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Program Targeting Efficiency: Strategies, Lessons Learned and Ways Forward

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A NEW APPROACH TO EVALUATING AND DESIGNING TARGETED SOCIAL PROTECTION

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A NEW APPROACH TO EVALUATING AND DESIGNING TARGETED SOCIAL

[**Abstract**: This paper is concerned with evaluating and designing targeted social protection programs. It derives a new targeting indicator that can be decomposed into two factors: targeting efficiency and mismatch in the program. Most targeted programs suffer from severe mismatch that reduces the targeting power of the programs. The paper demonstrates that the issue of mismatch can easily be and should be addressed right at the design stage of any program. Furthermore, the paper illustrates how the new targeting indicator developed here can be used to design a targeted program. The targeted program designed based on the Philippines data is relatively very simple and does not suffer from mismatch and at the same time has much better targeting efficiency than the three largest programs: *Bolsa Familia* in Brazil, *Di Bao* in the People's Republic of China (PRC), and *Progressa* in Mexico].

PROTECTION PROGRAMS

1. Introduction

The main objective of targeted government intervention is to reduce the deprivation suffered by the poor. The poor may suffer many kinds of deprivation. For instance, they may suffer from poor health or chronic unemployment or have low level of education. Projects or programs may be designed to so that the poor get greater access to various government services. The main binding constraint in designing targeted programs is identifying the genuine poor. If we have incomes or expenditures of individual families, then we can easily assess their poverty situation by comparing their income (or expenditure) against a predetermined poverty line. Such detailed information and administrative ability to use it is not present in most developing countries (Haddad and Kanbur 1991). In the absence of such information, targeting methods have been devised so that the poorest and most vulnerable members of the society receive the maximum benefits.

The number of targeted programs has increased many folds in developing countries.[1] Coady, Grosh, and Hoddinott (2004) have listed 85 programs in 36 countries. The programs follow different procedures to identify the beneficiaries. It is important to know how well different programs perform. To assess their performance, we need to know what policy objectives these programs have been designed to achieve. Most of the social assistance programs have the sole objective of reducing poverty subject to the relevant resources. It is then obvious that targeting should be closely related to the objective of poverty reduction. Many targeting measures have been devised in the literature. In a recent paper, Ravallion (2009) has provided a synthesis of almost all the measures proposed so far. The main message of his paper is that all the targeting measures are quite uninformative from the point of view of poverty impact. In this paper, we demonstrate that most of the targeting measures are closely linked with poverty reduction. This linkage is established with poverty gap ratio, which measures the amount by which households (or individuals) are poor, as well as the number of households that are poor.

Targeting efficiency is related to the selection of beneficiaries in the program. Since targeted programs are not based on the actual incomes or expenditures of household, in the process of selecting beneficiaries, there is the danger of committing two types of error. Type I error occurs when someone who deserves the benefits is denied them, and Type II error occurs when benefits are paid to someone who does not deserve them. Often, these two types of errors do not move in the same direction: attempts to reduce Type II error leads to increased commitment of Type I error. How can we overcome this hurdle?

To tackle this problem, we derive a new targeting indicator, which is a function of four factors: percent of poor targeted by the program, percent of beneficiaries in the program, Type I and II errors. The indicator is derived using the Cramer's phi statistic, which measures the association between poverty status of households or individuals and selection of beneficiary households or individuals. The higher the value of this indicator, better the power of targeting. This indicator has been shown to be closely linked with poverty reduction.

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[1] For an extensive review of cross-country experience of cash transfer programs see Subbarao, Bonerjee, Ezemenari,Braithwaite Graham, Carvalho, and Thomson (1997).

A program is said to be mismatched if the number of poor is not equal to the number of beneficiaries. Most targeted programs suffer from severe mismatch that reduces the targeting power of the programs. Thus, even if we have perfect information about the poor, we can have a poor program if the program suffers from mismatch. In practice, the issue of mismatch is somehow ignored. In this paper, we develop an indicator of mismatch that informs the extent the mismatch reduces the targeting efficiency. The issue of mismatch can easily be and should be addressed right at the design stage of any program.

A proxy means test, which is now widely used in developing countries, enables us to identify beneficiaries on the basis of easily identifiable variables that accurately predict a household to be in poverty. A nationally representative household survey makes it possible to conduct such a proxy means test. In this paper, we illustrate how the new targeting indicator developed here can be used to design a targeted program. This illustration is based on the Philippine's Family Income and Expenditure Survey 2006.[2]

The first step in designing a proxy means testing is to identify a set of variables that are well correlated with the poverty status of households. These selected variables must be easy to measure but at the same time should be able to predict with reasonable accuracy the poverty status of households. To accomplish this objective, we have developed a formula to calculate a correlation coefficient between any proxy variable with the poverty status of households. This correlation coefficient helps in identifying the proxy variables.

We have also evaluated the targeting efficiency of three largest programs: Bolsa Familia in Brazil, Di Bao in the People's Republic of China (PRC) and Progressa in Mexico. These programs have very complex procedures for targeting the poor. Each program has two or three stages of selecting the beneficiaries. Their administrative costs of selecting beneficiaries can be very high because of their complex eligible criteria. More importantly, these programs suffer from severe mismatch. The proxy means test developed here based on the Philippines data is relatively very simple and does not suffer from mismatch and at the same time has much better targeting efficiency.

2. Derivation of Targeting Indicator

Suppose N is the total population of households, and among them N_p are the poor, then the headcount ratio of poverty is given by

$$H = \frac{N_p}{N} \qquad (1)$$

Suppose that N_b are the households who benefit from the program, then the probability of selecting a beneficiary household is given by

[2] I am grateful to Celia Reyes for providing me the Philippines data set.

$$B = \frac{N_b}{N} \quad (2)$$

If we had the perfect information about the poor, then all beneficiaries of the program will be poor. This is not the case in practice. Suppose among N_b beneficiaries, N_{bp} are poor and the remaining $(N_b - N_{bp})$ are the non-poor beneficiaries. The probability of selecting a beneficiary among the poor is given by

$$B_p = \frac{N_{bp}}{N_p} \quad (3)$$

And similarly, the probability of selecting a beneficiary among the non-poor is given by

$$B_n = \frac{(N_b - N_{bp})}{(N - N_p)} \quad (4)$$

If there is no association between the actual poor and selection of a beneficiary, then the probability of selecting a beneficiary among the poor must be equal to the probability of selecting a beneficiary among the non-poor or the poor are as likely to be selected as the non-poor, in which case $B_p = B_n$. This situation may be characterized as having no information as to who the poor are so everyone has the same probability of being selected in the program.

A program may be classified as pro-poor if the probability of selecting a beneficiary among the poor is greater than that among the non-poor, i.e. when $B_p - B_n > 0$.

The proxy means testing can never identify the poor perfectly. Two kinds of errors are committed:

Type I error: Probability of not selecting a poor household as beneficiary.[3]

$$\alpha = (1 - B_p) \quad (5)$$

Type II error: Probability of selecting a non-poor household as beneficiary:

$$\beta = B_n \quad (6)$$

which gives

[3] Some studies refer to this as Type II error (Ravallion 2009). According to the standard statistical literature, Type I error is the probability of rejecting a null hypothesis. If our null hypothesis is that a household selected is poor, then the probability of not selecting this household in the program should be Type I error. Thus, we are following the statistical convention in defining Type I and Type II errors.

$$(1-\alpha-\beta) = B_p - B_n \qquad (7)$$

A program should be designed so that it is pro-poor: the poor are more likely to be selected in the program than the non-poor. The degree of pro-poorness can be measured by how much higher is the probability of selecting a poor in the program to the probability of selecting a non-poor in the program, which is measured by ($B_p - B_n$). Thus, how good is the proxy means testing can be measured by the magnitude of $(1-\alpha-\beta)$.

In the following 2×2 contingency table, we can measure the association between poverty status and selection of beneficiaries by Cramer's Phi statistics as

$$\varphi = (1-\alpha-\beta)\sqrt{\frac{H(1-H)}{B(1-B)}} \qquad (8)$$

When φ=0, it implies that there is no association between poverty and selection of beneficiaries or in other words, the poor are as likely to be selected in the program as the non-poor. It can be seen that $N\varphi^2$ is distributed as χ^2 distribution with 1 degree of freedom. This result allows us to test the null hypothesis of no association between poverty status and selection of beneficiaries.

The larger the value of φ, the greater the association between poverty status and selection of beneficiaries. As we showed above, this statistics is also related to the degree of pro-poorness of the program; the larger the φ, the greater the pro-poorness of the program.

2×2 Contingency table

	Poor	**Non-poor**	**Total**
Beneficiary	N_{bp}	$N_b - N_{bp}$	N_b
Non-beneficiary	$N_p - N_{bp}$	$(N-N_p) - (N_b-N_{bp})$	$N - N_b$
Total	N_p	$N-N_p$	N

In the case of perfect targeting, all the poor are selected as beneficiaries and all non-poor are completely left out, which can happen only when $\alpha = 0$, $\beta = 0$ and B=H—which from (8) gives $\varphi = 1$. Similarly, in the case of imperfect targeting, all poor are left out from the program and all non-poor are included, which can happen only if $\alpha = 1$, $\beta = 1$ and B=1-H—which from (B) gives $\varphi = -1$. Thus, our proposed targeting indicator φ lies between -1 and +1 and its magnitude gives an indication how good a given program can target the poor. Any program that gives negative value of φ should not be implemented because it is anti-poor (the poor have lesser chance of being selected than the non-poor). φ^2 is similar to the coefficient of determination in regression analysis: proportion of total variation that is explained by the proxy means test. In designing a program, we should aim at maximizing φ^2

3. Mismatch between Beneficiary and Poor Households

In designing any targeted program, we have to consider four parameters, namely, proportion of poor households H, who are being targeted, proportion of beneficiary households B in the population, Type I error α and Type II error β . These four parameters are very closely related. If B<H, we are likely to exclude more poor (and also more non-poor) households from the program, which implies higher Type I error and lower Type II error. If B>H, we are likely to include more of both poor and non-poor households in the program resulting in lower Type I error and higher Type II error. What is the correct size of any program? We would explore this issue in more detail in the paper. In almost all targeted programs we have encountered, B is never equal to H. An important implication of this is that even if we have perfect information about the poverty status of households (which household is poor and which is non-poor), the two types of errors can never be eliminated or in other words we can never have perfect targeting. If B is not equal to H, we can say that there is a mismatch between beneficiary and poor households.

If there is no mismatch and if we have perfect information about households' poverty status, we will naturally ensure that all poor households are included in the program and all non-poor households are excluded, which implies $\alpha = 0$ and $\beta = 0$, which on substituting in (8) gives $\varphi = 1$. Thus, we will have a perfect correlation between poor and beneficiary households. This is the ideal situation. The targeting efficiency of a program can then be judged by how far below φ is from 1. If for instance $\varphi = 0.4$, it means that the program is 40% efficient in targeting the poor. When there is no mismatch, the targeting indicator in (8) is given by

$$\varphi = 1 - \alpha - \beta \qquad (9)$$

which interestingly is the targeting differential measure (TD) proposed by Ravallion (2000). This measure informs how high the probability of selecting poor households in the program is over that of the non-poor households. This measure is suitable for ranking programs when there is no mismatch; the number of beneficiary households is exactly equal to the poor households. Most targeting programs in developing countries do not meet this requirement.[4]

Given that mismatch is so common, it is important to assess its impact in designing a targeted program. We have two kinds of mismatch. The most common mismatch is when B<H. The cost of any targeted program depends on what proportion of beneficiary households are included in the program; the larger B is, the greater the cost of the program will be. Most governments in developing countries have budget constraints so there is always a tendency to design programs that have B as small as possible. Suppose that we have perfect information on the poverty status of households, all beneficiaries will then be among the poor households so that Type II error denoted by β will be equal to 0. Type I error will occur because the program does not include all

[4] An excellent discussion of targeted programs in developing countries is given in the two books: (1) Coady,Gosh, and Hoddinott (2004) and (2) Subbarao, Bonnerjee,Braithwaite,Carvalho,Ezemenari,Graham, and Thomson (1997). It is interesting to note that almost all the programs synthesized therein are mismatched.

poor households; hence $\alpha = (H - B)/H$, which on substituting in (8) gives the upper limit of φ as

$$\varphi_u = \sqrt{\frac{B(1-H)}{H(1-B)}} \quad \text{if B<H} \qquad (10)$$

The mismatch may occur when B>H. If we have perfect information, this mismatch implies $\alpha = 0$ and $\beta = (B - H)/(1 - H)$, which on substituting in (8) gives the upper limit for φ as

$$\varphi_u = \sqrt{\frac{H(1-B)}{B(1-H)}} \quad \text{if B>H} \qquad (11)$$

$\varphi_m = 1 - \varphi_u \leq 1$ is the measure of mismatch; the larger (smaller) the value, the larger (smaller) the mismatch. $\varphi_m = 0$ when B=H, i.e., there is no mismatch.

Every targeted program has a decision rule that identifies a poor household from the non-poor household. The targeting efficiency of a program should be judged on the basis of how good the decision rule is. If we have perfect information about the poverty status of households, the decision rule will be able to pick only the poor households for inclusion in the program. In practice we do not possess the perfect information about households' poverty status, so we judge the targeting efficiency of the program by measuring how far below the targeting indicator is from the counterfactual situation of having the perfect information. Equations (10) and (11) give the upper limits of the targeting indicator under the perfect information. Thus, we define the targeting efficiency of a program as the ratio of targeting indicator φ to its upper limit φ_u as defined in (10) and (11):

$$\begin{aligned} \varphi^* &= \frac{(1-\alpha-\beta)H}{B} \; if \; B < H \qquad (12) \\ &= \frac{(1-\alpha-\beta)(1-H)}{(1-B)} \; if \; B > H \end{aligned}$$

Thus, the targeting indicator can be written as product of two components:

$$\varphi = \varphi^*(1 - \varphi_m) \qquad (13)$$

This decomposition allows us to know how good the program is in identifying the poor, and how much the mismatch is in the program. The issue of mismatch can be addressed more easily than the issue of targeting efficiency.

It will be useful to explain the idea of mismatch with an example. We have taken a hypothetical example of two programs operating in two cities, which is discussed by Ravallion (2009). In city A, 50% population is poor but the program has selected only the poorest 20% as beneficiaries. In city B, 10% population is poor but the program has selected the poorest 40% of the population as beneficiaries. City A has 20% beneficiaries but 50% poor whereas city B has 40% beneficiaries but only 10% poor. It is quite obvious that both programs have severe mismatch problems. Given this information, the measure of mismatch gave the values of .50 for city A and .59 in city B. Thus, both cities have severe mismatches but the mismatch is more severe in city B. There would

not have been any mismatch if the program in city A had chosen 50% beneficiaries, whereas in city B, only 10% beneficiaries would have been sufficient. Further, in city A, 40% of the poor are selected as beneficiaries whereas in city B, 100% of the poor are selected as beneficiaries. The target indicator is calculated as .50 in city A and .41 in city B, which means the program in city A is better targeted than in city B, even though 100% poor are covered by the program in city B. The target efficiency in both cities is computed to be equal to 1. This is the result we expected to obtain because in both cities, we have the perfect information about the poverty status of individuals, i.e., which household belonged to which percentile. Thus, even if we have perfect information on the poor, we can have a poor program if the number of beneficiaries is not in line with the number of poor. In practice, the issue of mismatch is somehow ignored. This example demonstrates that the issue of mismatch should be addressed right at the design stage of any program.

4. Linkage with Poverty Reduction

In this section, we attempt to link the targeting indicator developed here with poverty reduction. Many poverty measures exist in the literature that reflect the different facets of poverty. In designing a targeted program, we have to choose a poverty measure with which the program should be linked. The headcount ratio is a crude measure of poverty because it completely ignores the gap in incomes from the poverty line. The poverty gap ratio adopted here is more attractive because it measures the amount by which households (or individuals) are poor, as well as the number of households that are poor. There is a third measure called the severity of poverty, which has more attractive properties than the poverty gap ratio. This measure is somewhat more complex so we have chosen the poverty gap ratio.

A social protection program may be defined as pro-poor if it provides greater absolute benefits to the poor compared to the non-poor. Obviously, with a given fixed cost, a pro-poor program will lead to greater poverty reduction than a non-pro-poor program. Using this framework, Kakwani and Son (2007) derived the pro-poor policy (PPP) index for a wide range of poverty measures. Assuming that all beneficiaries receive exactly the same benefits from the program, the PPP index for the poverty gap ratio is obtained as

$$\delta = \frac{B_P}{B} \qquad (14)$$

where B_P is the percentage of beneficiaries among the poor and B is the percentage of beneficiaries in the whole population. The program will be pro-poor if the percentage of beneficiaries among the poor is greater than that of beneficiaries in the whole population or in other words, when $\delta > 1$. The larger the value of δ, the greater will be the degree of pro-poorness of the program.

Note that the value of δ does not depend on the size of the program in terms of its budget, which means that δ alone cannot inform the poverty impact of different programs with different budgets. The magnitude of reduction in poverty gap ratio is fully captured by the product of H, B and δ, which means that for given values of B and H, the magnitude of poverty reduction has a positive monotonic relationship with δ; the larger the δ, the greater the poverty reduction.

The targeting indicator φ defined in (8) can also be written as

$$\varphi = (\delta - 1)\sqrt{\frac{HB}{(1-H)(1-B)}} \qquad (15)$$

which shows that given H and B, φ has a positive monotonic relationship with δ. Since δ has a positive monotonic relationship with poverty reduction, so will φ. Thus, our proposed targeting indicator is closely linked with poverty reduction; for given *H* and *B* the higher the value of φ, the greater the poverty reduction. It will be useful to consider poverty reduction per unit cost to government. This indicator is important because our objective is to maximize poverty reduction with a given budget constraint. The reduction in poverty gap ratio per unit cost is captured by $\delta^* = H\delta$, which on substituting in (15) shows that for given *H* and B, φ has a positive monotonic relationship with δ^*,; the larger the value of φ, the greater the reduction in poverty gap ratio with fixed cost.

4. An Evaluation of Three Famous Welfare Programs

4.1 Brazilian Welfare Programs

Brazil has many welfare programs. We have applied our methodology to see how well different programs in Brazil are targeted (Table 1). The largest program in Brazil is Bolsa Escola, which benefits 10.9% of the total population. All programs together benefit about 22.6% of the total population. Note that these different programs are not mutually exclusive. Some families may receive benefits from more than one program.

A striking feature of the Brazilian welfare system is that Type I error is very high and Type II error is very small. It means that programs are efficient with respect leakage to the poor but a large proportion of poor are left out from programs. Except for unemployment insurance, all programs are pro-poor; the probability of selecting a poor in the program is much higher than the probability of selecting a non-poor in the program. This is indicated by the positive values of the targeting indicator.

Comparing different programs, we find that three programs, namely, Bolsa Familia, Bolsa Escola and Fuel Subsidy stand out as the best targeted programs with values of targeting indicator equal to 0.28, 0.30 and 0.27, respectively. Bolsa Familia is a new program that provides transfers to families with children. Bolsa Escola is an old program that was designed to enhance school attendance by children coming from the poor families.

The least efficient program is unemployment insurance, which is not even pro-poor. The BPC is a program that provides pensions to the poor. Its targeting indicator value is only 0.09, which cannot be regarded as well-targeted program.

The maximum value of targeting indicator is 0.30, which means that the criteria for identifying the poor explains only about 9% of poor population or in other words, other variables are undetected—which cumulatively account for and predict poverty in the population. These results suggest that welfare programs in Brazil, which are so famous, are not well targeted. This, however, may be a misleading conclusion because it ignores the loss of predictive power of the programs due to mismatch.

Targeting indicator is the product of targeting efficiency and mismatch. Targeting efficiency measures how good the decision rule is in identifying the poor population or to what extent the target indicator deviates from the situation of having perfect information about the poverty status of the population. Mismatch can occur even if we have perfect information. The targeting efficiency of Bolsa familia is 0.71, which we regard as a reasonably good targeting system. The mismatch index is 0.6, which reduces the predictive power of targeting by about 60%. Thus, the Brazilian major welfare programs have reasonable targeting efficiency but they suffer from severe mismatch between the number of poor who are targeted for the programs and the number of beneficiaries who are included in the programs.

Table 1: Targeting Efficiency of Welfare Programs in Brazil

Welfare program	Proportion of Beneficiaries	Errors Type 1	Type2	Targeting indicator	Targeting Efficiency	Mismatch Index
Bolsa Familia	0.058	0.836	0.017	0.28	0.71	0.60
Fome Zero	0.020	0.940	0.005	0.18	0.76	0.77
Bolsa Alimentacao	0.015	0.960	0.005	0.13	0.64	0.80
Bolsa escola	0.109	0.742	0.051	0.30	0.53	0.44
Peti-child labor	0.011	0.971	0.004	0.10	0.61	0.83
Unemployment insurance	0.015	0.991	0.017	-0.03	-0.16	0.80
BPC	0.018	0.962	0.010	0.09	0.44	0.79
Fuel subsidy	0.093	0.782	0.044	0.27	0.52	0.49
Other benefits	0.010	0.978	0.005	0.08	0.47	0.84
Proportion of poor	0.280					

Source/s: Author's calculations based on The Brazilian National household Survey 2004 (PNAD).

4.2 The People's Republic of China's Minimum Livelihood Guarantee Scheme

PRC's "Minimum livelihood guarantee Scheme", popularly known as *Di Bao* is one of the largest social protection programs in the developing world. The program started in 1999 and expanded rapidly. According to Ravallion (2009), the program covered 2.2 million people representing 6% of urban residents. The program is run by municipalities. The beneficiaries in the program are determined on the basis of income reported by persons seeking assistance. A person is included in the program if his or her reported income is less than a stipulated "poverty

line." Each locality determines its own poverty line. Although the local authorities conduct checks on eligibility, it is difficult to believe that the potential beneficiaries will not underreport their incomes. Furthermore, Ravallion (2009) points out that local authorities have considerable power over the program, including setting the Di Bao poverty lines, funding, and implementation. This means that the process of selecting beneficiaries is subjective, which can cause horizontal inequity when the program is implemented at the national level. Suppose there are two persons A and B who belong to two different municipalities but have exactly the same standard of living. It is possible that person A is classified as poor and person B is classified as non-poor. This can happen because the two municipalities are not using exactly the same criteria for selecting beneficiaries. There will be no consistency across the country.

Ravallion's (2009) has conducted a thorough evaluation of *Di Bao* using the PRC's Urban Household Short Survey for 2003–2004, covering 35 largest cities with the total sample of 76,000. He concluded that targeting performance is excellent by international standards. The program is a clear outlier in targeting performance internationally.

Across the 35 cities, 7.7% of the total population has a net income of less than the *Di Bao* poverty line. The percentage of beneficiary among the poor is found to be only 29%, which means that 71% of the poor are excluded from the program. This figure does not suggest that the Di Bao can be considered as an outlier in targeting performance internationally. However, the percentage of beneficiary among the non-poor is only 1.83%, which is very small. So the program has high under-coverage rate but low leakage rate. The targeting indicator φ proposed here is computed to be equal to 0.37, which falls well short of perfect targeting ($\varphi = 1$). Still, Di Bao performs better than Brazil's most well known Bolsa Familia, for which the value of φ is equal to 0.28. This result is surprising because the Bolsa Familia is Brazil's flagship program based on sophisticated objective criteria to identify the beneficiaries, whereas Di Bao uses subjective judgments by municipalities. To explain this anomaly, we calculated the mismatch index for Di Bao, which is found to be equal to 0.30, and which resulted in a targeting efficiency of 0.53. The Bolsa Familia on the other hand has much larger degree of mismatch with index value equal to 0.60. The targeting efficiency of Bolsa Familia was calculated to be equal to 0.71 as against the value of 0.53 for Di Bao. Thus, Bolsa Familia has much greater power than Di Bao in identifying the beneficiaries but it suffers from a more severe mismatch. Somehow, if Bolsa Famila had avoided a mismatch, it would have been much superior to Di Bao. We will discuss in the paper how we can avoid mismatch.

4.3 Mexico's Health, Education, and Nutrition Program (PROGRESA)

Conditional cash transfer (CCT) programs have been regarded as the modern way to reconcile safety nets (or more generally social protection policies) with investments in the human capital of the poor. The basic idea behind these programs is they reduce poverty in both the short and long run. Several Latin American countries have been pioneers of CCT programs. In particular, countries where large scale CCTs have been implemented are Mexico and Brazil. The first national CCT program was pioneered by Mexico in 1997. This was the most comprehensive program of education, health, and nutrition, called Progresa. It will be useful to evaluate the targeting efficiency of this program because it follows statistically rigorous methods to identify the beneficiary households who are supposed to be extremely poor.

The selection of beneficiary households is accomplished in three stages. At the first stage, communities are selected using a marginal index based on census data. The marginal index was developed for each locality in Mexico using the method of principal components based on seven variables:

- Share of illiterate population aged 15 years or more.
- Share of dwellings without running water.
- Share of household dwellings without drainage.
- Share of household dwelling without electricity.
- Average number of occupants per room.
- Share of dwellings with earth floor.
- Percentage of labor force working in agricultural sector.

The marginality index was divided into five categories. It is not known how good these indicators are in identifying the poor localities. Ideally, if we know the percentage of poor households in each locality, we could rank the localities, but such information is not available. Skoufias, Davis and Vega (2001) have attempted to assess the efficacy of selecting localities against consumption-based poverty maps. These poverty maps are themselves subject to large errors and therefore we cannot have a proper assessment of how good the marginality index is.

At the second stage, households are chosen within the selected communities. It involves a rather complicated procedure, which we do not need to discuss here. At the third stage, the communities are presented with a list of potential beneficiaries, and the final list is prepared. These three stages are so complicated we cannot assess the overall targeting efficiency of the program. We, however, make an assessment of the program at the second stage of selection using the information provided by Skoufias, Davis and Vega (2001). They used the data collected by Progresa in 1997 for 24,077 households residing in a sample of 506 marginal communities. On average, 78% of the households in the sample were Progresa beneficiaries. Table 2 presents the results on targeting indicator using three poverty lines.

Table 2: Targeting Indicator at the Second Stage of Selection by Progressa

	Percentage poor	Percentage beneficiaries	Type 1 Error	Type 2 error	Targeting indicator	Mismatch indicator	Targeting efficiency
Progresa targeting	25	78	6.63	72.97	0.21	0.69	0.70
Progresa targeting	50	78	10.80	66.94	0.27	0.47	0.51
Progresa targeting	78	78	16.27	57.98	0.26	0.00	0.26
Locality-level targeting	78	78	18.96	67.28	0.14	0.00	0.14

Source: Skoufias and Davis (2001).

The Type 1 error is 6.63% when extreme poverty of 25% is used. It means that 6.63% of extremely poor households are excluded by Progresa. As the poverty line increases, the exclusion error increases to 10.8% at the 50th percentile and 16.27% at the 78th percentile. The Type 2 is very high, which means that a large proportion of non-poor are included in the program. The targeting indicator has a value of only 0.21 for the extremely at the 25th percentile. Compared to the other programs we have looked at, these results clearly indicate that the targeting by Progresa is very poor. The value of targeting indicator when targeting is done at local level using marginality index is only 0.14. Thus, targeting is much inferior at the local level. This assessment should, however, be qualified because it provides only a partial assessment at the stage of selection among the households residing in the poorest communities.

5 Designing a Social Protection Program

In most low income countries, income is hard to measure. Moreover, many households consume from their own production. This situation makes it difficult to use income as a measure for identifying poor households. A proxy means test, which is now widely used in developing countries, enables us to identify beneficiaries on the basis of easily identifiable variables that accurately predict a household to be in poverty. A nationally representative household survey makes it possible to conduct such a proxy means test.

5.1 Proxy Variables

The first step in designing a proxy means testing is to identify a set of variables that are well correlated with the poverty status of households. These variables generally include household characteristics such as household composition, dwelling characteristics: type of roof, toilet, electricity connection, water supply, sanitation etc; households' labor force characteristics; land owned and operated, ownership of durables and so on. The variables selected must be easy to measure but at the same time they should be able to predict the poverty status of households with reasonable accuracy. To accomplish this objective, we should look at how a particular variable is correlated with poverty. Suppose for instance we believe that female-headed households have more severe poverty than male-headed households, then we can choose the female-headed households as one of the proxy variables in designing the program. This variable will be a good selection if a large proportion of female-headed households are poor.

Suppose B_j is the proportion of beneficiary households based on the jth proxy variable in the population, H is the proportion of poor households in the population, and B_j^P is the proportion of beneficiary households among the poor, then the correlation coefficient between the ith proxy variable and the poverty status of households is given by

$$\rho_j = \frac{\left(B_j^P - B_j\right)}{B_j}\sqrt{\frac{HB_j}{(1-H)(1-B_j)}} \quad (16)$$

Using the Philippines' Family Income and Expenditure Survey (FIES) 2006 and official poverty line, we calculated that the Philippines had 24.23% poor households. The percentage of female-headed households was 18.67 in the whole country but among the poor households, this percentage was 10.66. This means that poverty is less severe among the female-headed

households than that among male-headed households. Using (16), the correlation between female-headed households and the poverty status of households is calculated to be equal to –0.12. From this result, we can conclude that a female-headed household is not a good proxy variable. The variables relating to the ownership of assets generally have high correlation coefficient. For instance, possession of TV has correlation coefficient of -0.44, which implies that the poor households generally do not own television. The proxy variables are generally determined on an ad hoc basis. The correlation coefficient given in (16) can be used to develop a set of proxy variables in a more objective way.

If the proxy variable is not a binary (dummy) variable, then formula for the correlation coefficient in (16) will not be valid. Suppose the proxy variable Z_j is a continuous variable with mean μ_j and variance σ_j^2, then the correlation coefficient between Z_j and the poverty status of households will be given by

$$\rho_j = (\mu_j^P - \mu_j)\sqrt{\frac{H}{(1-H)\sigma_j^2}} \qquad (17)$$

where μ_j^P is the mean of Z_j among the poor households.

The household size is often used as a proxy variable because generally it has been found that poor households have larger households size than the non-poor households. In the case of the Philippines, we found that the average household size in the population is 4.82, whereas poor households have average household size equal to 5.88. The correlation coefficient from (17) is computed to be equal to 0.28, which is quite high and significant. Thus, the household size can be regarded as a good proxy variable.

The complete list of proxy variables along with their correlation with poverty is presented in Table A.1 in the appendix. The correlations of the selected variables are all statistically significant.

5.2 The Model Used

Having determined the proxy variables, the next step is to combine them into a composite index that can be used as the basis for identifying the beneficiary households. We should combine them in such a way that they provide the maximum probability of a household being identified as poor; the larger the probability, the better would be the targeting.

A household is defined as poor if its per capita income is less than the per capita poverty line. Suppose y_i^* is a variable that determines the poverty status of the ith household and can be determined by a set k proxy variables X_i by means of the following model:

$$y_i^* = X_i\beta + \epsilon_i \qquad (18)$$

where β is the vector of k coefficients and ϵ_i is the stochastic error term, which has 0 mean and constant variance. Although y_i^* is not observable, still we can relate it to the observed poverty

status of ith households z_i (which takes value 1 if the ith household is poor otherwise it takes value 0) defined as

$$z_i = 1 \; if \; y_i^* > 0 \qquad (19)$$
$$= 0 \; if \; y_i^* \ll 0$$

It can be easily seen that

$$E(z_i) = \pi_i = P(z_i = 1) = P(y_i^* > 0)$$

π_i is the probability that the ith household is poor. Our objective is to estimate π_i based on k proxy variables. We use the Logit model:

$$\pi_i = \frac{e^{X_i\beta}}{1+e^{X_i\beta}} \qquad (20)$$

This model can be estimated using the maximum likelihood method. Table A2 in the appendix presents the estimates of the k coefficients in β. The table also gives the t values, which inform whether a give proxy variable is statistically significant. If the t value is greater than 1.96, we can say that the proxy variable statistically significant at the 5% level of significance. It is noted that the coefficients corresponding to almost all proxy variables are statistically significant. It means that the proxy variables chosen have a significant impact in the determination of poverty status of households. Substituting the estimates of β from Table A2 in (20) we obtain the estimate of each household's probability of being poor.

5.3 Decision Rule

Having estimated each household's probability of being poor, we can now design a decision rule to determine which household should or should not be included in the program. We can have a decision rule that the ith household is a beneficiary for the program if its estimated probability of being poor denoted by $\hat{\pi}_i$ is greater than π, which is an exogenously determined cutoff point. Suppose *B* is the percentage of beneficiary households who are selected by this decision rule. Obviously, *B* will depend on the value of π; the larger the value of π, the smaller B will be. Using the households survey data from the Philippines we obtained the proportion of beneficiaries among the households in the whole population and also among the poor for different values of π. The results are presented in Table 3.

Based on the official poverty line, 24.23% of households are poor in the Philippines. This program has been designed to target all these households. It is noted that if π =.8931, the beneficiary households in the population are only 5%, which means there will be a high degree of mismatch. The percentage of beneficiaries among the poor and non-poor households is equal to 19.2 and 0.46, respectively. The targeting indicator is 0.37 and mismatch index is 0.59.

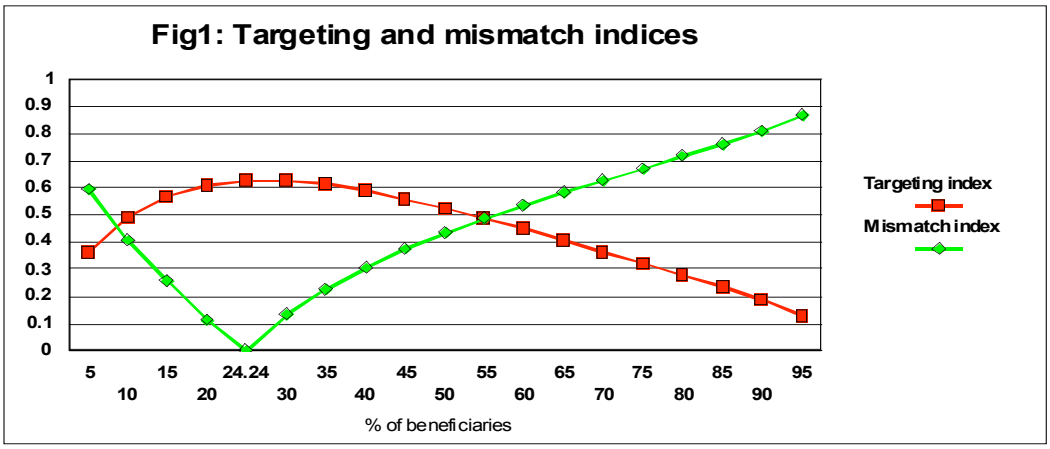
Our objective is to maximize the targeting indicator. Figure 1 shows the targeting indicator for different values of beneficiaries. This curve is an inverted U-shaped curve. The targeting indicator achieves the maximum value of 0.63 when the percentage of beneficiaries is equal to

the percentage of poor households in the population. At this point, the mismatch index is equal to 0 and obviously, targeting efficiency will then be equal to the targeting index, which 0.63. This is the maximum degree of targeting we can achieve with the proxy variables selected in the design of this program. The percentage of beneficiaries for this program is 24.23, which is exactly equal the percentage of target households. The percentage of beneficiaries among the poor is almost 72%, which means that 28% of the poor are left out of the program. The percentage of beneficiaries among the non-poor households is about 9%. Comparing the targeting efficiency of three major programs evaluated here we find that this program is far superior. For instance, the value of the targeting indicator for Brazil's Bolsa Familia is only 0.28 and that for PRC's *Di Bao* is 0.37.

Table 3: Targeting Indicator for Different Proportion of Beneficiaries

Cut off point for probability	in population	Proportion of beneficiaries among poor	Proportion of beneficiaries among non-poor	Targeting Index	Mismatch Index	Targeting Efficiency
0.8931	5	19.20	0.46	0.37	0.59	0.91
0.788	10	36.35	1.58	0.50	0.41	0.84
0.6682	15	51.01	3.48	0.57	0.26	0.77
0.5376	20	63.30	6.15	0.61	0.12	0.69
0.4293	24.23	71.94	8.98	0.63	0.00	0.63
0.3139	30	81.00	13.69	0.63	0.14	0.73
0.2282	35	87.03	18.36	0.62	0.23	0.80
0.1641	40	91.23	23.61	0.59	0.31	0.85
0.1191	45	94.29	29.24	0.56	0.37	0.90
0.084	50	96.56	35.11	0.53	0.43	0.93
0.0571	55	98.10	41.22	0.49	0.49	0.96
0.0384	60	99.00	47.53	0.45	0.54	0.97
0.0254	65	99.51	53.97	0.41	0.59	0.99
0.0162	70	99.72	60.50	0.37	0.63	0.99
0.0102	75	99.86	67.05	0.32	0.67	0.99
0.0057	80	99.95	73.62	0.28	0.72	1.00
0.003	85	99.98	80.21	0.24	0.76	1.00
0.0013	90	100.00	86.81	0.19	0.81	1.00
0.0003	95	100.00	93.40	0.13	0.87	1.00

Source/s: Author's calculations based on the Philippines' Household Income and Expenditure Survey (FIES) 2006.



5.4 Implementation

It should be noted that the well-known social assistance programs discussed above have very complex procedures for targeting the poor. Each program has two or three stages of selecting the beneficiaries. Their administrative costs of selecting beneficiaries can be very high because of their complex eligible criteria. The proxy means test developed here is relatively very simple and at the same time has better targeting efficiency. We have used about 20 odd proxy variables, which are well defined and information required on them can easily be collected. One can then design a two-page form that seeks information from households that want to be included in the program. On the basis of information provided in the form, the decision rule developed here will inform whether the household should be included in the program. The beneficiary households may be required to fill this form every year so that the decision can be made as to whether the household should continue or cease to be in the program. In order that this approach does not introduce potential exclusion error by not assessing those who do not apply for assistance, the program should be widely advertised within communities and also nationwide so that households who are in real need of assistance are not left out because of not knowing the existence of programs.

The proxy means test developed here targeted the poorest 24.23% households because these are the households that are regarded as officially poor in the Philippines. To avoid a mismatch, the percentage of beneficiary households should also be 24.23%, which will require large resources that many governments in developing countries may not be able to afford. The proxy means test developed could provide flexibility to the government with respect to the percentage of households that should be targeted. For instance, government resources might only allow targeting the bottom 10% of the poorest households. If so, the decision rule could then be designed to identify only the poorest 10% of the households. This methodology would allow such flexibility.

Once the beneficiaries have been selected, then the levels of payments should be determined so that we achieve a maximum reduction in poverty with given budget constraints. This can be achieved if payments are linked to meeting the minimum basic needs of households, which are determined by the poverty line. The rules governing the payments can be devised using the national household survey.

5.5 Community Based Monitoring System (CBMS)

CBMS is a community based poverty monitoring system, which began in the Philippines under the leadership of Dr Celia Reyes of the Philippines Institute of development Studies in the early 1990s but now is being implemented in 14 countries in Asia and Africa. It is increasing becoming an important tool to fighting poverty with facts.[5] It is an organized way of collecting ongoing or recurring information by communities. Its core indicators are designed to capture multiple dimensions of poverty. The information so collected is used by "local governments, national governments, NGOs and civil society for planning, budgeting, implementing local development programs as well as monitoring and evaluating their performance (Reyes and Due 2009).

Using the proxy variables, one can design a short questionnaire, which accurately provides the values of proxy variables from the households. The communities may conduct this survey on a regular basis and may identify poor households using the decision rule as designed here. This procedure, while carried out by communities, will provide poverty maps which are comparable across the country. The communities can do some fine tuning if there are obvious odd cases. Thus one can have a community-based monitoring as well as targeting system that has greater consistency across the country.

5 Some Concluding Remarks

This paper has developed a new targeting indicator, which is a function of four factors:

- The percentage of poor targeted by the program.
- The percentage of beneficiaries in the program.
- Type I error: percentage of poor not included in the program.
- Type II error: percentage of non-poor included in the program.

The main objective of targeted programs is to reduce poverty. Most national programs target households that have been identified as poor on the basis of certain poverty line. In order that no poor is left out from the program, the percentage of beneficiary households must be at least equal to the percentage of poor. The inclusion of every beneficiary in the program involves cost to the government so the poorer a country, the greater the cost of program. Many governments cannot afford these costs so the most social programs have very small proportion of beneficiaries relative to the target population. This creates a mismatch in the programs, which reduces the targeting efficiency of programs. In this paper, we developed a mismatch index that informs the

[5] For an excellent description of CBMS see the recent book by Reyes and Due (2009).

extent a mismatch reduces the targeting efficiency. The computations mismatch index shows that the three biggest programs, namely, Bolsa Familia in Brazil, Di Bao in the PRC, and Progress in Mexico suffer from severe mismatch, which results in huge loss of targeting efficiency. The issue of mismatch can easily be and should be addressed right at the design stage of any program.

The two types of errors do not move in the same direction: attempts to reduce Type II error leads to increased commitment of Type I error and vice versa. There is always tradeoff between the two errors. The targeting indicator derived here addresses the issue of this tradeoff by combining the two types of errors in a composite index. The indicator is derived using the Cramer's phi statistic, which measures the association between poverty status of households or individuals and selection of beneficiary households or individuals; the higher the value of this indicator, the better the power of targeting. This indicator has been shown to be closely linked with poverty reduction. Our empirical illustration based on the Philippine data shows that the proposed targeting can be useful to designing a well-targeted program.

The well known social assistance programs discussed in the paper have very complex procedures for targeting the poor. Each program has two or three stages of selecting the beneficiaries. Their administrative costs of selecting beneficiaries can be very high because of their complex eligible criteria. The proxy means test developed here is relatively very simple and at the same time has better targeting efficiency. Our study shows that designing complex selection procedures do not guarantee higher targeting efficiency.

In many African countries, 50 to 60 percent of population lives in poverty. The governments cannot afford to target all the poor. The proxy means test developed here could provide flexibility to the government with respect to the percentage of households that should be targeted. For instance, government resources might only allow targeting the bottom 10% of the poorest households. If so, the decision rule could then be designed to identify only the poorest 10% of the households. This methodology would allow such flexibility.

Using the proxy variables, one can design a short questionnaire, which accurately provides the values of proxy variables from the households. The communities may conduct this survey on a regular basis and may identify poor households using the decision rule as designed here. This procedure, while carried out by communities, will provide poverty maps which are comparable across the country. The communities can do some fine tuning if there are obvious odd cases. Thus one can have a community-based monitoring as well as targeting system that has greater consistency across the country.

This paper has covered a wide range of issue relating to evaluating and designing social programs in developing counties. It has developed simple techniques to tackle the complex targeting issues. The future work should be on application of the techniques to designing social protection programs in as many developing countries as possible.

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Appendix

Table A.1: Correlation Coefficients of Proxy Variables.

	Percentage of beneficiary in population	Percentage of beneficiary among poor	Correlation coefficient
Ownership of assets			
Television	69.6	33.5	-0.44
DVD/VCR	45.0	12.8	-0.37
Refrigerator	39.5	5.5	-0.39
Washing machine	29.6	2.6	-0.33
Air Conditioner	7.1	0.2	-0.15
Car	6.9	0.3	-0.15
Telephone	52.7	15.6	-0.42
Computer	6.6	0.1	-0.15
Microwave	6.0	0.1	-0.14
Electricity	82.1	54.5	-0.41
Sanitary toilet facilities			
No toilet	9.0	21.9	0.26
Others	1.5	3.0	0.07
Open pit	4.9	11.3	0.17
Closed pit	8.9	15.2	0.13
Water Sealed	75.8	48.7	-0.36
Household size			
Household size 1	3.9	0.7	-0.09
Household size 2	8.6	3.4	-0.11
Household size 3	14.0	6.7	-0.12
Household size 4	19.2	13.4	-0.08
Household size 5	18.9	19.1	0.00
household size 6	14.3	19.3	0.08
Household size more than 6	21.1	37.4	0.23
Age of household head			
less than 30	7.1	7.0	-0.00
30–39	22.6	28.6	0.08
40–49	27.0	30.2	0.04
50–59	21.6	17.6	-0.05
60+	21.7	16.5	-0.07
Education of household head			
Less than elementary	24.7	44.4	0.26
Elementary	18.9	25.5	0.10

High school incomplete	12.4	13.1	0.01
High school complete	21.8	13.0	-0.12
College incomplete	11.8	3.5	-0.14
Complete college	10.5	0.5	-0.18
Household headed by female	18.7	10.7	-0.12
Head not engaged in agriculture	75.8	44.5	-0.41
Urban households	49.6	20.2	-0.33
Dependency ratio	41.2	66.8	0.29
Percentage of poor households	24.2		

Table A.2: Estimates of Logit Model

	Coefficient	t_value
Ownership of assets		
Television	–0.534	–11.3
DVD/VCR	–0.438	–9.1
Refrigerator	–0.839	–14.4
Washing machine	–1.105	–14.1
Air Conditioner	–0.752	–3.5
Car	–0.965	–4.1
Telephone	–0.940	–21.9
Computer	–1.377	–3.8
Microwave	–1.384	–3.3
Electricity	–0.320	–6.6
Sanitary toilet facilities		
No toilet	0.613	11.2
Others	0.305	2.6
Open pit	0.246	3.8
Closed pit	0.235	4.5
Water Sealed		
Household size		
Household size 1	-	-
Household size 2	1.043	7.3
Household size 3	1.395	9.9
Household size 4	1.898	13.8
Household size 5	2.374	17.2
household size 6	2.888	20.3

Household size more than 6	3.437	24.4
Age of household head		
less than 30	-	-
30-39	0.079	1.1
40–49	0.193	2.7
50–59	0.218	2.8
60+	0.479	6.0
Education of household head		
Less than elementary	1.669	10.7
Elementary	1.434	9.1
High school incomplete	1.276	8.1
High school complete	1.057	6.7
College incomplete	0.949	5.7
Complete college	–	–
Household headed by female	–0.032	0.6
Head not engaged in agriculture	–0.690	–17.7
Urban households	–0.778	–19.2
Dependency ratio	2.263	14.0
Pseudo R^2	0.466	