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Multidimensional Targeting: Identifying Beneficiaries of Conditional Cash Transfer Programs

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Abstract

Conditional cash transfer programs (CCTs) have two main objectives: reduce poverty and increase the human capital of children. To reach these objectives, transfers are given to poor households conditioned on investments in their children's education, health, and nutrition. Targeting mechanisms used by CCTs have been generally successful in identifying the income poor, but have not fared as well in identifying households that under-invest in human capital. These mechanisms do not consider the multidimensional aspect of poverty, even when composite measures are used, as it does not capture each dimension-specific deprivation. This paper proposes a multidimensional targeting approach to identifying beneficiaries that explicitly take in consideration the multiple objectives of the CCTs and the multiple deprivations of the poor household. Results indicate that the proposed multidimensional targeting methodology significantly improves the selection of households with children who are most deprived in the dimensions often relevant to CCTs. In the case of Mexico's *Oportunidades*, ex-ante evaluation results indicate that the multidimensional identification of beneficiaries increases the welfare impact of transfers compared to alternative targeting models.

Keywords: Conditional Transfers, Targeting, Multidimensional Poverty, Ex-ante Evaluation.

1. Introduction

During the 1990s many developing economies adopted a new type of social program, conditional cash transfers (henceforth, CCT) which provide cash to poor households on the condition that they make pre-specified commitments such as investing in their children's human capital. The main objectives of a CCT are to alleviate poverty by raising the purchasing power of the household (redistributive effect) and to increase the human capital of poor children to break the intergenerational transmission of poverty (structural effect). In 1997, three CCTs were known to exist: the Bangladesh Food for Education Program, and the Latin American pioneers—*Bolsa-Escuela* in Brazil and PROGRESA (*Programa de Educación, Salud y Alimentación*) in Mexico. At the present time almost every country in Latin America has a CCT program or is in process to implement one. CCTs have become the largest social assistance programs in this region,¹ covering millions of people; in Mexico and Brazil CCT benefits a fifth of the population, and in Ecuador forty percent (Fiszbein and Schady 2009).

Conditionality and targeting are two essential features of CCTs. In the majority of these programs, the conditionalities take the form of co-responsibilities, that is, a form of social contract between the state, civil society, and beneficiaries. Conditionalities ensure investments in children's human capital and aid to justify income transfers to those who object targeted transfers as "pure handouts", because program beneficiaries take a number of concrete steps in favor of children's well-being. Specifically, the education component of the program usually consists of a cash stipend that is conditional on school enrollment, attendance, and school performance.² The transfer amount covers part of the direct costs of attending school as well as the household's opportunity cost of sending children to school. The health-nutrition component is mostly preventive health care: check-ups for children, pregnant and breastfeeding women, and household participation in community informative meetings; the health-nutrition transfer aims to cover the cost of a basic food basket and preventive health care.

Targeting is the other major feature of CCTs. In the Latin American context, CCTs generally emerged as replacements for less effective price subsidies or in-kind transfers, providing an entry point to reforming badly targeted programs and upgrading the quality of safety net instruments. As a result of the emphasis on the poverty criteria for targeting beneficiaries and the explicit use of targeting mechanisms to determine eligibility, CCT programs have shown significant redistributive results. The transfers are pro-poor and the coverage rate in the lowest deciles of the income distribution is high (around 45 percent of the CCT transfers are given to the poorest 20 percent of the population). After analyzing the redistributive power of 56 transfers programs in eight Latin America countries, Lindert *et al* 2006 show that CCTs are the class of programs with better targeting performance among all kinds of social spending in the region.

Despite the undeniable success of the CCT programs, current targeting mechanisms have been criticized for excluding poor households of the program. This is especially true when the CCT

¹ Rawling and Rubio 2005 show the specific differences in CCTs programs for six Latin American countries.

² Although these programs do not directly monitor school performance, evaluations show that performance is related to school attendance and the children's health and nutrition (Parker et al 2005 and Todd et al 2005).

covers a large number of households or in the more heterogeneous urban areas. Furthermore, there is also empirical evidence suggesting that exists room for improving the current targeting models (Coady *et al* 2004a, Coady and Parker, 2009). In view of this, the present paper proposes a new targeting methodology using a multidimensional approach that satisfies a set of axioms and can simultaneously encompass the two criteria that define the target objective of CCTs: poverty and under-investment in human capital. We propose a set of dimensions, indicators, and weights in tune with the essential objectives of CCT programs and use traditional and ex-ante microsimulation techniques to evaluate the performance of the proposed targeting model. We find that the multidimensional model identifies monetary poor more precisely than the current *Oportunidades* targeting model, and select households with characteristics that are more in line with the program objectives (for example, the multidimensional model is better in identifying households that do not send children to school). Another important result regards the expected impact of transfers in the occupational choice of children. The results of an ex-ante evaluation show that program's transfers have a greater impact on school attendance of potential beneficiaries selected by the multidimensional model relative to that of alternative targeting models.

The remainder of the paper is structured as follows. Section 2 describes current CCTs targeting models and their limitations, and in particular the targeting mechanism of *Oportunidades*; section 3 describes the methodology for identifying beneficiaries of CCT programs based on a multidimensional approach to poverty measurement (Alkire and Foster 2008); section 4 outlines and applies the methodology to the urban case of *Oportunidades*; section 5 evaluate the performance of new targeting methodology, and section 6 presents the concluding remarks.

2. Current CCT's targeting models and their limitations

In order to reach the poorest household, most CCT programs have used several targeting mechanisms. The most commonly used targeting sequencing has been generally geographic targeting followed by household proxy-means test. Based on the information of a poverty map, the poorest localities are chosen to participate in the program—geographic targeting. After selecting localities, a census takes place to capture information on households' main socioeconomic characteristics. Using data from this census, households are classified as “eligible” or “non-eligible” for the program through a proxy-means test—a formal algorithm used to proxy household welfare based on households' information and individual characteristics. Other forms of means-tests are the unverified means test used in Brazil and the verified means test, the gold standard of the means-test, used in the United States. The targeting mechanism that identifies households as potential beneficiaries is known as household or individual targeting. In addition, some programs use community-based targeting or community vetting of eligibility lists to increase transparency. Fiszbein and Schady 2009 have shown that about two thirds of countries that have CCTs programs use geographic targeting; about two thirds use household targeting, mostly via proxy-means test; and many countries use a combination of geographical and proxy-means. Finally, a self-targeting takes place, since once households are notified of their eligibility they must decide whether or not to participate in the

program.³ Some programs implement self-targeting as the first targeting mechanism, requiring households to pre-register for the program. The importance of each targeting mechanism may be different according to stages and size of the program. The role of geographic targeting tends to be reduced and that of the proxy-means test to increase as the program reaches national coverage or expands to less deprived localities (Coady 2006; Grosh *et al* 2008; Coady and Parker 2009).

The statistical methods used in proxy-means tests and their sophistication vary substantially across CCT programs. Proxy-means test generates a score (a probability or an index) for each potential beneficiary household. To calculate this score, indicators—which must be easily observable characteristics—are selected and their respective weights are obtained from statistical analysis using information from a detailed national household survey. The diversity of the methodologies within Latin America samples the alternatives being used. Costa Rica and Jamaica estimate a consumption model based on simple OLS regression; Colombia and Ecuador construct a well-being index based on principal components analysis; Uruguay opts for a poverty model based on probit analysis; and Mexico defines a poverty score based on discriminant analysis.⁴ Eligibility is determined by checking the score—linear combination of selected indicators and its corresponding weights—against a particular cutoff point or poverty line. In other words, the proxy means test generates a poverty measurement used to define household eligibility. Proxy-means tests are a promising cost-effective alternative for targeting cash transfers in developing countries, especially when high degrees of informality in the labor market exists, which hinders the collection and verification of detailed information on household income or consumption levels (Coady *et al* 2004b; Castaneda and Lindert 2005). Since it was first implemented in Chile in the 1980s, proxy-means tests have been monitored and its implementation and use refined over the years (Larrañaga 2003; Coady *et al* 2003).

Researchers and policymakers are aware of the CCTs' targeting errors. Important recommendations have been made to improve the performance of current proxy-means, including: (a) using the latest information to obtain up to date weights; (b) incorporating socio-economic variables that are more stable over time and are less susceptible to manipulation by the informants—for instance, household attributes at the geographical level; (c) estimating current models differentiating residence areas; (d) changing the cutoffs to acceptable levels of leakage (proportion of household that are program beneficiaries and are not poor) or under-coverage (proportion of poor household that are not beneficiaries of the program), (e) using alternative estimation methods (for example, logistic regression instead of discriminant) or modifying the dependent variable of current specifications (for example, using income directly rather than poverty status), (f) improving the quality of information obtained from the potential beneficiaries through additional controls in the whole process of the data collection (DNP 2003; Coady and Parker 2004; Rubalcava 2004; Catañeda and Lindert 2005, among others).

³ For an exhaustive review and evaluation of targeting mechanisms see Coady *et al* 2004b.

⁴ Significant variations also exist in how the implementation is done —whether households are visited; whether some variables are verified as part of the application process for all or for a sample of applicants; whether the staff members who help complete applications are permanent or contract workers and to which agency they report; and other such differences

While the above recommendations are useful, they do not address a major shortcoming of current targeting methodologies: poverty is considered essentially a monetary phenomenon. Academics and practitioners are progressively acknowledging the multidimensional nature of poverty. The argument is that income deprivation does not necessarily reflect well deprivations in other important dimensions such as health and education. In fact, the notion that a higher income would allow a household to deal with all other deprivations is based on the assumption that there are competitive markets for goods and services related to the health care of children, nutrition, and education. However, education as well as other public goods is provided in imperfect markets, and therefore, higher income does not always permit a household to face its deprivations (Tsui 2002; Bourguignon and Chakravarty 2003).

Many may argue that the targeting methods currently used by CCT programs take into account the multidimensionality of poverty, since a variety of household characteristics are included in the proxy-means test used to compute the score. However, this is not a truly multidimensional approach, but a rather unidimensional one: it does not capture each dimension-specific deprivation. If one agrees that poverty is multidimensional, but uses an income approach to reach the poor, there is a significant risk of mistargeting. Additionally, the literature has pointed out that such models leave open the possibility of two or more equally valid models generate different conclusions about the level of household poverty (Duclos *et al* 2006) and that they usually produce poverty measures that violate some important desirable axioms that a multidimensional index must respect (Bibi 2005).

The CCT targeting models used so far have been explicit to reach the income criterion, but less focused on the under-investment in human capital. In other words, the targeting has not been aligned with CCTs' objectives and its target population.⁵ After the selection of a geographical area, while the monetary poverty of household has been directly estimated with a proxy-means test, the human capital has been identified indirectly through demographic characteristics (households that have children in the "right" age group and pregnant and lactating women). Consequently, the relative success of CCTs in reaching poor households has been focused primarily on the monetary dimension of poverty and less on other relevant dimensions⁶.

To take in consideration the two criteria for eligibility of the target population (poverty and investment in human capital), a few countries have used innovative targeting strategies to better identify its target population. For example, the Chile Solidario CCT program applies a "dual targeting" mechanism to identify beneficiaries. First, poor households are identified with a traditional proxy-means test and then a social worker in conjunction with the household identifies how the household under-invests in human capital to agree on minimum conditions that must be reversed (Fiszbein and Schady 2009). This is an alternative that can be very

⁵ The target population of CCTs are poor households that under-invest in the human capital of their children (Fiszbein and Schady 2009).

⁶ For example, although the Panama's CCT has reached a number of households similar to the size of the target population, two important groups of extreme poor are not beneficiaries of the *Red de Oportunidades*: 67 percent of children aged 6 to 14 years old that does not attend school, and 48 percent of the children aged 0 to 4 years old that has chronic malnutrition. These calculations are available upon request.

effective, but that involves high costs for the program as it requires intensive interaction between the household and the social worker, not only for diagnosis but also for monitoring.

2.1 The case of PROGRESA / *Oportunidades* program

One of the oldest CCT programs is the Mexican program *Oportunidades*, formerly called PROGRESA. This program was implemented in 1997 and since then it has increasingly been expanding its household coverage. In 2009, the program reached all the country's municipalities and virtually all of its localities, covering around a fifth of all households. The evidence has shown that this is one of the CCT programs with bigger impacts on the population's well-being (Rawlings and Rubio 2005; Handa and Davis 2006) and with better performance in terms of the distributive impact (Lindert *et al* 2006; Levy 2006). There is also evidence that the income transfers under PROGRESA-*Oportunidades* program are successful in improving health indicators, increasing school attendance, and reducing current poverty as well as inequality indicators (Levy 2006; Fiszbein and Schady 2009).

The program selects its beneficiaries through a two-stage targeting strategy that combines geographic targeting and proxy-means testing. Since its beginning, the first stage consists of the identification of poorer localities based on a "marginality index" constructed with information from the population census data and the application of the principal components analysis. For the final geographical selection, the program takes into consideration the availability of a minimum supply of health clinics and schools, so that households can comply with co-responsibilities. The second stage of the process involves the identification of eligible households, within the localities selected in the first stage, by applying a proxy-means test. To this end, the program collects socioeconomic information of the all households living in intervention localities through the implementation of the ENCASEH in rural areas and ENCASURB in urban areas.⁷ In urban localities with a low "marginality index" a preliminary self-selection of families into the program takes place: first, the families voluntarily ask to be incorporated into the program, at that point household information is collected (first at the local office and then at the household). During the first phase of the rural expansion program, the targeting process also included an additional stage, based on a validation through community assemblies of eligible household lists, which aimed at correcting leakages or under-coverages of the first two stages.

Between 1997 and 2001 the proxy means test equation was estimated separately for 41 groups of rural localities using information from the ENCASEH and discriminant analysis technique (Regional Scoring System). In 2002 the targeting mechanism was changed as the program expanded to urban areas. This led to the development and estimation of a new scores model: Unique Scoring System (SUP is the Spanish acronym for "Sistema Unico de Puntajes"), estimated using economic poverty as dependent variable, discriminant analysis, and a single source of national information (ENIGH⁸ 2000). The estimation takes into account the heterogeneity between the rural and urban areas as well as other regional disparities in the

⁷ ENCASEH is the Spanish acronym of National Survey of Household Socioeconomic Characteristics and ENCASURB of National Survey of Urban Household Socioeconomic Characteristics.

⁸ The ENIGH is the Spanish acronym of National Survey of Household Income and Expenditure, the nationally representative household survey.

specification of the single equation. A household is eligible according the SUPs if its score exceeds a given cut-off point.⁹ The SUP is the proxy means model currently being used to determine eligibility of households for purposes of entry and continuity in the program.

The Mexican program is perceived to be well targeted, has been evaluated extensively, and has been used as a benchmark by other CCTs. Evaluations of the targeting strategy were carried out at different stages of the program, leading to adjustments and refinements of the mechanism as the program expanded. Behrman *et al* 1999 analyze the rural targeting of PROGRESA and show that the method used to target beneficiaries at that point was the most cost-effective to reduce poverty (severity and depth) in comparison with consumption-based targeting or geographical targeting. The authors point out that exclusion errors were occurring as the targeting mechanism failed to identify households with a small number of members or households without young children. Evaluations of the expansion to urban areas, which includes self-selection as households request to be beneficiaries of the program, indicate that the targeting mechanism are sound, although its predictive power is reduced in relatively richer communities and with households that are close to the poverty line. A quantitative evaluation by Coady and Parker 2004 find under-coverage of about 24 percent and leakage of about 22 percent. The authors point out that the leakage does not seem to be very critical, as around 15 percent of these households were close to the poverty line. A qualitative evaluation carried out by Escobar and Gonzales de la Rocha 2003 shows that the targeting mechanism was positively perceived by households as it bypasses political affiliations and local leaders.

Comparative evaluations shed light on the performance of different targeting methods. Skoufias et al 2001 analyze the contribution of the different targeting methods used by PROGRESA in rural areas and compare the program's method to alternative selection methods and universal targeting. The results indicate that PROGRESA's targeting method is more effective in identifying the extremely poor localities or households but not as good to discriminate among localities or households in the middle of the income scale. Furthermore, the authors point out that the results of the geographical targeting "raises some serious questions about the costs and benefits associated with the practice of household targeting within poor localities". This is further analyzed by Coady 2006 who extends the previous work and evaluates the relative incremental contribution of different targeting mechanisms including demographic targeting and self-selection in the first 130 rural localities beneficiaries of the program. The author concludes that the contribution of the individual targeting (proxy-means) could increase as the program expands to less deprived localities. Finally, Coady and Parker 2009 evaluate the relative contributions of two different targeting methods in urban areas: an initial self-selection process by households who acquire knowledge of the program and a proxy means test. They consider performance in terms of the effectiveness of the program at channeling a high proportion of benefits to lower welfare households. Their findings highlight the importance of proxy means targeting in the context of universal knowledge, and call for further improvements in this mechanism to reduce targeting errors.

⁹ The value currently used by the program is 0.69. For more details on the targeting mechanism of PROGRESA/Oportunidades, see Orozco and Hubert 2005, Regalia and Robles 2006, and Coady and Parker 2009.

Despite the huge expansion of *Oportunidades* and the success of its targeting mechanism in the first years, the program's coverage of poor households has become a major challenge in recent years. The most recent nationally representative household survey (ENIGH 2008) shows that the program benefited 714 thousand urban households and 3 million 521 thousand rural households, equivalent to around 30 percent and 120 percent of the urban and rural poor, respectively.¹⁰ The latter implies that *Oportunidades* reaches only 14 percent of urban poor households and 59 percent of rural poor households. The empirical evidence suggests that the relationship between poverty and the variables of the current household targeting model (SUP) has eroded as the poverty profile has changed. Table 1 shows that, on average, the poor have improved in the variables currently considered by the program's targeting model, a result that calls for a revision of the current targeting mechanism. Table 1 also displays the average correlation between income poverty and each of the independent variables of the SUP model (discriminant equation). The correlation is reduced by 26-27 percent from 2000 to 2006, affecting the model's predictive power to distinguish between poor and non-poor households. As highlighted by Coady and Parker 2009 "improvements in the proxy-means algorithm to increase its correlation with welfare can help to further decrease under-coverage and leakage". Finally, the ENIGH 2008 shows targeting errors regarding dimensions that go beyond the monetary dimension: 44 percent of Mexican extremely poor children aged 9 to 18 years old that do not attend school are not beneficiaries of the program, that is, children living in poor households that are not investing in the human capital of them.¹¹

[Table 1 goes about here](#)

3. A new multidimensional targeting criterion

This section describes the proposed household targeting methodology which draws from the identification step of the family of multidimensional poverty measures developed by Alkire and Foster (2008). Such family of measures satisfies a set of properties considered desirable in poverty measurement.¹² The identification implies –first– defining a cutoff point for each considered dimension, and –second– defining an *across-dimensions* cutoff, as the number of dimensions in which the household should be deprived so as to belong to the poor group. The second cut-off is the novelty of the approach. So far, the existing approaches to multidimensional poverty measurement are usually confined to using one of the two extreme approaches to the identification of the poor: “union” or “intersection”. The first requires to be deprived in at least one dimension, while the second requires to be deprived in all considered dimensions. While the Alkire and Foster's approach allows for these two typical extreme criteria, it also allows for intermediate –and likely more useful– cases. In what follows we formally present the proposed targeting methodology.

¹⁰ In Mexico there are three official poverty lines. Throughout the text the poverty definition used is the capability poverty (pobreza de capacidades) since it is the poverty line used by the *Oportunidades* program which is defined as follows: the inability to obtain a basic food basket and meet the necessary health and education expenses, even if the household were to use all its available income solely for these purposes (CONEVAL2007).

¹¹ Calculations are available upon request.

¹² Among the latest reviews of these assumptions is the study conducted by Kakwani and Silber 2008.

Let $y = [y_{ij}]$ be the matrix of achievements, where each element y_{ij} is the achievement of household $i = 1, \dots, n$ in dimension $j = 1, \dots, d$. Let z_j be the deprivation line or cutoff point for dimension j . Then one can define the deprivation matrix $g^0 = [g^0_{ij}]$. Each element g^0_{ij} is such that $g^0_{ij} = 1$ if $y_{ij} < z_j$, that is, it takes the value one if household i is deprived in dimension j , and $g^0_{ij} = 0$ if $y_{ij} \geq z_j$, that is, it takes value zero if household i is not deprived in dimension j . Suppose also that each dimension has a weight attached, so that there is a row vector $w = [w_j]$, where w_j is the weight associated with dimension j . The weights are such that they add up to the total number of dimensions d . Based on matrix g^0 weighted by w , one can obtain a column vector $c = [c_i]$ where each element c_i indicates the sum of weighted deprivations for each household i ($c_i = \sum g^0_{ij} * w_j$). At this point the second cut-off value needs to be defined; this will indicate the number of weighted deprivations in which the household needs to be deprived so as to be identified as poor. Name that cutoff as k . That k value can range from the weight of the least weighted dimensions to the total number of dimensions d . Then, an identification function $\rho_k(y_i, z)$ is defined, such that $\rho_k(y_i, z) = 1$ if $c_i \geq k$, that is, the identification function takes value 1, indicating that the household is multidimensionally poor because the number of weighted deprivations is equal to or greater than k , and $\rho_k(y_i, z) = 0$ if $c_i < k$, i.e., household i is multidimensionally non-poor because the number of weighted deprivations is less than k .

With the values from the identification function a column vector $p = [p_i]$ can be constructed, with $p_i = 1$ or $p_i = 0$ depending on whether household i was identified as poor or not. Once the poor households have been identified, it is possible to construct a censored column vector named $c_i(k)$ such that $c_i(k) = c_i$ if the household was identified as poor ($\rho_k(y_i, z) = 1$) and $c_i(k) = 0$ otherwise. From this vector one can obtain a simple 'score' (column) vector $s = [s_i]$ where $s_i = c_i(k)/d$ indicates the score of household i . In words, the score indicates the fraction of weighted dimensions in which each poor household is deprived. Note that there may be households experiencing deprivations, but with score zero because they have not been identified as multidimensionally poor. It is also worth noting that by taking the mean of vector p , the *multidimensional headcount ratio* H is obtained ($H = \sum p_i / n$). Also, by taking the mean of the score vector s , the *adjusted headcount ratio M0* is obtained.

Our proposal is to use the identification function $\rho_k(y_i, z)$ as the targeting criterion for CCT programs and the score value s_i as a tool to prioritize among the households. H will indicate the proportion of beneficiary households and $M0$ will indicate the average proportion of weighted deprivations suffered by the beneficiaries.

Four properties of this identification methodology are worth noting which make it particularly suitable as a targeting criterion. In the first place, if a poor household's performance improves in a non-deprived dimension, this will not affect its identification as poor. In other words, a high achievement in one dimension cannot compensate for deprivation in other dimensions. For CCT targeting purposes, this means that eligibility is not affected by performances in dimensions not relevant for the program. This establishes a clear advantage of this method over the traditional unidimensional (proxy-means test) ones, which implicitly allow for substitution between dimensions. Secondly, if a household becomes deprived in one additional dimension, it may now fall into the group considered poor. For targeting purposes, that means that an increase in the

number of deprivations directly increases the chances to become eligible for the program.¹³ Third, this targeting criterion allows combining cardinal and ordinal well-being indicators, since all of them are dichotomized when establishing people's deprivations. Finally, the score vector s can be used to prioritize selected household if the CCT program must be implemented or expanded sequentially, from the most to the least deprived, or to tie transfer levels directly to the score (e.g., by increasing the benefits for those with lower scores and decreasing them for those with higher scores) with the purpose to improve the impact of the transfer on households' welfare (Coady and Parker 2009).

Furthermore, the proposed targeting mechanism allows for a full consideration of the programs objectives, as one can define the dimensions in line with the objectives of the CCT. The traditional means-test considers only monetary poverty or the use a single cutoff point for well-being synthetic indices, leaving aside the human capital related dimensions: education and health-nutrition. Hence, the methodology allows for prioritizing dimensions when deciding the weighting as will be further discussed.

4. Operationalising the multidimensional targeting for the case of urban *Oportunidades*

This section presents an illustration of how the new proposed methodology can be put in practice. Typically, CCT programs have intended to improve achievements in three dimensions: education, health-nutrition, and income. With the proposed multidimensional targeting, these dimensions can now be explicitly addressed and households experiencing coupled deprivations in these dimensions will receive a higher score and therefore, higher priority.

Although the selection of dimensions is actually determined by the program's objectives, the selection of indicators, deprivation cutoffs, weights, and across-dimensions cut-off opens a variety of possibilities. In all cases, choices need to be carefully justified as they will impact directly the target group. In what follows, we propose a specific selection for each case and we provide robustness checks for some of these choices. Clearly other combinations are also possible. It is worth emphasizing that two general criteria were followed in the selection of indicators. One of them is their availability in both the survey that determines the program eligibility as well as in the national household survey. All the proposed indicators are available on both the ENIGH 2006 and the ENCASURB (CCT urban census). The other general criterion intends to avoid the selection of indicators that may create negative incentives on the behavior of households (Coady *et al* 2004b); such distortions are considered an important targeting cost (Paes de Barros and Carvalho 2006). For example, if children not attending school was one of the indicators used by the program to select beneficiaries, this could create an incentive for households not to send their children to school in order to qualify for the program. All indicators related to the most immediate outcomes of the program are excluded from the models. Instead, we choose indicators that are highly correlated with the final indicators of interest, but are not subject to direct household manipulation (we refer to these as "intermediate indicators").

4. 1 Indicators and cut-offs

¹³ Alkire and Foster (2008) refer to the first property as "deprivation-focus" and to the second as "dimensional monotonicity".

Within each dimension we propose to include one *intermediate indicator* and, for the education and health dimensions, we also propose to include a number of *risks indicators*. Intermediate indicators are called as such because they are considered to be an effective means to an intended end of the CCT program. The intermediate indicator for education is grade retention of children aged 6 to 12, and a household is considered deprived if it has at least one child in this age group who is two or more grades behind in the school calendar. We base this selection on CONEVAL 2008. The intermediate indicator for health is access to health insurance. A household is considered deprived if at least one member does not have access to health insurance from institutions such as IMSS, ISSSTE, PEMEX, Popular Insurance, among others. Finally, the intermediate indicator for the monetary dimension is the per capita household income, and a household is considered deprived if suffer economic poverty, that is, has insufficient income to afford basic needs. We estimate income using the projections of an income regression model (see annex 1) and a cutoff that reproduces the official poverty ('capability poverty') rate at the household level stated by CONEVAL 2007.

Risk indicators included in the education and health dimension intend to capture the probability or vulnerability that households could suffer deprivations in these dimensions. By including such indicators, the program would benefit currently deprived households as well as households that have a high risk of becoming deprived. Given that CCT programs have especial interest in improving the conditions of the young population, we consider that the selection of risk indicators should draw from empirical evidence on the causes of child malnutrition and school performance¹⁴. By focusing on the causes rather than the observable symptoms of such phenomena, the effects of CCT programs would be more likely to last over time and avoid negative incentives. For example, child malnutrition could be reversed by attacking its most obvious manifestations, but this may have only temporary effects if they disappear. Actions to address causes, such as those that improve maternal nutritional knowledge, could have lasting effects or long term (Appoh and Krekling 2005).

The literature for Mexico (Hernández *et al* 2003; Gómez 2003; González *et al* 2007; World Bank – SEDESOL 2008) finds evidence that malnutrition is basically related to the quantity and quality of food consumption, which are in turn determined by socioeconomic and demographic conditions. Specifically, the education of the mother and other family members, the presence of young children, a high concentration of indigenous people, the supply of and access to health services, and sanitary conditions in the house are all closely related to child malnutrition levels and household health in general. Regarding school performance (or lack of it, i.e. under-education), the literature indicates the importance of the following: economic poverty, parents' education, cumulative schooling as a function of age, presence of minor children, and factors of educational supply (such as availability of trained teachers and educational infrastructure), in addition to child malnutrition itself and neighborhood characteristics (López 2004; Muñiz 2001; Giorguli 2002). A revision of the conceptual and empirical discussions on these topics is beyond the scope of this paper. However, we argue that the selection of indicators to be used in the

¹⁴ In the framework of these models, the urban-rural differences are captured through the characteristics of the places where the households reside, which play a relevant role for understanding individual behavior. The conceptual schemes for those models can be found in UNICEF 1998 and World Bank 2004.

targeting mechanism should draw from the results this literature provides.¹⁵ Combining such results with the availability of indicators in the two relevant surveys (ENIGH 2006 and ENCASURB) we selected ten risk indicators.

All the 13 selected indicators (three intermediate and ten risk ones) are listed in Table 2 and the dimension to which they correspond is indicated. It is noteworthy that some indicators are present in more than one dimension. Seven indicators are associated with the education dimension; ten are associated with the health-nutrition dimension; and only one to the monetary dimension. It is noted that we considered the indicator on the educational level of other household members to be related to the health/nutrition dimension according to UNICEF 2009 and World Bank - SEDESOL 2008. The rationale is that more educated members of the household are more able to value nutritional foods and help with sensible intra-family sharing of foods and nutrients in favor of women and children¹⁶. The table also provides the deprivation cut-offs for each dimension as well as the formula used to define the weights, which are explained in the following section.

Table 2 goes about here

4.2 *Weights*

Determining the weights of each indicator is always an arbitrary decision. The literature indicates that selection should ideally be open to criticism so that it can gain reasonable public acceptance, since there are no universal guidelines for defining them¹⁷. It also indicates that any weighting scheme should be accepted if consistent with the trade-offs that exist between the dimensions. Because there is no consensus in how to measure these trade-offs, Decancq and Lugo 2008 have suggested to use common sense and be cautious in interpreting the rankings obtained from the group of dimensions. We propose giving the same weight to each dimension (education, health-nutrition, and income) and different weights for each deprivation (or indicator) according to its participation in each dimension. The formula used for obtaining these weights is presented in Table 2. Robustness exercises are conducted to analyze the sensitivity of the results to different weighting alternatives.

4.3 *Minimum number of deprivations*

As explained in Section 2, one of the advantages of Alkire and Foster's methodology is that it allows for a range of identification criterion from the union to the intersection approach. When indicators are not equally weighted, the union approach corresponds to being deprived in the indicator that has the lowest weight (k equals the weight of such indicator in this case). However,

¹⁵ UNICEF 1998 (Figure 5) shows an example of how complex it can be taken into account the diversity of the causes of child malnutrition to assess nutritional status and identify the most appropriate mix of actions.

¹⁶ In the education dimension, the mother's schooling and the other school aged members' education are considered to influence the school performance of a child directly. For this reason, according to cited literature, the other household members' education was not considered.

¹⁷ On this issue, the alternatives cited by Alkire and Foster 2008 for multidimensional poverty measurement include arbitrary weights and statistical weights (with factor analysis and multiple correspondence) based on surveys, value judgments, or some combination of these alternatives.

this criterion usually gives high poverty rates, especially when the total number of indicators is high. Indeed, such estimates may include households that happen to be deprived in just one indicator (even the least relevant) for other reasons than poverty. On the other extreme, when the intersection approach is used, households are required to be deprived in all considered indicators. This criterion usually leads to a very low poverty rate, including only the extremely poor households, who are deprived in all dimensions. Therefore, the extremes might not be useful to identify and target beneficiaries, and intermediate cases can be more relevant.

In the context of the CCT programs, one alternative for defining “minimum deprivations” is to determine it as function of the program’s desired scope (in terms of the number of beneficiaries), budget availability, and also matching the official poverty measurement. The fact that the k value can be in an ample range, allows selecting the value that suits the mentioned three criteria. Figure 1 presents the estimated fraction of the beneficiary population (households with multiple deprivations) of the urban *Oportunidades* program for each possible minimum of deprivation – the second cutoff, k —, ranking from the minimum possible value of zero to the maximum of 13, since 13 indicators are used. The thick bold line depicts the results obtained with the mentioned weighting system, and the other two depict results with two alternative weighting systems: first, a set of weights in which the income dimension receives 30% more weight and alternatively, another in which it receives 30% less weight with respect to the baseline weighting structure. It is noteworthy that when the three lines overlap, it means that the fraction of the population identified as poor (i.e. as beneficiaries of the program) is independent of the weighting system used. This occurs in the neighborhood of $k=7$ and produces a poverty estimate of about 11 percent. It is worth noting that this estimate is coincident with the income poverty rate of 2006.¹⁸

[Figure 1 goes about here](#)

5. Evaluating the new targeting methodology

A natural question that arises is how the proposed new multidimensional targeting method performs as compared to the existing ones. This section compares the performance of alternative targeting models and evaluates the relative performances with three techniques. As previously discussed, household targeting models commonly used by CCT programs focus primarily on the monetary dimension and the evaluation techniques traditionally used to assess targeting effectiveness are on this line. We aim at comparing beyond the monetary dimension by using alternative techniques to access if the proposed multidimensional model selects beneficiaries with deprivations in the dimensions relevant to the CCTs. In the first place, we analyze the distribution and coverage of the selected households by each targeting model along quintiles of the income distribution; this is a traditional way to evaluate the unidimensional targeting performance of beneficiary identification. Secondly, we compare household characteristics of the potential beneficiaries selected by each targeting model. Two indicators that are relevant for CCT programs are considered and average values of the indicators are compared along the cumulative distribution of household income poverty. Third, we use a micro-simulation

¹⁸ The proposal and results are consistent with the suggestion made by Alkire and Foster 2008 that repeated applications and reasonable evaluations can lead to a range of plausible values for “minimum deprivations” and a single value can then be selected for the main analysis and alternative values to check its robustness.

technique to ex-ante evaluate the expected impact of transfers on school attendance and labor participation for children selected with each targeting model.

We compare the targeting performance of the following household identification models: (1) the current *Oportunidades* model (current SUP) which is the model that officially selects beneficiaries of *Oportunidades*, (2) the updated *Oportunidades* model, which we estimate using the same variables and methodology currently used in the SUP model, but consider recent survey data (updated SUP), (3) an alternative income proxy means that we estimate with ordinary least squares (income proxy), and (4) our proposed multidimensional targeting model.

In order to estimate the weights of all models we use information from the ENIGH 2006, with the exception of the current SUP (the current *Oportunidades* model) which uses the information from ENIGH 2000. It is worth note that a household is eligible for the program according the SUP models if the estimated score exceeds a given cut-off point; while according to the income proxy-means test a household is eligible if its estimated income is below a minimum income level or poverty line; finally, according to the multidimensional model, a household is eligible if it suffers at least a given minimum number of deprivations. The weights are available in table 2 (the multidimensional model) and Annex 1 (SUP and income models).

5.1 Distribution and coverage: targeting performance according to the monetary dimension

This sub-section analyzes the performance of the four targeting models through a monetary lens. We define “distribution” as the number of eligible households in each quintile expressed as a percent of total eligible households in all quintiles and “coverage” as the number of eligible households in a quintile expressed as a percent of total households in the quintile under consideration. The higher the percentage of each indicator in the lowest quintile, the better the targeting performance of the method analyzed. A greater percentage of eligible households in the lowest income quintile indicate that the targeting model has performed well in identifying the income poor.

Table 3 shows the distribution and coverage of the selected households by the alternative targeting models in each income quintile. The comparison is carried out considering the poorest 10 percent selected by each model (for the case of multidimensional model it implied using $k=7.4$). This adjustment is necessary to fairly compare the four alternatives given that each model is likely to select a different number of beneficiaries. Regarding the “distribution”, note that 70 percent of the selected households with the income and multidimensional models are in the poorest quintile, 8 percentage points higher than the current SUP and 5 percentage points higher than the updated SUP. It is also noted that both SUP models shows higher percentages in the richest 40 percent of the distribution (first two quintiles)—leakage error, that is, non-poor households selected to receive *Oportunidades*.

The models’ performance is somewhat comparable with respect to coverage in the different quintiles. While none of the models is able to cover half the lowest quintile, all models are poor—with more coverage in the first quintile of the distribution. The main conclusion from this analysis is that the multidimensional model selected households with lower targeting errors than

the SUP models and has a similar performance (about the same proportion of targeting errors) to the income model. The latter result is surprisingly good because the multidimensional model, unlike income models that consider only the monetary dimension of poverty, takes into account other key dimensions of CCT programs. Consequently, the profile of selected households with these two methods is different and is the focus of the next subsection.

[Table 3 goes about here](#)

5.2 Targeting performance beyond the monetary dimension

As the CCT program aims at the income poor that under invest in children's human capital (its target population), we propose to use indicators related to the investment in human capital of children in order to analyze the targeting performance beyond the monetary dimension. Child labor and school attendance are two of the indicators considered¹⁹. We profile the selected group of beneficiaries by each alternative targeting model. Figure 2 shows the average values of two indicators for different levels of cumulative household poverty (poverty defined according to the scores of each method). The dominance of the multidimensional model in identifying the most deprived households is clear, particularly in the lower levels of the welfare distribution²⁰. For example, consider the indicator that aims at capturing households that are not investing in education: the school non-attendance of the poorest 15 percent selected with the multidimensional model is 42 percent higher than the non attendance of the poorest according to the updated SUP model and 9 percent higher according to the income model. Similar performance is observed for child labor. For the same population group and targeting models, percentages are 44 and 12 percent, respectively. It is noteworthy that differences that are much larger if one consider the poorest 5 percent.

[Figure 2 goes about here](#)

5.3 Expected impact of transfers on children's occupational choice.

One final way to compare targeting models is by quantifying the potential impact of the program transfers on the children's occupational choice. While this is an unorthodox way of evaluating a targeting strategy, it goes beyond the simple analysis on the accuracy of predicting monetary or multidimensional poverty status of households. We use ex-ante microsimulation techniques, i.e. methods designed to predict the impact of a program using behavioral models, which are estimated using econometric techniques at individual unit level (Todd and Wolpin 2007). We model a discrete choice variable that expresses the labor participation and school attendance of a child. For this purpose, we follow Bourguignon *et al* 2003 and assume that adults in the household decide on the occupational choice of the child based on a utility function, which

¹⁹ Due to the limited thematic coverage of the data sources used we restrict the analysis to these two indicators, but ideally should use indicators that account for outcome or impact indicators of CCT programs.

²⁰ In the case of multidimensional model, results for each percentile meant to used different levels of k (between 3.4 and 9.5).

depends on the characteristics of the child and of the household, education supply, and also the child's potential labor income²¹.

The models are estimated using information from the ENIGH 2006 and the *Oportunidades* scheme of transfers in place during the second half of 2006. We excluded from the sample all households that were beneficiaries of the program to avoid any bias in the estimation process; the final sample size used is still fairly large since 93 percent of the urban household total sample is not beneficiaries of *Oportunidades*.

Table 4 summarizes the results of the exercise. It shows the variation of transfers' impact on school enrollment and child labor participation, i.e. the difference between the situation before and after the *Oportunidades* transfers. The results are shown for the 5 percent and 15 percent poorest households selected with each targeting model. Note that for the poorest 15 percent, the *Oportunidades* transfers generate an increase in school attendance 54 percent greater if households are selected through multidimensional targeting compared to the current SUP model (8.5 percent versus 5.5 percent for children aged 9-18 years) and 16 percent greater than the alternative income model (8.5 versus 7.3 percent). For the 5 percent poorest (or extremely poor), the multidimensional model performance is superior to all other models under analyses in increasing school attendance and reducing child labor, particularly for children between 16 and 18 years of age²². This is in line with our priors since the multidimensional model explicitly considers the many dimensions of poverty and is better at identifying households that suffer deprivations and risks.

[Table 4 goes about here](#)

6. Concluding remarks

This paper proposes a model for targeting beneficiaries of CCT programs that takes into account the two criteria that defines the target population of CCT programs: poverty and under-investment in human capital. The selection of indicators is in line with results of studies on the determinants of child malnutrition and school performance and the model is based on the axiomatic approach of multidimensional poverty measurement (Alkire and Foster 2008). After building the identification function and a deprivation score using the information from the nationally representative Mexican household survey, we show that it is feasible to select households with attributes that better fits the objectives of a CCT program. Moreover, using ex-ante evaluation microsimulation techniques, the paper shows that a selection based on a multidimensional approach achieves a greater impact of transfers on the welfare of beneficiaries when compared to a targeting mechanism based on traditional approaches.

²¹ Annex 2 details model specifications and econometric details. For details on the methodology see Bourguignon et al 2003 for Brazil. Finally, we use the methodological procedure from Azevedo and Robles 2010 for Mexico, which relaxes one of identification assumptions to reduce possible biases of overestimation.

²² The results of the analysis in this section are robust in the sense that they did not suffer significant changes when other weights were used in the multidimensional model.

The implications of these findings should be considered in light of both equity and efficiency arguments. The reduction of targeting errors implies the possibility of a better use of public resources dedicated to social programs because resources will more effectively reach households with multiple deprivations. In addition, the proposed targeting model increases the impact of public resources, because the transfers would be given to households that have on average more deprivations, leading to a more efficient use of program resources. Thus, a change in the methodology to select beneficiaries is likely to contribute to achieving the fundamental objectives of CCT programs, particularly developing the human capital of children.

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Table 1: Descriptive Statistics: Variables of the *Oportunidades* current targeting model, SUP (2000 – 2006)

Variables	Urban Area				Rural Area			
	Average		Correlation ¹		Average		Correlation ¹	
	2000	2006	2000	2006	2000	2006	2000	2006
Age of the household head	45.2	46.5	-0.050*	-0.012	48.3	48.0	-0.065*	0.017
Female head of household (%)	19.6	26.1	-0.042*	0.024	16.2	23.1	-0.070*	-0.015
Households with children aged 0-11 (%)	97.2	85.9	0.323*	0.191*	133.8	116.2	0.381*	0.258*
Head of household with 0 years of education (%)	7.9	5.6	0.127*	0.144*	26.7	18.2	0.129*	0.155*
Head of household with 1-5 years of education (%)	16.7	13.9	0.153*	0.067*	33.2	32.3	0.086*	0.043*
Does not have access/right to medical service (%)	43.4	44.7	0.193*	0.173*	79.8	77.7	0.263*	0.207*
Demographic dependency (%)	72.0	69.3	0.291*	0.194*	98.8	96.9	0.312*	0.247*
Crowding: # of members / # of rooms	2.2	1.6	0.400*	0.274*	3.2	2.3	0.487*	0.324*
Dwelling with dirt floor (%)	2.4	2.5	0.168*	0.144*	22.3	15.4	0.343*	0.251*
Dwelling with shared or no bathroom (%)	7.0	5.4	0.075*	0.127*	23.3	15.6	0.183*	0.129*
Dw. w/unshared bathroom w/ no water conn. (%)	14.4	15.8	0.237*	0.173*	20.6	48.7	-0.063*	0.107*
Household without car or truck (%)	60.2	52.3	0.192*	0.16*	79.3	69.9	0.234*	0.194*
Household without gas stove (%)	3.0	5.0	0.071*	0.109*	27.6	22.7	0.407*	0.344*
Household without refrigerator (%)	14.2	11.2	0.278*	0.205*	47.1	35.4	0.385*	0.278*
Household without washing machine (%)	34.3	24.7	0.196*	0.186*	69.1	54.3	0.314*	0.249*

¹ Bi-variable with capability poverty

* Significant at 1%. On average, 26% less correlation with capability poverty in 2006 compared to 2000 in the rural area and 27% in the urban area.

Source: Calculations based on the 2000 y 2006 ENIGH.

Table 2: Dimensions, deprivations and weighting

Deprivations at household level (1)	Dimensions			Description	Weights of indicators in each in each dimension						Total weight each indicator (2)	
	Edu- cation	Health / Nutrition	Mone- tary		Edu- cation		Health / Nutrition		Mone- tary		Sum	d=13
Grade retention of members aged 6 - 12	X			At least one member with 2 or more grades below the age corresponding level (3)	0.14	+	0.00	+	0.0	=	0.14	0.619
Low education of members aged 16-21	X			At least one member with less than 9 years of schooling (4)	0.14	+	0.00	+	0.0	=	0.14	0.619
Low schooling of spouse	X	X		Spouse with less than 9 years of schooling (4)	0.14	+	0.10	+	0.0	=	0.24	1.052
Number of young children	X	X		Households with 3 or more children aged 0-11 (6)	0.14	+	0.10	+	0.0	=	0.24	1.052
Economic poverty	X	X	X	Insufficient income to afford basic consumption basket (5)	0.14	+	0.10	+	1.0	=	1.24	5.386
% Indigenous in the municipality of resid	X	X		% Indigenous people above the median (7)	0.14	+	0.10	+	0.0	=	0.24	1.052
# Schools in the municipality of residence	X			# primary and secondary schools below the median (8)	0.14	+	0.00	+	0.0	=	0.14	0.619
No affiliation to health insurance		X		At least one member without affiliation to any health insurance	0.00	+	0.10	+	0.0	=	0.10	0.433
Low education of other hh members		X		Older than 21 with less than 9 years of schooling (4)	0.00	+	0.10	+	0.0	=	0.10	0.433
Dwelling without piped water		X		Without public water inside or outside the home (inside or outside the home)	0.00	+	0.10	+	0.0	=	0.10	0.433
Dwelling without sanitary sewer		X		No sanitary sewer connected to public network	0.00	+	0.10	+	0.0	=	0.10	0.433
Households with overcrowding		X		# persons per room greater than or equal to 2.5 (9)	0.00	+	0.10	+	0.0	=	0.10	0.433
# Physicians in the residence municipality		X		# Physicians in contact with the patient below the median (10)	0.00	+	0.10	+	0.0	=	0.10	0.433
Total	7	10	1		1		1		1		3	13

(1) Defined with specific cutoff points for each indicator (see "Description" on this Table).

(2) Giving equal weights to each dimension and different weights to each indicator according to their participation in each dimension.

(3) According to the definition suggested in CONEVAL 2008.

(4) Corresponding to basic education as defined by the General Law of Education.

(5) Capability poverty, according to CONEVAL 2007. Income is estimated with the projections of a income regression model and a cutoff that reproduces the official poverty rates at the household level.

(6) The national median number of children is 2 per poor household.

(7) 1.90 percent is the median percentage in urban areas for capabilities poor households.

(8) 203 primary to upper secondary schools is the median in urban areas for capabilities poor households.

(9) Rooms counting the kitchen but not the bathroom. 2.5 is the cutoff point used by CONEVAL 2008 to define overcrowding.

(10) 117 physicians is the median in urban areas for capabilities poor households.

Table 3: Distribution and coverage of potential beneficiaries (Urban areas)*

Model	Income quintile**					Total
	I	II	III	IV	V	
Distribution (%)						
Income proxy	70.4	22.1	5.7	1.7	0.1	100.0
Current SUP***	62.3	22.0	9.2	4.5	2.0	100.0
Updated SUP****	64.7	21.5	9.0	3.6	1.2	100.0
Multidimensional	69.2	22.8	5.9	2.0	0.1	100.0
Coverage (%)						
Income proxy	44.6	12.8	3.0	0.8	0.1	10.0
Current SUP	39.5	12.8	4.8	2.1	0.8	10.0
Updated SUP	40.9	12.5	4.7	1.7	0.5	10.0
Multidimensional	44.3	13.4	3.1	0.9	0.1	10.0

* selecting the 10% poorer household with each model.

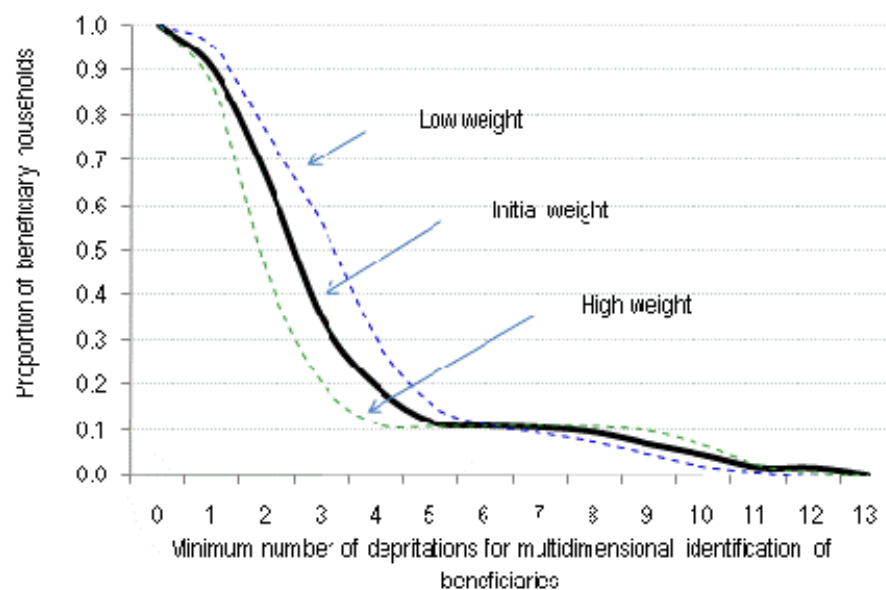
** Five population groups of equal size based on per capita income (I poorer and V less poor).

*** weights calculated by *Oportunidades* with ENIGH 2000.

**** weights calculated with ENIGH 2006

Source: Author's calculation Based on ENIGH 2006

Graph 1: Proportion of urban beneficiary households for each minimum deprivations (Urban areas)



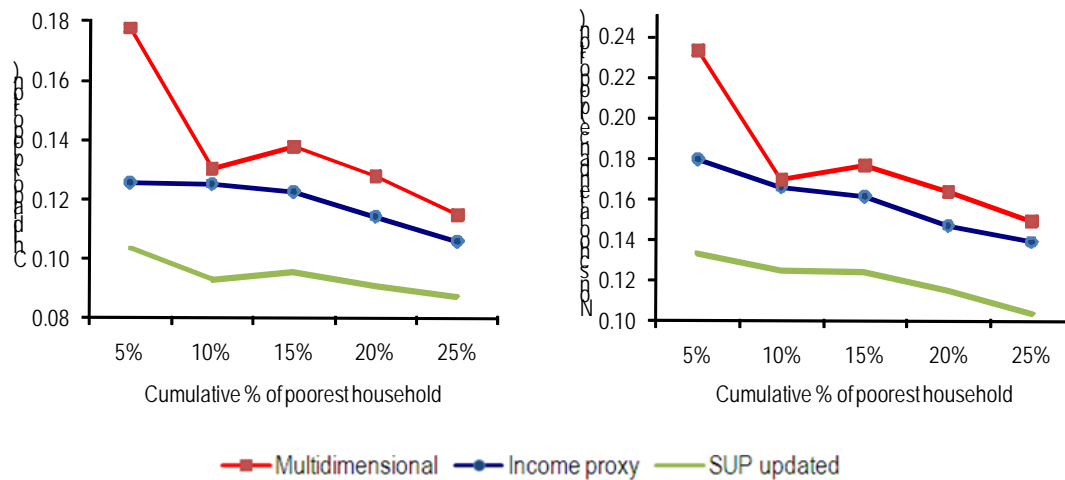
Initial Weight: consider the weights described in Table 2,

Low weight: 30% lower for monetary dimension with respect to the baseline (initial) weight structure

High weight: 30% higher for monetary dimension with respect to the baseline (initial) weight structure

Source: Author's calculation Based on ENIGH 2006

Graph 2: Child labor and Non-school attendance in household selected by three targeting models (Urban areas)*



* Child labor and non-school attendance were estimated for members aged 12 – 17 years
 The different levels of poverty (between 5 - 25 percent) were defined with each targeting models' score.
 Source: Author's calculation based on ENIGH 2006

Table 4: Percentage change of the simulated impact of *Oportunidades*' transfers* on school attendance and labor force participation of poor children selected by four targeting models (Urban areas)

School attendance and labor force participation of children selected by alternative models	Poorest 5 percent				Poorest 15 percent			
	9-12	13-15	16-18	Total	9-12	13-15	16-18	Total
Observed								
No attending school	-29.9	-19.0	-15.2	-18.1	-22.0	-34.5	-24.1	-26.9
Attending school	1.9	6.6	32.0	6.0	0.8	8.4	33.3	6.9
Attending & working	0.0	0.0	0.0	0.0	0.0	0.0	5.6	1.9
Attending & not working	1.9	6.8	36.5	6.2	0.8	8.9	36.7	7.1
Income proxy								
No attending school	-11.2	-24.3	-10.7	-15.4	-17.6	-24.8	-21.2	-22.1
Attending school	0.7	11.6	37.2	6.1	0.7	7.9	44.4	7.3
Attending & working	0.0	0.0	0.0	0.0	0.0	0.0	7.0	2.7
Attending & not working	0.7	12.1	44.2	6.3	0.7	8.3	51.4	7.5
Current SUP								
No attending school	-9.1	-9.3	-12.7	-11.0	-21.1	-21.1	-19.1	-19.9
Attending school	0.7	4.0	57.6	3.9	0.8	7.1	44.3	5.5
Attending & working	0.0	0.0	0.0	0.0	0.0	0.0	9.7	2.8
Attending & not working	0.7	4.4	72.0	4.0	0.8	7.7	51.3	5.6
Updated SUP								
No attending school	-9.1	-10.1	-12.8	-11.4	-17.6	-18.1	-16.7	-17.3
Attending school	0.7	4.7	53.1	3.7	0.6	6.1	52.7	4.9
Attending & working	0.0	0.0	0.0	0.0	0.0	0.0	5.8	1.7
Attending & not working	0.7	5.1	63.1	3.9	0.6	6.7	67.6	5.0
Multidimensional model								
No attending school	-11.9	-17.5	-17.5	-17.1	-15.6	-27.2	-20.9	-22.2
Attending school	0.6	7.6	59.7	7.9	0.7	8.5	49.5	8.5
Attending & working	0.0	0.0	6.7	2.5	0.0	0.0	7.3	2.6
Attending & not working	0.7	8.1	71.3	8.1	0.7	9.1	56.2	8.7

* according to the *Oportunidades* scheme of transfers in the second half of 2006

(www.oportunidades.gob.mx/Wn_Inf_General/Padron_Liq/Mon_Apoyos)

NOTE: earnings and school attendance behavior models were considered for the simulations

Source: ENIGH 2006 (includes only urban households that are not beneficiaries of the program)

Annex 1

Model of log per capita household income (1)

Variables	Coef
Demographics	
Household size (log)	-0.697*** (0.010)
Demographic Dependency	-0.074*** (0.006)
House / Household	
Dwelling and household deprivations Index	-0.096*** (0.002)
Number of rooms	0.082*** (0.003)
Household head	
Schooling (1 more than 9 years, 0 otherwise)	0.250*** (0.009)
Wage earner (1 non-earner, 0 otherwise) (3)	0.344*** (0.020)
Other members	
Employment of older than 17 years (4)	0.110*** (0.005)
Wage earner without benefits	-0.240*** (0.009)
Geographic	
Area of residence (1 rural, 0 urban)	-0.040*** (0.010)
Patrimony poverty at municipality level (5)	-0.006*** (0.000)
Constant	9.384*** (0.023)
Adjusted R Square	0.676
Number of observations	20350

(1) Estimated with robust standard errors

(2) Sum of 20 dummy variables expressed as deprivations

(3) in a household's business

(4) 1 employed (no spouse or household head), 0 otherwise

(5) from www.coneval.gob.mx

Note: standard errors between brackets

Source: Author's calculation based on INEGI "ENIGH 2006"

Current and updated discriminant model (SUP)*

	Current*	Updated**
Overcrowding: number of persons per room	0.139	0.214
Demographic Dependency:	0.176	0.203
Female head of household	-0.02	-0.131
Households with children aged 0-11	0.255	0.277
Age of the household head	0.005	0.004
Does not have access/right to medical service	0.475	0.47
Head of household with 0 years of education	0.38	0.3
Head of household with 1-5 years of education	0.201	0.207
Dwelling with shared or no bathroom	0.415	0.316
Dwelling with bathroom no water connection	0.22	0.273
Dwelling with dirt floor	0.475	0.571
Household without gas or electrical stove	0.761	0.727
Household without refrigerator	0.507	0.356
Household without washing machine	0.127	0.28
Household without car or truck	0.159	0.268
Dwelling rural area	0.653	-0.053
Dwelling in region1, 2 y 3	-0.516	-0.618
Dwelling in region4	-0.51	-0.64
Dwelling in region5	-0.328	-0.56
Dwelling in region6	-0.352	-0.458
Dwelling in region7	-0.657	-0.699
Dwelling in region8 y 9	-0.391	-0.516
Dwelling in region10 y 17	-0.293	-0.744
Dwelling in region11	-0.511	-0.631
Dwelling in region12	-0.66	-0.701
Dwelling in region13	-0.376	-0.663
Dwelling in region14	-0.413	-0.767
Dwelling in region15	-0.143	-0.671
Dwelling in region16 y 19	-0.07	-0.436
Constant	-0.579	-1.315
Number of observations		20327
% true classification		83.1

* estimated with 2000 ENIGH data

** estimated with 2006 ENIGH data (capabilities poverty as dep variable)

Note: coefficients are from Canonical discriminant function

Source: Author's calculation Based on INEGI "ENIGH 2000 and 2006"

Annex 2

Ex-ante microsimulation model used to estimate the impact of transfers on household welfare.

It models the discrete variable, S_{ij} , which expresses the labor force participation and attendance of a child living in the household i . This indicator variable takes the value of zero (S_{i0}) when the child goes to school; it is equal to one (S_{i1}) when the child is studying and working outside the home; and the value of two (S_{i2}) when the child is studying and not working outside the home. We assume that household i choose option j based on a utility function ($U_i(j)$) that depends on the characteristics of the child, home and educational supply (Z_i), the child's contribution to household income (y_{ij}), household income less the child's income (Y_{-i}) and a random variable that expresses the unobserved heterogeneity of family behavior (v_{ij}). Thus, the household i chooses option k if and only if $U_i(k) + v_{ik} > U_i(j) + v_{ij}$ for $k \neq j$.

We assume that the functional form of $U_i(j)$ is linear:

$$U_i(j) = Z_i\gamma_j + (Y_{-i} + y_{ij})\alpha_j + v_{ij},$$

where γ and α are the parameters to be estimated. We also assume that the child's income for his work in the labor market (w_i) are determined according to a standard model of labor income:

$$\log w_i = X_i\delta + m^*E + u_i,$$

where X_i are the child's individual characteristics; E is a dummy variable that takes value of 1 if the child studies and works is zero otherwise; u_i is the random term representing unobserved heterogeneity in earnings; and δ and m are the parameters to be estimated.

The child's working income (in the market and at home, y_{ij}) is proportional to their actual or potential income earned in the market (w_i):

$$y_{i0} = Kw_i, y_{i1} = My_{i0} = MKw_i, y_{i2} = Dy_{i0} = DKw_i,$$

where K is the value of the observed relationship between y_{i0} and w_i , D is not observed and $M = \exp(m)$ is obtained from estimating the earnings model. With the above assumptions and specifications, it follows that the utility of household i choosing option j is described as:

$$U_i(j) = Z_i\gamma_j + Y_{-i}\alpha_j + w_i\beta_j + v_{ij}, \text{ where } \beta_0 = \alpha_0K, \beta_1 = \alpha_1MK \text{ y } \beta_2 = \alpha_2DK.$$

Consequently, if α , β , γ , w_i and v_{ij} are known, the choice made by households will be one that maximizes utility. This expression represents the utility of household i for the option j without program transfer, i.e., the reference case. To simulate the impact of transfers we consider poorer households selected with each targeting model, the level of transfers corresponding to the second half of 2006 (which distinguishes age, sex and school grade the child is attending) and assume that responsibilities (or conditionalities) are accomplished. The household i will choose the option that maximizes utility $U_i(j)$ among the following options:

(i) If the household is not selected by the targeting model:

$$U_i(j) = Z_i\gamma_j + \alpha_jY_{-i} + \beta_jy_i + w_{ij}, \text{ for } j=0,1,2$$

(ii) If the household i is selected by the model:

$$U_i(j) = Z_i\gamma_j + \alpha_j(Y_{-i} + A) + \beta_j w_i + v_{ij}, \text{ for } j=0$$

$$U_i(j) = Z_i\gamma_j + \alpha_j(Y_{-i} + A + B) + \beta_j w_i + v_{ij}, \text{ for } j=1,2$$

where A is the share of unconditional transfers and B is the proportion of transfers that are conditional on school attendance. That is, with these transfers, household i will choose k if and only if $U_i(k) + v_{ik} > U_i(j) + v_{ij}$ for $k \neq j$.

The earnings model is estimated using Ordinary Least Squares (OLS) and the occupational choice model with a multinomial logit. The former provides to the latter the potential earnings of each child, including those who do not work outside the home. With the second model it not possible to know directly the values of γ_j , α_j and β_j because one of the options is taken as reference, that is, the multinomial logit model only estimates $(\alpha_j - \alpha_0)$, $(\beta_j - \beta_0)$ and $(\gamma_j - \gamma_0)$ if the selected reference is $j=0$. However, with these estimates and indicated assumptions, it follows that:

$$\alpha_1 = (a_1 - b_1 / K) / (1 - M),$$

$$\alpha_0 = (\alpha_1 - a_1),$$

$$\alpha_2 = (\alpha_1 + a_2 - a_1), y$$

$$D = (b_2 + \alpha_0 K) / (\alpha_2 K)$$

where a_j and b_j are the estimated coefficients of multinomial logit model corresponding to Y_{-i} and w_i for $j=1,2$, respectively. Because the residuals cannot be observed in a multinomial logit model, the $v_{ij} - v_{i0}$ was generated for an interval consistent with the observed choice. For example, if household i chooses option 1, $v_{i1} - v_{i0}$ is obtained, after the estimate of both models, such that it satisfies the inequality:

$$Z_i\gamma_1 + a_1 Y_{-i} + y_i b_1 + (v_{i1} - v_{i0}) > \text{Sup}[0, Z_i\gamma_2 + a_2 Y_{-i} + y_i b_2 + (v_{i2} - v_{i0})],$$

which can be achieved if one takes into account the following rules:

$$v_{ik} = -\ln[-p_{ik} * \ln()] \quad \text{si } j=k$$

$$v_{ij} = -\ln[\exp(-v_{ik}) * (p_{ij}/p_{ik}) - \ln()] \quad \text{si } j \neq k$$

where $() = \text{uniform}()$, a function that produces uniformly distributed random numbers for the interval $[0,1)$.

Further details are provided in Bourguignon *et al* (2003) or Azevedo and Robles (2010).