prove more effective at reducing undercoverage of eligible households, in the absence of eligibility criteria that are strongly associated with the underlying program objectives (in our case, poverty alleviation), it may also result in large leakage of benefits to nonpoor households. Avoiding an adverse trade-off between decreasing undercoverage and increasing leakage requires clear and effective eligibility criteria that strongly correlate with poverty and rigorously implemented.

As always, there are remaining concerns regarding the separate identification of benefit and cost impacts because some unobserved cost determinants may correlate with the determinants of benefits. Our identification of the effects of benefits relies on variation due to program rules and pre-program schooling. For future work, our estimation suggests the usefulness of studies of participation in environments with experimental variation in benefits. Another area in which other data sources would be welcome is the formation of expectations; we assume rational expectations as a simple way to close the model, but we cannot exclude the possibility of systematic biases in the perception of the later stages. Another issue that we do not explore in this paper is the possibility of correlated errors in estimating the determinants of participation at the different stages. Addressing this possibility would require a move away from a simple recursive estimation approach.

In summary, both the model developed in this paper and the empirical results indicate the need to view program participation as an outcome of a disaggregated participation process, especially where the program design allows for a strong element of self-selection. Such an approach reinforces the need to consider the costs and benefits facing households at each stage and to design targeting and eligibility strategies accordingly. An empirical identification of the factors that determine outcomes at each of the participation stages also requires sufficiently disaggregated data on outcomes at these stages and variables that may explain these outcomes. Administrative-level information and data (such as advertising strategy and resources and the level and distribution of program budgets) that can be mapped to household-level data may be extremely valuable for identifying policy levers that can improve participation outcomes without adverse effects.

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