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DAVID P. COADY, SUSAN W. PARKER

Program Participation Under Means-testing and Self-selection Targeting Methods

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David P. Coady is a Technical Assistance Advisor in the Fiscal Affairs Department at the International Monetary Fund , 700 19th Street NW, Washington, DC 20431. Email: dcoady@imf.org. Most of the work was done while he was a Research Fellow at the International Food Policy Research Institute.

Susan W. Parker is a Profesora/Investigadora, División de Economía, CIDE, Carretera Mexico-Toluca No. 3655, 1210 Mexico DF Mexico. Email: susan.parker@cide.edu.

Abstract

Using data that enables us to distinguish between the different components of program participation (i.e. knowledge, application and acceptance), we investigate the determinants of household behavior and program implementation in a social safety-net program that combines administrative and self-selection targeting methods. High undercoverage of eligible households primarily reflects lack of knowledge and binding budget constraints in poor areas. High leakage to ineligible households reflects the combination of their high levels of knowledge, application and acceptance. Lowering undercoverage will require greater program awareness among the poor living in non-poor areas and this is likely to come at the expense of substantial leakage to the non-poor unless improvements are made to the verification process. Our results also suggest that in the presence of a budget constraint the administrative selection process gives priority to the poorest households and those with children.

Resumen

En este trabajo investigamos los determinantes del comportamiento del hogar y la puesta en práctica del programa en una red de seguridad social que combina métodos de selección administrativo y de autoselección, utilizando información que nos permite distinguir entre los diferentes componentes de la participación del programa (es decir conocimiento, aplicación y aceptación). La alta subcobertura de hogares elegibles refleja principalmente la falta de conocimiento y las restricciones presupuestarias en áreas pobres. La alta filtración de hogares no elegibles muestra la combinación de sus altos niveles de conocimiento, aplicación y aceptación. Para disminuir esta subcobertura se requerirá una mayor difusión del programa entre los pobres que viven en áreas no pobres y esto puede ocurrir a expensas de una filtración importante de los no pobres a menos que se mejoren los procesos de verificación. Nuestros resultados sugieren que ante la presencia de una restricción presupuestaria el proceso administrativo de selección le dé prioridad a los hogares más pobres y a aquellos con niños.

Introduction

The use of means testing for determining eligibility for social safety-net programs has become increasingly popular in developing countries concerned with improving program targeting performance (Coady, Grosh and Hoddinott, 2004a). However, it is widely recognized in developed countries that means testing often has adverse implications for program participation by eligible households (Atkinson, 1989; Moffit, 2003). Indeed, the problem of low take-up levels also applies to universally available programs in developed countries (Currie, 2004), reflecting the important role that self-selection can play in program participation levels by different socio-economic groups.

In spite of the potential for trade-offs between program coverage of the eligible population and targeting performance, very little empirical evidence exists on the nature and magnitude of these trade-offs, especially for developing countries. The present paper contributes to filling this gap by analyzing the determinants of participation in a prominent social safety-net program in Mexico that combines administrative targeting based on means testing with a strong element of self-selection by households. The program in question is *Oportunidades*, which 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 the fact that it continues to act as a prototype for social safety-net reforms in other developing countries, especially in Latin America (Skoufias, 2004).

To a large extent, the paucity of evidence on the determinants of participation reflects the absence of sufficiently detailed survey data to support such an analysis. Blundell, Fry and Walker (1988) examines participation by eligible households in a housing benefit program in the UK. The analysis uses national household survey data containing information on receipt of program benefits combined with the simulation of program eligibility based on knowledge of program eligibility rules, which are applied to the socio-economic information available in the survey. In the context of the same program, Duclos (1995) extends the concept of participation to allow for targeting errors made by program agents, which result in both "errors of omission" (i.e. undercoverage of eligible households that apply) and "errors of inclusion" (i.e. leakage to non-eligible households that apply).[1] However, due to data deficiencies, both papers are unable to provide insights into the finer details of program participation since household knowledge of the program, the household's decision to apply, and the program agent's decision as regard eligibility are all subsumed within one binary participation

[1] Duclos (1995) also highlights the potential for "analyst error" in determining eligibility in household surveys based on incomplete data. See also Pudney, Hernandez and Hancock (2002) for an analysis of pensioner take-up of means-tested income support in the UK.

variable. In identifying specific policy prescriptions aimed at improving coverage and targeting performance, more detailed information on these different components of participation is particularly useful.

We are aware of only two papers in the literature that empirically analyze the different components of program participation. Heckman and Smith (2003) combine data from a number of different sources to investigate the sources of inequality of participation among different groups of eligible individuals for the Job Training Partnership Act in the USA. However, data limitations resulted in both application and acceptance outcomes being combined into a single step. The only paper we are aware of that undertakes a similar analysis for a developing country program is Micklewright, Coudouel and Marnie (2004), which investigates the sources of inequality of participation among households for a social assistance program in Uzbekistan using nationally representative household survey data. Under this program, the central government allocates funds to a group of community elders that has complete autonomy over the selection of program beneficiaries, subject only to very broad guidelines from the government. Although the authors are able to separately distinguish between knowledge, application and acceptance characteristics of households within one household dataset, they are unable to match households to community groups and thus are unable to disentangle the relative importance of central and community budget allocations in the overall targeting performance of the program. In addition, the absence of any explicit detailed rules for determining benefit levels means that they are unable to control for the level of benefits a household would receive if it participated. These difficulties are further confounded by the fact that the survey used does not contain any comprehensive measure of household income.

Rarely does one have access, either in developed or developing countries, to a data set that is designed specifically to investigate the different components of program participation. In this paper we use a unique dataset that enables us to distinguish between the different components of participation (i.e. knowledge, application and acceptance). This detail allows us to analyze separately the determinants of household behavior and program implementation. The specific tailoring of the questionnaire to the issue of targeting also means that many of the measurement problems encountered in earlier papers (e.g. in determining true eligibility or the expected level of benefits if selected as a beneficiary) are likely to be substantially reduced, even if not eliminated completely. In addition, we are able to match these household data with program data disaggregated to the level of program offices, which allows us to capture differential patterns of participation across program office segments reflecting such things as varying resource and capacity constraints. An added advantage is that our data allow us to construct a comprehensive measure of household consumption, which is widely perceived as a good proxy for household “permanent income”.

In this paper we are concerned with the determinants of program participation and the implications for the program’s targeting performance. As Atkinson (1995) points out, how one undertakes an assessment of targeting performance and interprets the results should depend both on whether the objectives of the program are clear (e.g. the definition of the target group) and on how much agreement there is about these objectives. With regard to the program under consideration, the targeting objectives are very clear in the sense that the target group is very precisely defined by a statistical proxy-means algorithm that attaches numerical weights to specific household socio-economic characteristics in order to calculate a household score. These scores are then compared to a score cut-off to identify eligible households. In the present paper we use this separation of households into eligibles and non-eligibles as the basis of our analysis. However, we recognize that although these classifications may be explicit and clear they may or may not command wide support. For example, as in much of the literature, one may consider economic welfare as the correct basis for targeting households in such programs so that a comprehensive evaluation of targeting performance requires an assessment of the “vertical efficiency” of the program’s targeting with reference to some comprehensive measure of household income.[2] For the most part, in this paper we abstract from this issue and focus on the program’s definition of eligibility.

The format of the paper is as follows. In Section 1 we present a brief discussion of issues that arise in the application of means testing, followed by a description of the program and the targeting methods used. Section 2 provides a data description. In Section 3 we motivate and describe the methodology used to evaluate targeting and present the results from this analysis. In Section 4 we set out a simple model that helps to motivate and structure our empirical investigation of the various components of participation. We then use regression analysis to identify various factors that determine targeting outcomes, examining separately their effects on knowledge of the program, the household decision to apply for the program and the acceptance or rejection of applicants by the program office. Finally, Section 5 provides some concluding remarks.

[2] See Weisbrod (1977) for a discussion of vertical and horizontal targeting efficiency, and Coady and Skoufias (2004) for a formal interpretation of these within standard welfare theory.

1.- The Program and Targeting Methods[3]

1.1.- Program Description

In August 1997, the Government of Mexico officially launched its flagship *PROGRESA* social safety-net program in rural areas. The program was considered successful and in 2002 was expanded –under its new name, *OPORTUNIDADES*- to include small and medium urban localities. The new urban program has continued to use a combination of geographic and proxy-means targeting methods to identify poor households. However, the application of this previous approach to household targeting in rural areas, whereby a census of the socio-economic characteristics of all households in participating localities was undertaken, was deemed too costly for urban areas where poverty rates are much lower. It was therefore decided to introduce a strong element of self-selection by households.

1.2.- Targeting Methods

In order to identify the poorest urban localities for the expanded program, the government used the 2000 national household income and expenditure survey (ENIGH2000) to develop a *discriminant analysis* model based on household income and other socio-economic characteristics. Once the model and coefficients were determined, (see Appendix Table 1 for the variables used and their scores) the weights and cut-off score were applied to the 2000 national census (NC2000) to identify the poorest urban blocks where the program will be implemented (the variables included in the model are common to the NC2000).

Once participating communities were identified, an information campaign was initiated at the municipal and community levels to inform people of the existence and objective of the program, the rules for program eligibility, and how to apply for the program. A range of media was used, including: TV and radio advertisements; the distribution of flyers; placing posters in churches, schools, health clinics and market places; and loudspeaker announcements. In principle, these were to be concentrated in the poorest blocks. The population was informed that a program office would be located in or near their locality during the months of June-August 2002, which they should visit to apply for the program. Decisions regarding the precise nature of the publicity campaign and its financing were decentralized to municipalities.

When households turned up at the program module they were asked to provide information on their address and on the specific socio-economic

[3] See Grosh (1994) and Coady, Grosh and Hoddinott (2004) for more detailed discussion of the design and implementation of different targeting methods.

characteristics that are used to calculate their score. This information was entered immediately into a computer and the applicant informed whether or not they are deemed eligible at this stage. Those found to be initially eligible were informed that they would be visited over the following weeks to verify the information given and were given a paper slip containing their identifier, name, address and so on. Program officials were then expected to visit the potential beneficiaries in their home and fill out a new questionnaire containing information on the same socio-economic characteristics. This information was then processed back at the module and the new eligibility status of the applicant determined.

Applicants were told to return to the module to confirm their eligibility status and be incorporated if selected. If incorporated, they signed a program registration form, received their electronic program card (or stamps if they do not have access to a bank), and also were given program literature explaining the objectives, design and requirements of the program. If an applicant did not return to the office then they were not incorporated. If the information regarding an applicants' address was wrongly processed, and if they could not be located even after some investigative work, such households were also not incorporated. In addition, because more poor households showed up than planned, the existence of a budget constraint meant that program places had to be rationed - e.g. based on a first-come first-served basis, the proxy-means score or on other household characteristics observed by program officials. All program offices were closed at the end of August 2002, and households received their first transfers in November 2002 – see Appendix Table 2 for details on the transfer schedule.

2.- Data Description

The dataset used in this analysis is the baseline of the Urban Evaluation Survey of Oportunidades (2002), carried out between September and December, 2002 by the National Institute of Public Health (INSP). Two surveys were collected: (i) a census survey of all households in a random selection of blocks in participating localities (henceforth, CENSUS) and (ii) a sample survey of a subset of these households (henceforth, SAMPLE). The latter used a more detailed questionnaire and both surveys included the variables that were used to calculate the proxy-means score used as the basis of household participation.

The CENSUS sample was selected by first choosing a random sample of eligible localities, e.g. localities where incorporation was planned for 2002 (INSP, 2002). From this sample of localities, all blocks with poor populations greater than 50 households were selected, for a total of 99 such blocks in the sample. From the remaining blocks, a probability-weighted sample of 50 blocks was chosen with the inverse of their poor population as weights. A

CENSUS survey of all 20,859 households in these 149 blocks was carried out, containing information on the socio-economic characteristics used to calculate the proxy-means score as well as some other information, including whether the household had been selected into the program.

Using the CENSUS information, a discriminant score was calculated for each household, and households were classified into three groups: Poor, Quasi-Poor (i.e. those just above the cut-off), and Non-Poor. A stratified random SAMPLE of households, based both on these classifications and on self-reported beneficiary status, was chosen. In particular, all households that self-reported to be a beneficiary in the CENSUS data, were selected to be interviewed in the SAMPLE data. A random sample for each of the three groups was selected for those households who reported they were not beneficiaries i.e. for the Poor, Quasi-Poor and Non-Poor non-beneficiaries[4].

To evaluate overall targeting performance, we use the CENSUS survey of all households in the sample of localities. To identify the various sources of this performance, we use the SAMPLE data, which gives information on households' knowledge of the program, whether they apply and if so whether they are accepted.

3.- Targeting Performance

3.1.- Targeting Outcomes

To motivate our approach to evaluating the targeting performance of the program we first present a very simple model to capture the components of the social welfare impact of a transfer program. Social welfare is specified as a standard Bergson-Samuelson function:

$$W[V^1(\mathbf{p},y^1), \ldots.., V^h(\mathbf{p},y^h), \ldots.., V^H(\mathbf{p},y^H)]$$

where V($\mathbf{p}$,y) is the indirect utility function for households (denoted by superscript *h*), $\mathbf{p}$ is the vector of commodity prices faced by the household and *y* is total household income defined through the household budget constraint as:

$$y^h = \mathbf{w}.\mathbf{l}^h + m^h = \mathbf{p}.\mathbf{x}^h$$

[4] For the purposes of this paper, we determine the weights used for the household observations in the SAMPLE data for each of the four household groups by merging the CENSUS data to the SAMPLE data and identifying the proportions of households in the SAMPLE data with information for each group. Note that these weights then reflect both the probability of their selection as well as response rates.

where **w** is a vector of factor prices, $\mathbf{l}^h$ is the supply of factors by the household, m^h is lump-sum transfers from the government to the household, and $\mathbf{p}.\mathbf{x}^h$ is total household expenditures on commodities. Household indirect utility is assumed to be decreasing in commodity prices, increasing in factor prices and increasing in lump-sum transfers. A transfer program can be characterized by a vector d**m**={dm^h} where $dm^h>0$ for beneficiary households and $dm^h=0$ for non-beneciary households. The social welfare impact of a transfer program is then:[5]

$$dW = \sum_h \frac{\partial W}{\partial V^h}\frac{\partial V^h}{\partial m^h} dm^h \equiv \sum_h \beta^h dm^h \text{...(1)}$$

where β^h is the social valuation of extra lump-sum income to the household (i.e. the so-called “welfare weight” of each household). Multiplying and dividing the r.h.s. of (1) by the program budget gives:

$$dW = \sum_h \beta^h \frac{dm^h}{\sum_h dm^h}\sum_h dm^h \equiv \sum_h \beta^h \theta^h \sum_h dm^h \text{...........(2)} \equiv \lambda B$$

where θ^h is the share of the transfer budget going to each household. Since λ increases with the share of transfers accruing to the lower-income households with relatively higher welfare weights, it can be interpreted as an index of the targeting performance of the program. Note that if welfare weights are such that “poor’ and “non-poor” households have weights of unity and zero respectively and transfers are uniform, then the welfare impact of a program is simply the share of the beneficiary households that are poor times the budget.

Consider now a reference program that has a target “poor” population and a budget sufficient to give a uniform unit transfer to each poor household. Assume that poor households can be perfectly identified so that all beneficiaries are poor, i.e. λ=1. Under (2), the welfare impact of this reference program is simply the number of poor households. In practice, the welfare impact of a program can be smaller than for the reference program because targeting is imperfect and/or the budget is smaller, i.e. not all beneficiaries are poor and/or the *potential coverage* of the program is less than the size of the poor population. Below we use these two indicators to evaluate the welfare impact of the program. Note that increasing the welfare impact of the program to nearer that of the reference program requires either better targeting performance and/or a larger budget to increase potential coverage.

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5 We abstract from the general equilibrium welfare effects arising from, for example, the efficiency and equity implications of having to finance the program. See Coady and Harris (2004) for such an analysis.

Table 1 presents the results of our evaluation of targeting performance. Households are classified into three welfare groups based on the discriminant score constructed using the CENSUS data, i.e. as Poor, Quasi-Poor (i.e. just above the cut-off score) and Non-Poor.[6] Under this classification scheme, 39 % of households are found to be Poor, 19 % Quasi-Poor and 42 % Non-Poor. Using program administrative information that enables us to identify which of these households were actually incorporated into the program, we find that the total number of program beneficiaries in the treatment area is 4,728 households, out of a total population of 20,859 households (i.e. 22.7 %). This compares with the 39 % of households classified as Poor (i.e. 8093/20,859). Therefore, the potential coverage for the program, i.e. assuming zero leakage to non-poor households, is 58.4 % of Poor households. In other words, even if the program was perfectly targeted, with all beneficiaries being classified as Poor, the undercoverage rate would still be 41.6 % so that this amount of the undercoverage of the program is really due to program size and not bad targeting.

From Table 1 we can also see that only 3678 Poor households (i.e. 45.4 %) are beneficiaries, so that the total undercoverage rate is 54.6 %. Therefore, 76.2 % of the total undercoverage rate (i.e. 41.6 %age points of the total 54.6 % undercoverage rate) is due to *inadequate* program size, with the remaining 23.8 % being due to imperfect targeting. Therefore, the actual undercoverage rate is 30 % higher than the minimum that could be achieved with perfect targeting.

Note also that much of the leakage accrues to those households immediately above the threshold for program eligibility (i.e. to Quasi-Poor households). Around 19 % of Quasi-Poor households and 3.5 % of Non-Poor households participate in the program, and these account for 15.6 % and 6.6 % of total program beneficiaries respectively. This pattern of leakage results in 77.8 % of beneficiaries being classified as Poor households (i.e. 3678/4728).

In order to further evaluate the above targeting performance it is useful to divide the share of Poor households in total beneficiaries by their overall population share, e.g. by the head count. Since their population share indicates what Poor households would receive under random selection (i.e. no targeting), this ratio represents how much more Poor households receive compared to this alternative. From the final column, we see that Poor households receive around twice as much as they would without targeting, while Quasi-Poor and Non-Poor households receive 16.6 % and 84.5 % less than under this alternative. [7]

[6] We will use the tern *non-poor* (i.e. without capitals) to refer to both Quasi-Poor and Non-Poor households.

[7] This targeting performance is impressive when compared to that of programs reviewed by Coady, Grosh and Hoddinott (2004) where the median targeting performance of programs in the Latin America and Caribbean (LAC) region was 1.56, i.e. the poor received 56 % more than their population share. The median performances of programs using means and proxy-means targeting methods were 1.55 and 1.50 respectively (See Coady and Parker, 2004 for more details).

3.2.- Sources of Targeting Performance

We now turn to an analysis of the factors behind the existing targeting errors. To identify the sources of targeting performance, we use the SAMPLE data, appropriately weighted to reflect the sampling scheme and non-response patterns. In this survey, households were asked a series of questions aimed at determining if they knew about the program, if they knew where the program module was located, if they went to the module to apply for the program, and if they were selected as a beneficiary. Each question was asked conditional on replying in the affirmative to the previous one.

Within a given budget constraint, increasing the poverty impact of the program requires improving targeting performance. This, in turn, requires understanding where in the process Poor households are lost to the program and non-poor households wrongly included. Are Poor households excluded because they don't know about the program, because they know but don't apply, or because they apply and are wrongly rejected by the proxy-means test? Table 2a presents information on how the different welfare classifications evolve through each of these stages. Column 1 shows the %age of households by classification that reports knowing about the program. Note that a substantial 24 % of Poor households in treatment areas report not even knowing about the program. Of those who know, a very high 92 % know where the office is located and, in turn, a high 92 % of these actually go. Of those that apply, 80 % are actually registered as beneficiaries, with the remaining 20 % (wrongly) excluded from the program.

Table 2b translates these numbers in Table 2a into the %age of Poor households lost at each stage. For example, the %age of the Poor lost due to deciding not to go to register is given by the %age who know (76 %) times the %age of those who know where to go (0.925) times (1-the %age of those who know where to go to register), i.e. approximately 0.059. The final column indicates that 51 out of every 100 poor households are not registered as beneficiaries. The first column tells us that 24 of these (i.e. over 50 %) are excluded at the very first stage, i.e. by the fact that they do not even know about the program. The next two columns tell us that nearly 12 of these (around 27 %) know but either do not find out where to go, or do but decide not to go. The penultimate column tells us that 11 of these (nearly 20 %) go but were wrongly rejected by the program. Thus, although there is undercoverage at all stages, it is at the very first stage (i.e. program knowledge) that most Poor households are lost to the program. Decreasing undercoverage will then require substantial improvements in knowledge of the program among Poor households.

Tables 2a and 2b also provide information on the source of leakage to non-poor households. Although less Quasi-Poor and Non-Poor households know about the program, still a substantial proportion in each group (i.e. 61 % and

41 %, respectively) is aware of the program. Furthermore, a very high %age of those non-poor households who know actually apply (80 % and 68 %, respectively) and a high %age of those applying are actually accepted (53 % and 32 % for quasi poor and non-poor households, respectively). The fact that so many of the non-poor households who know about the program actually apply suggests that one of the main advantages expected from the use of self-selection, i.e. not having to devote program resources to collecting and processing information on these households, does not materialize. But perhaps more problematic is that the benefits from using a proxy-means test are reduced since a significant %age of the non-poor applying are actually accepted as beneficiaries. Note that a higher %age of the Quasi-Poor are accepted when applying, relative to the case for Non-Poor households, consistent with officials being less able to distinguish the former from Poor households when implementing the targeting mechanism.

Improving the poverty impact of the program thus requires substantially increasing the poor's knowledge of the program. However this raises the important concern that any attempt to decrease undercoverage by improving knowledge may come at the expense of increased leakage, which is currently relatively low.

4.- The Determinants of Participation

The preceding analysis shows that a large fraction of eligible Poor households do not become beneficiaries whereas a large %age of ineligible non-poor households do in fact become beneficiaries. Using multivariate regression analysis, below we now examine which factors appear to be more important at the different stages of the process as well as their net impact on targeting outcomes. We start by presenting an economic model of program participation, which helps to structure our empirical analysis, motivate our model specification and guide our interpretation of the empirical results. We then present the results from our empirical analysis.

4.1.- An Economic Model of Take-up

The model of take-up presented here draws heavily on the work of Pudney, Hernandez and Hancock (2002).[8] Consider a household deciding whether or not to apply for the program. Let $V_0[y; \mathbf{X}, \mathbf{U}]$ be the utility a household achieves from pre-transfer "original income", y (think of this as being adjusted for needs, e.g. household *per capita* or per adult equivalent income), and **X** and **U** are observed and unobserved household socioeconomic

[8] See also Moffit (1983), Cowell (1986), Blundell, Fry and Walker (1988), Atkinson (1989) and Duclos (1995) for related discussions.

characteristics respectively. The utility reached in the event of receiving program benefits is then given by the transformed utility function V_1[y + B(**W**) – C(y, **Z**); **X**, **U**], where B is the level of transfers a household would receive if deemed eligible for the program, **W** is the set of household characteristics determining the level of benefits, C is the cash equivalent of the costs incurred by households in attempting to gain access to the program and **Z** is the set of characteristics determining these costs.

For example, **W** will include some measure of income for a directly means-tested program or household socio-economic characteristics for a proxy-means tested program. C is the cash equivalent of the total utility cost associated with program take-up so that **Z** is intended to capture a range of physical, psychological, sociological and informational factors. In general, the functional form of V_1 should capture such things as the fixed costs of attempting to access the program, the perceived uncertainty associated with the selection process, as well as the ongoing costs associated with receiving the benefits. In this model, then, inequality in participation is seen as arising from variation in the benefits and costs of participation across households.

A household will take-up the program if $V_1 > V_0$. Since V is monotonic and continuous in y this is equivalent to:

$$B > V_1^{-1}[V_0] - y \quad (3)$$

where V_1^{-1} [V_0] is the post-transfer utility function inverted with respect to total income, i.e. the total amount of income a household with utility given by V_1 would need to reach pre-transfer utility V_0. Since take-up involves households incurring costs, we expect the right-hand side of (3) to be positive. The right-hand side of (3) thus captures a household's monetary valuation of take-up costs and can be interpreted as an equivalent variation. Note that if V_0 and V_1 are functionally identical, then the take-up condition becomes B>C.

Following Moffit (1983), we can specify the right-hand side of (3) as:

$$V_1^{-1}[V_0(y;X,U);X,U] - y = e^{Z\alpha+u} \qquad (4)$$

so that the take-up condition becomes:
ln B > **Zα** + **u,** where **u** are unobserved characteristics affecting take-up costs. The conditional take-up probability can then be written as:

$$\Pr(Participation \mid B, Z) = \Pr[u < \ln B - Z\alpha] = F(\frac{\ln B - Z\alpha}{\sigma})$$

where Φ^2=Var(**u**) and F is the distribution function of the random variable **u**/Φ. This equation amounts to a standard binary response model of discrete choice, with ln B and **Z** as explanatory variables. The coefficients of these explanatory variables are 1/Φ and -**α**/Φ respectively, so that **α** can be estimated as minus their ratio.[9]

The above model interprets take-up, and its associated costs, very broadly to encompass household knowledge about the program, the household decision to apply conditional on knowledge, and the program official's decision to classify a household as eligible. Costs encompass both the associated economic costs (e.g. of finding out about the program, applying for the program and meeting any program participation requirements) but also the broader psychological and social costs associated with applying for and receiving state support. Since the nature and magnitude of these costs are likely to differ across the various stages of participation, so too will the estimated coefficients on household socioeconomic characteristics. Because of this, the net effect of any socioeconomic characteristic on the single binary participation outcome may be difficult to anticipate *a priori* or interpret *ex ante*. The household data set we use in this paper allows us to overcome this deficiency since it was purposely designed to be able to identify eligible households as well as to identify the outcomes from the different components generating the participation outcome. By matching these data with program data disaggregated at the program office level, we are also able to better distinguish between household-level and program-level determinants of outcomes.

4.2.- Specification of Regression Equations

We now discuss some of the factors identified in the literature that can be expected to affect the various stages of the participation outcome, with special reference to the program under consideration in this paper and its design. We examine those affecting the knowledge, application and acceptance outcomes in turn.

Determinants of knowledge of the program

It is likely that a household's level of education affects its ability or propensity to acquire, process and act on program information, e.g. individuals who have higher education levels may be more likely to find out and process details about the program. Furthermore, individuals who are more "connected" to the community or have experience as beneficiaries of

[9] Note that take-up costs can be estimated by substituting estimates of into (4). See Blundell et al (1988) for an example. Pudney et al (2000) highlights the need to allow for self-selection into the program when estimating these costs.

other programs may also be able to process program information more efficiently. Language spoken may also be important; to the extent most program information is in Spanish, speaking a native indigenous language may reduce the probability of finding out about the program. Given the focus of the program on children, households with children may be more likely to hear of the program, especially those with children regularly attending school. Finally, it is likely that an important factor is the intensity with which advertising was carried out within each community.

In the regression analysis, we include indicators of household education and language spoken. With respect to previous program participation and involvement in the community, we employ two variables, one variable measuring whether anyone in the household is a beneficiary in any other social program, and another measuring whether household members participate in any community organization. [10]

With respect to advertising, we unfortunately do not have data on variables such as expenditures on advertising by block or municipality. However, since the advertising strategy involved concentrating on the poorest blocks, we include a block-level variable indicating the %age of the block in which the household is located that is classified as poor. We expect advertising to be greatest in the poorest blocks. Given the range of media used in disseminating information on the program, we also include binary variables indicating whether a household has a television or radio. In addition, in order to pick up unobserved poverty-related characteristics that are likely to influence knowledge, we also include *per capita* household consumption as an explanatory variable (we include quintile dummies to allow for non-linearities).

Determinants of application

The model presented above is particularly relevant for the analysis of household decisions to apply or not for the program, conditional on knowledge of the program. A household takes into account expected benefits and costs of applying for the program. Expected benefits of the program are a function of the probability of receiving benefits, conditional on applying, weighted by the amount of benefits received if deemed eligible. We calculate potential benefits (i.e. the maximum benefits that a family could receive if it were to become a beneficiary) by applying the schedule set out in Appendix Table 2 to the SAMPLE data and include its log in our regression analysis.

With regard to the expected costs of enrolling in the program, an important component relates to costs associated with travelling to the office.

[10] These are admittedly crude measures, and particularly that related to program participation may be endogenous, e.g. program beneficiaries are not permitted to participate in programs such as *Liconsa* (a targeted subsidized milk program). For this reason, we explored specifications with and without these variables. In general, the effects of other variables do not change with respect to the inclusion of these last two variables.

We use distance from the nearest office to proxy the costs of applying, i.e. we expect households located farther from the office, to be less likely to apply for the program. We also include indicators of demographic structure; in particular, we expect that having small children or a disabled individual in the household may increase the costs of going to the office. It is also often suggested that younger households (e.g. as captured by the age of the head of household) have fewer inhibitions against receiving social assistance. Finally, we include whether the household has a vehicle, which could reduce time spent getting to the office. Since the private value attached to transfers is likely to be a decreasing function of income, we also include *per capita* household consumption as an explanatory variable.

Determinants of acceptance

One expects that the score attained by the household, based on the socio-economic characteristics reported at the office, will have a dominant effect on whether an applicant household gets accepted into the program. In fact, in the absence of measurement error and information constraints, one expects a household's score to fully determine its participation conditional on application. However, because of measurement error, it is unlikely that the proxy-means score we calculate based on our CENSUS data will exactly correspond to that calculated by program officials based on information reported at the office and subsequently verified. Since we expect a non-linear relationship between acceptance and the score, we use a set of binary variables indicating the classification of a household as extremely poor, moderately poor, Quasi-Poor or Non-Poor.

One expects some variation across blocks in acceptance patterns reflecting the rigor with which household-reported information was (or could be) verified by program officials. In addition, in informal conversations, program officials indicated that since more households turned up than expected (i.e. compared to the predicted poverty rates), the existence of a budget constraint meant that many potentially eligible households were not considered for incorporation into the program and therefore the information they provided was not verified. While specific information on the extent to which budgets were binding across blocks was not available, we were able to construct a variable to proxy for this factor, namely, the %age of households classified as eligible at the program module whose socio-economic conditions were subsequently verified by program officials. Since we expect this %age to be positively correlated with budget availability, we also expect it to be positively correlated with a household's probability of being accepted, conditional on applying.

Finally, for all of our empirical models, with respect to the block-level variables proposed (e.g. distance to office and %age of Poor in the block), these may be correlated with other unobserved block or community level variables. Obviously the inclusion of block-level fixed effects means that we cannot simultaneously include block-level continuous explanatory variables. We thus first include, in turn, state fixed effects and then community fixed effects in our regressions that also include block-level continuous variables. Note that a block is quite a small entity so that significant relationships of block-level variables in this context are thus considered to be quite robust. Also, in a final set of regressions, we control for block-level fixed effects and interact our block-level variables with consumption quintile dummies. This specification helps to determine whether the effects of the block-level variables vary by poverty status. By including block-level fixed effects in these specifications, we completely control for all unobserved block-level variables that might be correlated with our variables of interest.

The regression that we estimate is the following:

$$U_h = \alpha + E_h\lambda + X_h\beta + X_b\delta + u_c + \varepsilon_h$$

where U_i is a binary variable indicating whether a household is a beneficiary or not, E_h represents the classification of eligibility of household h, X_h represents household observed characteristics described above, X_b represents a set of block-level and module-level characteristics . The model also includes community fixed effects, u_c, that sweep out any community characteristics which may be correlated with whether households are beneficiaries or not. ε_h corresponds to an error component that reflects all remaining unobserved characteristics of the model.

Controlling for block-level fixed effects and interacting block-level variables with consumption quintile dummies, the regression becomes:

$$U_h = \alpha + E_h\lambda + X_h\mathrm{B} + X_b\delta + E_hX_b\phi + u_b + \varepsilon_h$$

where u_b is a block-level fixed effect, the other variables are as defined as above, and the main coefficient of interest to us will be Φ, which tells us whether the effect of the block-level variable is different for different consumption quintiles. Similar regressions are carried out for the probability of knowing about the program, the probability that one applies for benefits (conditional on knowledge), and the probability that one becomes a beneficiary (conditional on applying). Our regression analysis is carried out separately for eligible and non-eligible households. Appendix Table 3 presents descriptive statistics of our explanatory variables for eligible and non-eligible households.

4.3.- Results

We look separately at the population of eligibles and non-eligibles, as defined by the proxy-means score. In all regression specifications we include variables capturing head-of-household characteristics, household-level characteristics and block-level characteristics. As discussed in the last section, we experimented with different specifications including the level of aggregation for area fixed effects. The detailed results from these specifications are presented in Appendix Tables 4-5 for both the eligible and non-eligible populations separately. Our results are generally quite robust to these various specifications, so in the text we concentrate on the specification with block-level variables and community fixed effects. The results below also come from ordinary least squares regressions on the binary variables; although the estimated coefficients are not efficient they are consistent. Since the results were very similar to those from logit regressions we present these because they are somewhat easier to directly interpret in the presence of fixed effects.

Table 3 presents the results for *eligible* households. The final column presents the results for the (unconditional) participation outcome. The first three columns present the results for the various sequential components of the participation outcome, i.e. knowledge, application conditional on knowledge, and acceptance conditional on application. We start by looking at the block-level variables. The significantly positive coefficient on the %age of households verified by the program office in the acceptance equation is consistent with the existence of a budget constraint. The fact that the positive effect of this variable on participation arises solely through the acceptance decision reinforces our interpretation.

The proportion of poor households in the block is significantly positively associated with participation. In other words, eligible households not participating in the program are more likely to live in blocks with lower poverty rates. This, of course, is consistent with the program information strategy, which concentrated on the poorest blocks. But this positive effect of the block poverty rates hides very different effects on knowledge and acceptance. Living in a relatively poor block substantially increases the probability that a household will know about the program, but also decreases the probability of being accepted conditional on applying. The latter effect is again consistent with the budget constraint being tighter in the poorest blocks where many households can be expected to present themselves at the program office.

As expected, greater distance to the office is negatively associated with the overall participation probability, consistent with this capturing higher travel costs or remoteness. However, the insignificant coefficients on distance in the knowledge, application and acceptance regressions mean that we are unable to attribute this distance effect across these components with much confidence.

Using the census proxy-means score, we separate eligible (i.e. Poor) households into two groups, the extreme and moderate poor. The positive significant coefficient on the “extreme poor” dummy variable indicates that those eligible households classified as extremely poor based on the proxy-means score have a higher probability of participation, and this effect comes through both higher probabilities of application and acceptance. In the absence of measurement error or a budget constraint, one would not expect the acceptance probability to differ across moderate and extreme poor households. However, the presence of a budget constraint will require program agents to, explicitly or implicitly, ration program access among eligible households. A higher probability of acceptance for the extreme poor would therefore be consistent with the rationing process favouring these households, e.g. either because program agents attach priority to households based on the magnitude of the proxy-means score obtained by the household or because program places are filled on a first-come first-serve basis and the extreme poor are quicker to apply on average.

Of course, some of this result could in principle be due to measurement error since our classification of households into eligible and non-eligible households is based on CENSUS data variables, which may not exactly correspond to the variables reported to program officials at program offices. The existence of such measurement in our proxy-means variable means that we may be classifying some households wrongly as eligibles when they are in fact ineligible based on office data. One expects that, for a given margin of error, such misclassification is more likely around the eligible-ineligible cut-off score. The positive coefficient in the application regression is more difficult to interpret, but would be consistent with households having knowledge of the scoring equation.

We also separate households into groups according to the consumption quintile into which they fall – the first quintile being the poorest. Conditional on proxy-means scores, the poorest households as measured by consumption (Q1) exhibit a substantially higher probability of program participation. Poverty is strongly positively associated with knowledge of the program. Households falling in the two lowest consumption quintiles are also more likely to apply for the program, consistent both with these perceiving a higher probability of acceptance or attaching a greater value to additional income. In addition, conditional on their score, households falling within the poorest consumption quintile have a higher probability of being accepted. One possible interpretation of this is that program officials may be compensating for the fact that the proxy-means algorithm is an imperfect indicator of economic welfare, especially since acceptance requires a prior visit by the program agent to households during which they will presumably observe other correlates of poverty status not included in the algorithm. Or it may be that the poorest households are the first to apply and beneficiary status is determined on a first-come, first-serve basis.

Contrary to our expectations, the coefficient on the logarithm of potential *per-capita* transfers is insignificant overall and in each of the component parts of participation. Controlling for potential transfers, households with more pre-school children have a lower probability of participating, although this is insignificant. But the corresponding coefficient in the application equation is significantly negative, which could reflect physical difficulties associated with getting to the program office to apply. This is a potentially worrying outcome given the priority attached to small children by the program. Households with school-aged children are more likely to participate, reflecting both a higher probability of knowing about the program and a higher probability of acceptance conditional on applying, the former finding may reflect the advertising strategy of targeting information posters at schools. Program agents may also be giving priority to households with school-aged children when rationing program places.

With respect to other household characteristics, having a vehicle in the household increases the probability of participation, reflecting a higher probability of applying conditional on knowledge. This is consistent with possession of a car decreasing the cost of getting to the program office to apply. Having a car does not affect the probability of knowing about the program or being accepted conditional on applying. Having a television also increases the participation probability, reflecting a positive and significant effect on the probability of knowing about the program. The former is consistent with our hypothesis that having a television, and thus hearing advertisements about the program, makes it more likely that one will find out about the program.

The insignificant coefficient on the household being classified as indigenous (i.e. the household head speaking an indigenous language) masks a statistically insignificant negative effect on knowledge of the program, a significant negative effect on the probability of applying for the program, but a significant positive effect on the probability of being accepted conditional on applying. Therefore, although speaking an indigenous language does appear to have adverse implications for the probability of the indigenous population finding out and applying for the program, the positive relationship with acceptance suggests that program officials may give some priority to indigenous households that do show up.

Although the coefficient associated with household participation in community organizations is positive, it is statistically insignificant. Program participation is also positively correlated with a household's history of participation in other social programs, reflecting greater knowledge of the program. This highlights the importance of being networked into groups that can facilitate information diffusion on the existence of programs.

Table 4 reports the results from the same regressions as above, but for the sample of *non-eligible* households. Interestingly, unlike for eligible households, the coefficient on the %age of households verified by the program module while positive (and smaller in magnitude) is never significant. In other words, the existence of budget constraints has apparently no role to play in explaining leakage, which is to be expected. Living in a poor block increases the probability that a non-eligible household will participate and this effect is clearly coming through the positive effect on household knowledge of the program. In other words, non-eligible households participating in the program are more likely to live in blocks with high poverty rates. While greater distance to the program module does appear to act as a deterrent to participation by non-eligible households, this effect appears to come through the associated lower probability of knowing about the program rather than through the application or acceptance decisions. This effect may therefore be capturing remoteness being associated with less exposure to program advertising.

Unlike the eligible population, higher potential benefits are associated with a higher probability of participation by non-eligible households and the relevant coefficient is robust and positive over all specifications. As expected, the positive effect of benefit levels on the participation decision comes solely through increasing the probability that an ineligible household will apply. In other words, ineligible households who would receive higher benefits if accepted are more likely to apply for the program.

We find that households classified as Quasi-Poor based on their test score have a higher probability of participation compared to Non-Poor households. This suggests that leakage is higher for households just on the wrong side of the cut-off score. This effect appears to come through this group having both a higher probability of being aware of the program and applying. Of course, some of this effect may also reflect measurement error in our proxy-means variable, as discussed earlier. Controlling for proxy-means scores, the probability of participating decreases substantially with household *per capita* consumption, reflecting the fact that these households have higher probabilities of knowing, applying and being accepted. The poorest households are thus more likely to find out about the existence of social safety net programs. Their higher probability of applying, conditional on knowledge, is consistent with these households perceiving a higher probability of being accepted as well as attaching a higher value to transfers. The large and significantly positive coefficient for the poorest consumption quintile in the acceptance equation is consistent with program agents using their own judgement regarding poverty to override the proxy-means score when is it clearly inconsistent with their own observations. But, again, some of this effect could reflect the fact that consumption is correlated with measurement error in our proxy-means variable.

Non-eligible households with pre-school children are also more likely to participate, reflecting a higher probability of program awareness. Pre-school children also increase both the probability of applying and the probability of being accepted, in other words, leakage is positively correlated with a household having a pre-schooler. The probability of knowing about the program also increases with the number of primary school age children. Households with children of secondary school age also have a higher probability of knowing about the program, although they also have a lower probability of being accepted conditional on applying.

Program participation is also positively correlated with household participation in community organizations as well as with household participation in other social programs. As expected, in both cases this reflects a greater probability of knowing about the program and of applying conditional on knowledge.

Finally, in Table 5 we focus on how the effects of some of our policy variables may vary with poverty status, as measured by consumption, in block fixed effects models. The empirical advantage of this specification is that it allows us to control for block-level fixed effects while still allowing us to compare whether the block-level variables are greater for poor versus non-poor households.

Table 5 reports only the results of interactions with consumption quintiles (with those in the highest consumption quintile as base) for the participation regression and each of its component parts. The results show important differences in effects by poverty status. Looking first at potential transfers, the results show that potential transfers have a higher effect in determining who becomes a beneficiary for the poorest two quintiles, consistent with these households attaching a greater value to extra income.

Turning to block-level variables, distance from the module has a larger absolute negative effect on the probability of becoming a beneficiary, conditional on eligibility, for the poorest two quintiles. This is due to these households being less likely to find out about the program, less likely to apply, and less likely to receive benefits conditional on applying. The last effect would also be consistent with these households being more likely to turn up late at the program office or program agents being less likely to bother to travel long distances to verify their reported information. Or the cost of applying may increase non-linearly with distance. With respect to the interactions between the %age of poor households on the block and poverty status, in general the interactions of households' consumption with the %age of poor households on the block is positive for the lowest consumption groups. This is suggestive that, for the poorest households, living in a high poverty area has a greater positive effect on becoming a program beneficiary than for the less poor. However, the insignificant coefficients on the various components of participation mean that we cannot determine with much confidence which route this effect takes.

Conclusions

Although there is substantial information regarding the existence of non-take-up by eligible households of means-tested transfers, there is relatively little evidence on the different sources of this non-take-up and the determinants of household and program agent behavior. In this paper, we contribute to filling this gap by evaluating the targeting performance of Mexico's *Opportunidades* program, which combines administrative targeting based on proxy-means testing with a strong element of self-selection on the part of households. Our data allow us to distinguish between the various components determining household participation in the program: household *knowledge* of the program, the household decision to *apply*, and the program agent's decision to *accept*. By matching this data with program-level data disaggregated to the program-office level we are also able to control for various program-level factors influencing targeting outcomes, e.g. varying budget and administrative constraints.

Our results indicate that there is substantial undercoverage of poor households, with only 45 % of eligible poor households receiving the program. However, our analysis of the source of undercoverage highlighted the concern that although knowledge was substantially lower among non-poor households, a high proportion of those who knew actually applied and, even more surprisingly, a high %age of those applying were accepted. Given that improving knowledge among poor households may simultaneously improve knowledge among the non-poor, it is necessary to look for ways for decreasing applications by these households (to avoid the costs of collecting and processing their information) and also to improve the application of the proxy-means test (to avoid excessive leakage).

The results from our regression analysis suggest that improving targeting requires increasing the awareness of poor households living in non-poor blocks. In addition, we find evidence that the existence of a budget constraint, especially in poorer blocks, was an important source of undercoverage, especially for more remotely located poor houeholds. But our results also suggest that the administrative selection process may be giving priority (implicitly of explicitly) to very poor households wrongly classified as non-poor, households with school-aged children or households classified as extremely poor based on the proxy means score.

Increasing program awareness among the poor in non-poor blocks is also likely to lead to improved awareness among the non-poor. Given their high propensities to apply and be accepted, this has important implications for program resources devoted to processing this information and for program leakage. It is therefore important to improve procedures for processing and verifying reported information on household socio-economic characteristics.

There are a number of reasons why the proxy-means score may not succeed in eliminating households classified as non-poor by the proxy-means algorithm. One possibility is that program agents may override the proxy-means classification where is it substantially at odds with their “observed” poverty status of the household. While this may not necessarily be a bad thing, it does suggest that the ability of the proxy-means score to accurately identify poor households needs to be evaluated. Alternatively, households may simply be reporting false information at program offices to improve their chances of being accepted. This then raises the issue of the rigor of the verification process, which needs to be evaluated further.

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Table 1 – Targeting Performance of the Program

Census Welfare Category	Census Population	Population Share	Program Beneficiaries	Beneficiary Share	Targeting Performance
Poor	8093	0.388	3678	0.778	2.005
Quasi Poor	3906	0.187	738	0.156	0.834
Non Poor	8860	0.425	312	0.066	0.155
Total	20859	1.000	4728	1.000	-

Note: The program participation rates for each welfare category are: Poor=45.4 %, Quasi Poor=18.9 %, and Non Poor=3.5 %.

Table 2a – Sequence of Undercoverage and Leakage (Conditional on Previous Answer)

Census Welfare Category	Know	Know where	Go	Accepted (Survey)	Accepted (Program)
Poor	0.690	0.901	0.892	0.799	0.928
Quasi Poor	0.583	0.832	0.779	0.589	0.587
Non Poor	0.399	0.740	0.658	0.595	0.347

Note: The numbers in the table are based on the 9817 treatment households (out of the 10527 sampled households in treatment areas) that completed the survey questionnaire. Before adjusting for this attrition, the expansion factors for these treatment households were approximately 1.061, 1.671, 1.703 and 4.515 for beneficiary, poor non-beneficiary, quasi-poor non-beneficiary and non-poor non-beneficiary households respectively (all based on the census reported beneficiary status). After adjusting for attrition these weights increased to 1.116, 1.801, 1.819 and 5.004 respectively.

Table 2b – Sequence of Undercoverage and Leakage

Census Welfare Category	Don´t Know	Don´t Know Where	Don´t go	Not Accepted	Accepted
Poor	0.310	0.069	0.067	0.111	0.443
Quasi Poor	0.417	0.098	0.107	0.155	0.223
Non Poor	0.600	0.104	0.101	0.079	0.116

Note: Each row gives the %age of each classification category excluded at different stages of the process.
For example, 31 out of every 100 poor households excluded are excluded due to not knowing about the program. The numbers in the table are based on the 9817 treatment households that completed the survey questionnaire expanded using the appropriate expansion factors.

Table 3

The Determinants of Program Participation and Its Component Parts

Eligible households in treatment group

	Knowledge	*Application (Conditional on Knowledge)*	*Acceptance (Conditional on Applying)*	*Overall Participation*
	CFE	*CFE*	*CFE*	*CFE*
Household head characteristics				
Age	0.00086	0.00142	-0.00134	0.00081
	[0.00072]	[0.00065]**	[0.00081]*	[0.00080]
Gender (1=male)	-0.03462	0.02877	0.02634	0.00164
	[0.02515]	[0.02165]	[0.02705]	[0.02796]
Indigenous (1=indigenous)	-0.01007	-0.01402	0.01813	-0.00355
	[0.00790]	[0.00711]**	[0.00934]*	[0.00879]
Years of schooling	-0.00093	-0.00095	0.00041	-0.00208
	[0.00076]	[0.00069]	[0.00086]	[0.00085]**
Disabled	0.07558	0.01103	0.01645	-0.00931
	[0.04347]*	[0.03973]	[0.04855]	[0.04833]
Female HH or spouse working in 2001	0.00782	0.01973	0.02179	0.01928
	[0.01447]	[0.01213]	[0.01534]	[0.01609]
Male HH or spouse working in 2001	0.05916	0.00559	0.01371	0.0617
	[0.02431]**	[0.02159]	[0.02663]	[0.02702]**
Household characteristics				
Vehicle in HH	0.03406	0.14164	-0.03574	0.13449
	[0.04640]	[0.04642]***	[0.06197]	[0.05158]***
Television in HH	0.0467	-0.0235	0.02634	0.03887
	[0.01560]***	[0.01334]*	[0.01646]	[0.01735]**
Radio in HH	-0.00701	0.00793	-0.02346	-0.01616
	[0.01306]	[0.01123]	[0.01394]*	[0.01451]
Children aged 0-5	0.00667	-0.01465	-0.01042	-0.00853
	[0.00830]	[0.00718]**	[0.00892]	[0.00922]
Children aged 6-11	0.02308	0.00264	0.02168	0.04896
	[0.00650]***	[0.00546]	[0.00682]***	[0.00722]***
Children aged 12 -17	0.0133	0.00865	-0.00618	0.01916
	[0.00798]*	[0.00683]	[0.00850]	[0.00888]**
Potential benefits				
Log of potential transfer	0.00419	-0.01767	-0.00247	-0.0045
	[0.01243]	[0.01111]	[0.01383]	[0.01382]
Welfare indicators				
Extreme poverty	0.02278	0.03453	0.05361	0.0936
	[0.01425]	[0.01226]***	[0.01521]***	[0.01584]***

Consumption Q1	0.12054	0.0736	0.05671	0.20067
	[0.02534]***	[0.02397]***	[0.02976]*	[0.02817]***
Consumption Q2	0.1207	0.06247	0.00648	0.14367
	[0.02389]***	[0.02307]***	[0.02868]	[0.02656]***
Consumption Q3	0.1119	0.02746	0.01624	0.10971
	[0.02395]***	[0.02333]	[0.02906]	[0.02662]***
Consumption Q4	0.08382	0.01446	-0.00263	0.06113
	[0.02465]***	[0.02457]	[0.03036]	[0.02740]**
Block level variables				
Distance to module	-0.00076	0.00621	-0.00451	-0.01881
	[0.00715]	[0.00705]	[0.00872]	[0.00795]**
% poor households in block	0.51	0.00385	-0.19548	0.24745
	[0.07311]***	[0.06659]	[0.08210]**	[0.08128]***
% verified poor in module	0.44704	0.51125	4.70335	2.96214
	[1.14395]	[1.12450]	[1.31841]***	[1.27166]**
Other				
Participates in community organ.	0.00782	0.01973	0.02179	0.0032
	[0.01447]	[0.01213]	[0.01534]	[0.01742]
Receives other social program	0.05916	0.00559	0.01371	0.10506
	[0.02431]**	[0.02159]	[0.02663]	[0.01554]***
Constant	-0.35098	0.16657	-3.65603	-2.79748
	[1.12000]	[1.10074]	[1.29444]***	[1.24503]**
Observations	4565	3005	3207	4565
R-squared	0.06	0.03	0.04	0.11

Note: Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Regressions include controls for other HH characteristics including : if household has dirt floor, a dummy indicating if there is a refrigerator and gas stove, and home ownership, as well as the number of men and women by age groups (18-39, 40-59, and 60 or older. SFE, CFE and BFE denote the inclusion of state-level, community-level and block level fixed effects respectively.

SFE =State fixed effects. CFE = Community fixed effects. BFE = Block fixed effects.

Beneficiary is defined according to administrative records from Oportunidades.

Table 4

The Determinants of Program Participation and Its Component Parts

Non-Eligible households in treatment group

	Knowledge	*Application (Conditional on Knowledge)*	*Acceptance (Conditional on Applying)*	*Overall Participation*
	CFE	*CFE*	*CFE*	*CFE*
Household head characteristics				
Age	0.00002	-0.00033	0.00158	0.00051
	[0.00089]	[0.00128]	[0.00155]	[0.00071]
Gender (1=male)	-0.01226	0.0233	0.04697	0.05465
	[0.03230]	[0.04369]	[0.05462]	[0.02609]**
Indigenous (1=indigenous)	0.01108	-0.01332	0.0028	0.00289
	[0.00925]	[0.01412]	[0.01834]	[0.00747]
Years of schooling	-0.00052	-0.00176	-0.00107	-0.00083
	[0.00081]	[0.00122]	[0.00150]	[0.00065]
Disabled	-0.00503	0.10673	0.06585	0.01544
	[0.05083]	[0.07480]	[0.10038]	[0.04106]
Female HH or spouse working in 2001	0.03594	0.00623	0.03418	0.00163
	[0.01662]**	[0.02368]	[0.02975]	[0.01342]
Female HH or spouse working in 2001	-0.00446	-0.04983	-0.05624	-0.05933
	[0.02999]	[0.04210]	[0.05196]	[0.02422]**
Household characteristics				
Vehicle in HH	0.09682	0.19625	0.08149	0.04033
	[0.02558]***	[0.05013]***	[0.07367]	[0.02067]*
Television in HH	-0.04483	-0.0042	-0.07897	-0.03435
	[0.02653]*	[0.03392]	[0.04092]*	[0.02143]
Radio in HH	-0.03617	-0.05155	-0.024	-0.04122
	[0.01718]**	[0.02342]**	[0.02845]	[0.01388]***
Children aged 0-5	0.0269	0.0384	0.07324	0.03787
	[0.01319]**	[0.01825]**	[0.02306]***	[0.01065]***
Children aged 6-11	0.02743	0.00128	-0.01074	-0.00829
	[0.00995]***	[0.01411]	[0.01778]	[0.00804]
Children aged 12 -17	0.01978	-0.00149	-0.03312	-0.01092
	[0.01076]*	[0.01470]	[0.01841]*	[0.00869]
Potential benefits				
Log of potential transfer	-0.00496	0.04099	0.03513	0.02241
	[0.01436]	[0.02083]**	[0.02584]	[0.01160]*
Welfare indicators				
Quasi poor	0.03196	0.04365	-0.02001	0.06859
	[0.01701]*	[0.02309]*	[0.02875]	[0.01374]***

Consumption Q1	0.0983	0.26482	0.2162	0.1999
	[0.03240]***	[0.04220]***	[0.05237]***	[0.02617]***
Consumption Q2	0.09849	0.20785	0.07366	0.10705
	[0.02612]***	[0.03539]***	[0.04474]*	[0.02110]***
Consumption Q3	0.06398	0.12124	0.04661	0.0594
	[0.02264]***	[0.03270]***	[0.04209]	[0.01828]***
Consumption Q4	0.04655	0.08937	0.06536	0.04853
	[0.02008]**	[0.03138]***	[0.04064]	[0.01622]***
Block level variables				
Distance to module	-0.02876	0.01713	-0.01026	-0.01858
	[0.00693]***	[0.01243]	[0.01497]	[0.00560]***
% poor households in block	0.79131	0.15899	-0.1222	0.37352
	[0.08119]***	[0.12072]	[0.14935]	[0.06558]***
% verified poor in module	-1.20666	0.02549	3.06084	0.65144
	[1.26093]	[1.71628]	[2.02702]	[1.01855]
Other				
Participates in community organ.	0.08283	0.06936	0.00974	0.03472
	[0.01839]***	[0.02533]***	[0.03197]	[0.01486]**
Receives other social program	0.09949	0.0345	0.01336	0.06306
	[0.01760]***	[0.02367]	[0.02895]	[0.01422]***
Constant	1.41372	0.02957	-2.54427	-0.63144
	[1.22304]	[1.67620]	[1.98448]	[0.98794]
Observations	3775	1604	1390	3775
R-squared	0.1	0.11	0.07	0.11

Note: Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

SFE =State fixed effects. CFE = Community fixed effects. BFE = Block fixed effects.

Beneficiary is defined according to administrative records from Oportunidades.

Table 5
Determinants of knowing, applying and receiving benefits from Oportunidades (Consumption quintiles and Block level variable interactions)

	Knowledge	Application (Conditional on Knowledge)	Acceptance (Conditional on Applying)	Participation (Unconditional)
DISTANCE TO MODULE				
Distance to module*Q1	-0.00808	-0.00917	-0.01444	-0.01395
	[0.00435]*	[0.00529]*	[0.00684]**	[0.00429]***
Distance to module*Q2	-0.00524	-0.01118	-0.01404	-0.0125
	[0.00426]	[0.00523]**	[0.00681]**	[0.00419]***
Distance to module*Q3	-0.00482	-0.0067	-0.01224	-0.00617
	[0.00435]	[0.00533]	[0.00694]*	[0.00428]
Distance to module*Q4	-0.00878	-0.00932	-0.00569	-0.00537
	[0.00437]**	[0.00544]*	[0.00716]	[0.00430]
% Poor households in block				
% Poor households in block*Q1	-0.00237	-0.03935	-0.02263	0.28601
	[0.09293]	[0.11701]	[0.14574]	[0.09146]***
% Poor households in block*Q2	-0.0576	-0.04557	0.07488	0.24848
	[0.08905]	[0.11591]	[0.14618]	[0.08767]***
% Poor households in block*Q3	0.04648	-0.01432	0.17918	0.25303
	[0.08502]	[0.11648]	[0.14711]	[0.08361]***
% Poor households in block*Q4	0.13508	-0.13605	0.07718	0.20602
	[0.08382]	[0.12331]	[0.15621]	[0.08251]**
POTENTIAL PER CAPITA TRANSFER				
Potential *per capita* transfer*Q1	0.01626	0.0404	0.00307	0.03836
	[0.02202]	[0.02608]	[0.03364]	[0.02165]*
Potential *per capita* transfer*Q2	0.04343	0.03463	0.01195	0.04696
	[0.02168]**	[0.02645]	[0.03414]	[0.02133]**
Potential *per capita* transfer*Q3	0.01143	0.02283	0.00467	0.02844
	[0.02162]	[0.02684]	[0.03512]	[0.02128]
Potential *per capita* transfer*Q4	-0.00842	0.04253	-0.01944	-0.00322
	[0.02173]	[0.02823]	[0.03693]	[0.02138]
Constant	0.33412	0.54621	0.45151	0.12029
	[0.08971]***	[0.11865]***	[0.15801]***	[0.08826]
Observations	8188	4545	4517	8195
R-squared	0.06	0.1	0.09	0.15
Number of blocks	127	124	124	127

Note: Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. Regressions include all the controls for block-level fixed effects, household head characteristics, household characteristics, potential benefits and welfare included in the previous regressions.

Appendix

Table 1.
Variables and Weights Used to Estimate Discriminant Score
(*Poor, x>=0.69; Quasi Poor, 0.69<=x>=0.12; Non Poor, x<=0.12)*

Variables (x)	Definition	Coefficient associated
HACINA	Number of people / Number of rooms in the house	0.139*HACINA
DEPEND	Total number of people in the household	0.176*DEPEND
SEXO	The head of the household is a woman	-0.02*SEXOJ
SS	Does not have access/right to medical service	0.475
NINOS	Total number or children <11 years	0.255*NINOS

ESC*	Years of education of the household head
	(0=never went to school or didn't reach any level)
	(1=primary education, 1st grade).
		If (ESCJ1=1), mpESC=0.380
		If (ESCJ2=1), mpESC=0.201
		If (ESCJ1=0 & ESCJ2=0), mpESC=0

EDAD	Age of the head of the household	0.005*EDADJ

BAO	BAO11=does not have bath
	BAO12=have bath but without water
		If (BAO11=1), mpBAO=0.415
		If (BAO12=1), mpESC=0.22
		If (BAO11=0 & BAO12=0), mpBAO=0

PISO	Floor is not paved (1/0)	0.475
ESTGAS	Do not have gas heating system (1/0)	0.761
REFRI	Do not have a refrigerator (1/0)	0.507
LAVA	Do not have washing machine (1/0)	0.127
VEHI	Do no have vehicle (no car nor truck)	0.159
RURURB	House is rural area	0.653
REG	Region (19 regions)	Reg1,2,3= -0.516 ; Reg4= -0.051 Reg5= -0.328; Reg6= -0.352 Reg7= -0.657; Reg 8&9= -0.391 Reg10&17= -0.293; Reg11= -0.511 Reg12= -0.66; Reg13= -0.376 Reg14= -0.413; Reg15= -0.143 Reg16&19= -0.07; Remaining=0
CONS	Constant	-1.579

Table 2.
Transfer Levels by Grade and Gender (pesos per month, 2002)

	Boys	***Girls***
Primary School		
Grade 3	100	100
Grade 4	115	115
Grade 5	150	150
Grade 6	200	200
Middle School		
Grade 7	290	310
Grade 8	310	340
Grade 9	325	375
High School		
Grade 10	490	565
Grade 11	525	600
Grade 12	555	635

Note: Education transfers are conditional on 85% school attendance. There is a cap on the amount households can receive in education grants: 1680 pesos if the household has children attending high school, 915 otherwise. Households also receive a monthly "food transfer" of 150 pesos, conditional on regular attendance at health centers.

Table 3
Descriptive Statistics

Variable	*Eligible*	Non Eligible						
	Incorporated	Non Incorporated	Incorporated	Non Incorporated				
	N	Mean	N	Mean	N	Mean	N	Mean
Household head characteristics								
Age	3048	39.19	2289	40.18	939	41.50	3434	41.88
Sex	3060	0.76	2305	0.76	939	0.75	3440	0.79
Indigenous	3077	0.24	2326	0.21	941	0.17	3472	0.17
Years of schooling	3060	5.45	2304	6.01	939	6.46	3440	7.91
Disabled	3077	0.98	2687	0.98	941	0.98	3822	0.98
Household characteristics								
Vehicle in HH	3077	0.99	2687	0.98	941	0.98	3822	0.89
Television in HH	3077	0.76	2687	0.66	941	0.84	3822	0.83
Radio in HH	3077	0.61	2687	0.54	941	0.66	3822	0.68
House ownership	3077	0.73	2687	0.58	941	0.70	3822	0.64
Dirt floor	3077	0.59	2687	0.40	941	0.31	3822	0.14
Refrigerator	3077	0.77	2687	0.73	941	0.47	3822	0.41
Gas stove	3077	0.33	2687	0.36	941	0.15	3822	0.18
Children aged 0-5	3077	0.96	2327	0.95	941	0.53	3472	0.42
Children aged 6-11	3077	1.33	2327	1.01	941	0.72	3472	0.65
Children aged 12-17	3077	0.75	2327	0.65	941	0.69	3472	0.63
Women aged 18-39	3077	0.87	2327	0.89	941	0.82	3472	0.86
Women aged 50-59	3077	0.26	2327	0.25	941	0.33	3472	0.36
Women aged 60 or older	3077	0.10	2327	0.13	941	0.13	3472	0.12
Men aged 18-39	3077	0.73	2327	0.74	941	0.69	3472	0.77
Men aged 50-59	3077	0.23	2327	0.24	941	0.27	3472	0.33
Men aged 60 or older	3077	0.09	2327	0.11	941	0.11	3472	0.11
Eligible benefit								
Log of potential transfer	3077	4.46	2327	4.47	941	4.68	3472	4.65

Table 4

Determinants of Program Participation (Eligible households)					
	SFE	SFE	SFE	CFE	BFE
Household head characteristics					
Age	-0.0009	0.00008	0.00031	0.00081	0.00096
	[0.00047]*	[0.00075]	[0.00080]	[0.00080]	[0.00075]
Gender (1=male)	0.01464	0.02504	0.03534	0.00164	-0.0132
	[0.01562]	[0.01882]	[0.02013]*	[0.02796]	[0.02628]
Indigenous (1=indigenous)	-0.00819	-0.0059	-0.00289	-0.00355	-0.00722
	[0.00797]	[0.00790]	[0.00884]	[0.00879]	[0.00779]
Years of schooling	-0.00117	-0.00119	-0.00176	-0.00208	-0.00138
	[0.00081]	[0.00081]	[0.00086]**	[0.00085]**	[0.00079]*
Disabled	-0.01092	-0.00921	-0.01081	-0.00931	-0.00999
	[0.04776]	[0.04752]	[0.04904]	[0.04833]	[0.04635]
Female HH or spouse working in 2001				0.01928	0.01113
				[0.01609]	[0.01493]
Male HH or spouse working in 2001				0.0617	0.06369
				[0.02702]**	[0.02541]**
Household characteristics					
Vehicle in HH	0.09379	0.1055	0.13332	0.13449	0.11805
	[0.05092]*	[0.05061]**	[0.05221]**	[0.05158]***	[0.04956]**
Television in HH	0.05059	0.04453	0.04196	0.03887	0.03996
	[0.01632]***	[0.01636]***	[0.01734]**	[0.01735]**	[0.01621]**
Radio in HH	-0.02335	-0.02679	-0.02018	-0.01616	-0.02636
	[0.01370]*	[0.01362]**	[0.01463]	[0.01451]	[0.01338]**
Children aged 0-5		-0.01126	-0.0064	-0.00853	-0.0097
		[0.00861]	[0.00931]	[0.00922]	[0.00846]
Children aged 6-11		0.05837	0.05343	0.04896	0.05561
		[0.00669]***	[0.00724]***	[0.00722]***	[0.00662]***
Children aged 12 -17		0.01818	0.01909	0.01916	0.02131
		[0.00836]**	[0.00897]**	[0.00888]**	[0.00820]***
Potential benefits					
Log of potential transfer	0.01444	-0.00527	-0.00117	-0.0045	-0.00672
	[0.01034]	[0.01318]	[0.01398]	[0.01382]	[0.01288]
Welfare indicators					
Extreme poverty	0.13045	0.09694	0.09675	0.0936	0.08259
	[0.01420]***	[0.01477]***	[0.01600]***	[0.01584]***	[0.01461]***
Consumption Q1	0.23495	0.20321	0.21624	0.20067	0.19373
	[0.02432]***	[0.02613]***	[0.02822]***	[0.02817]***	[0.02595]***
Consumption Q2	0.18147	0.15602	0.15693	0.14367	0.15435
	[0.02423]***	[0.02482]***	[0.02686]***	[0.02656]***	[0.02438]***

Consumption Q3	0.12127	0.10377	0.11947	0.10971	0.10911
	[0.02462]***	[0.02478]***	[0.02695]***	[0.02662]***	[0.02421]***
Consumption Q4	0.0714	0.06622	0.07331	0.06113	0.05812
	[0.02560]***	[0.02549]***	[0.02779]***	[0.02740]**	[0.02481]**
Block level variables					
Distance to module			0.00037	-0.01881	
			[0.00048]	[0.00795]**	
% poor households in block			0.15266	0.24745	
			[0.05483]***	[0.08128]***	
% verified poor in module			1.00623	2.96214	
			[0.28996]***	[1.27166]**	
Other					
Participates in community organ.				0.0032	-0.00908
				[0.01742]	[0.01640]
Receives other social program				0.10506	0.08867
				[0.01554]***	[0.01473]***
Constant	0.11214	0.15649	-0.9472	-2.79748	0.11597
	[0.09087]	[0.10522]	[0.29931]***	[1.24503]**	[0.10390]
Observations	5294	5294	4565	4565	5294
R-squared	0.07	0.09	0.1	0.11	0.09

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Regressions include controls for other HH characteristics including : if household has dirt floor, a dummy indicating if there is a refrigerator and gas stove, and home ownership, as well as the number of men and women by age groups (18-39, 40-59, and 60 or older. SFE, CFE and BFE denote the inclusion of state-level, community-level and block level fixed effects respectively.

SFE =State fixed effects. CFE = Community fixed effects. BFE = Block fixed effects.

Beneficiary is defined according to administrative records from Oportunidades.

Table 5

Determinants of Program Participation (Non-Eligible households)

	SFE	*SFE*	*SFE*	*CFE*	*BFE*
Household head characteristics					
Age	0.00031	0.00074	0.00105	0.00051	0.00064
	[0.00044]	[0.00069]	[0.00071]	[0.00071]	[0.00069]
Gender (1=male)	-0.01632	0.00818	0.00615	0.05465	0.04996
	[0.01451]	[0.01802]	[0.01865]	[0.02609]**	[0.02506]**
Indigenous (1=indigenous)	-0.00048	-0.00086	0.00053	0.00289	-0.00066
	[0.00704]	[0.00702]	[0.00760]	[0.00747]	[0.00684]
Years of schooling	-0.00071	-0.00086	-0.00069	-0.00083	-0.00085
	[0.00065]	[0.00065]	[0.00066]	[0.00065]	[0.00064]
Disabled	-0.00334	-0.00041	0.01138	0.01544	0.01639
	[0.04089]	[0.04085]	[0.04204]	[0.04106]	[0.03955]
Female HH or spouse working in 2001				0.00163	-0.007
				[0.01342]	[0.01282]
Male HH or spouse working in 2001				-0.05933	-0.04957
				[0.02422]**	[0.02333]**
Household characteristics					
Vehicle in HH	0.06405	0.05368	0.0461	0.04033	0.04831
	[0.02098]***	[0.02109]**	[0.02095]**	[0.02067]*	[0.02063]**
Television in HH	-0.04878	-0.03871	-0.02947	-0.03435	-0.04536
	[0.02077]**	[0.02080]*	[0.02160]	[0.02143]	[0.02050]**
Radio in HH	-0.04206	-0.03554	-0.03998	-0.04122	-0.033
	[0.01353]***	[0.01354]***	[0.01414]***	[0.01388]***	[0.01318]**
Children aged 0-5		0.04003	0.04376	0.03787	0.03231
		[0.01053]***	[0.01085]***	[0.01065]***	[0.01027]***
Children aged 6-11		-0.00264	-0.00654	-0.00829	0.00132
		[0.00776]	[0.00816]	[0.00804]	[0.00758]
Children aged 12 -17		-0.01171	-0.01726	-0.01092	-0.00554
		[0.00843]	[0.00880]**	[0.00869]	[0.00827]
Potential benefits					
Log of potential transfer	0.00661	0.02621	0.0263	0.02241	0.02195
	[0.00866]	[0.01133]**	[0.01179]**	[0.01160]*	[0.01105]**
Welfare indicators					
Extreme poverty	0.06985	0.07162	0.06652	0.06859	0.05968
	[0.01290]***	[0.01319]***	[0.01390]***	[0.01374]***	[0.01304]***
Consumption Q1	0.19376	0.21196	0.2106	0.1999	0.18477
	[0.02340]***	[0.02533]***	[0.02616]***	[0.02617]***	[0.02530]***
Consumption Q2	0.12469	0.13564	0.12477	0.10705	0.10596
	[0.01934]***	[0.02040]***	[0.02126]***	[0.02110]***	[0.02021]***
Consumption Q3	0.08137	0.08998	0.07237	0.0594	0.07463
	[0.01709]***	[0.01767]***	[0.01845]***	[0.01828]***	[0.01740]***
Consumption Q4	0.05117	0.05888	0.0541	0.04853	0.04918

	[0.01566]***	[0.01589]***	[0.01646]***	[0.01622]***	[0.01556]***
Block level variables					
Distance to module			-0.00067	-0.01858	
			[0.00050]	[0.00560]***	
% poor households in block			0.29939	0.37352	
			[0.04647]***	[0.06558]***	
% verified poor in module			0.26154	0.65144	
			[0.19697]	[1.01855]	
Other					
Participates in community organ.				0.03472	0.03424
				[0.01486]**	[0.01457]**
Receives other social program				0.06306	0.05414
				[0.01422]***	[0.01396]***
Constant	0.07861	-0.0132	-0.3711	-0.63144	0.01666
	[0.07081]	[0.08458]	[0.20936]*	[0.98794]	[0.08378]
Observations	4315	4315	3775	3775	4315
R-squared	0.07	0.08	0.1	0.11	0.07

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Regressions include controls for other HH characteristics including : if household has dirt floor, a dummy indicating if there is a refrigerator and gas stove, and home ownership, as well as the number of men and women by age groups (18-39, 40-59, and 60 or older. SFE, CFE and BFE denote the inclusion of state-level, community-level and block level fixed effects respectively.

SFE =State fixed effects. CFE = Community fixed effects. BFE = Block fixed effects.

Beneficiary is defined according to administrative records from Oportunidades.