Discussion Papers in Economics

Identifying Targeting with Nonparametric Methods: An Application to an Indian Microfinance Program.

Rohini Somanathan
Isha Dewan

Discussion Paper 03-11

July 2003

Indian Statistical Institute, Delhi
Planning Unit
7 S.J.S. Sansanwal Marg, New Delhi 110 016, India

Identifying Targeting with Nonparametric Methods: An Application to an Indian Microfinance Program.*

Rohini Somanathan
University of Michigan and Indian Statistical Institute

Isha Dewan
Indian Statistical Institute

July, 2003.

Abstract

We discuss nonparametric methods and statistical tests that are appropriate to assess poverty targeting in public programs. These methods explicitly account for the possibility that the population distributions of participants and non-participants cross. Crossing points provide us with upper bounds on the income of those who have been excluded from the program. Applying these methods to data from a microfinance program in the state of Jharkhand in India, we find evidence that very poorest households are largely excluded from the program.

*The Consultative Group to Assist the Poorest at the World Bank funded our data collection efforts. We are grateful to them and to Charlie Brown, Julie Cullen, Roger Gordon and E. Somanathan for useful discussions.

1 Introduction

Every public program faces the challenge of reaching intended beneficiaries. Documented deficiencies in many of the older social transfer mechanisms have led governments, non-government organizations and donor institutions to embrace institutions which use innovative methods of transferring resources to poor households. Some of these (such as the Grameen Bank of Bangladesh), provide credit to poor households for micro-enterprises, some (like Mexico's PROGRESSA or social funds in Peru), subsidize investments in social and physical infrastructure and others (such as the Employment Guarantee Schemes in India) provide opportunities for employment on local infrastructure projects during periods of food scarcity. Central to evaluating the success of these programs is an assessment of how well they target the poor.

While many of the schemes mentioned above have undoubtedly transformed the lives of millions of rural households, there is some concern that they may not be adequately serving the very poor. The very poor may be too poorly informed, educated or nourished to take advantage of the program, they may not possess required documents such as birth certificates or proofs of residence, they may be socially ostracized or agency problems may lead bureaucrats to direct resources to other groups. Morduch (1998) finds that eligibility rules are often violated in microcredit programs in Bangladesh. There is also empirical evidence from a variety of social programs in both developed and developing countries that information sets differ, even among those eligible, and that participation rates vary widely and are sensitive to program design.[1] This paper is mainly concerned with methods of identifying targeting when social programs are likely to neglect the very poor. We believe these are superior to those currently employed in the literature and that their use will make it more likely to detect such neglect.

Two approaches are commonly used to examine targeting in public programs. The first uses parametric models which estimate the probability that a household participates in the program as a function of income or other characteristics of the targeted group. Logit or Probit models are often used to incorporate nonlinearities in the marginal effects of income on participation. The second approach uses differences in the share of participants and non-participants in some pre-determined intervals of the income distribution, say income quartiles, quintiles or deciles. This is especially common in studies concerned with the

[1] Heckman and Smith (2003) use data from a job training program and shows how information can have significant effects on participation. Atkinson (1995) compares family allowance programs in Western Europe in the post-war period and discusses the role of differences in design.

incidence of public spending on infrastructural facilities (van de Walle, 1995, Castro-Leal, 1999). With no targeting, the share of an income group in the benefits of public spending would be equal to its population share and in well targeted programs the share of benefits to the poor is high relative to their population share.

Both these approaches can be problematic if inclusion probabilities are not monotonic in income. Most programs are designed to exclude the relatively wealthy, but they may also exclude very poor households who are without complementary resources needed to derive benefits from the program. In such cases, estimates from parametric models, which assume that the probability of participation is monotonic in each of the explanatory variables or allow only for specific types of nonlinearities could be misleading. This is well illustrated in Paxson (2002) where logit estimates indicate that the benefits from investments in infrastructure are decreasing in income, but nonparametric regressions reveal that the poorest 7% of households are less likely to benefit than the slightly richer ones. If the set of households with low participation rates is small relative to the population, they may also remain undetected when examining the proportion of program participants in arbitrarily chosen intervals of the income distribution, especially if the are in income groups where other households have high participation rates.

We present, in this paper, nonparametric methods and statistical tests which can be used to assess poverty targeting and apply them to data from a microfinance program in India. These methods explicitly account for the possibility that a program excludes the poorest among the eligible population. We estimate the population distribution of participants and non-participants with empirical distributions functions and test for differences in these distributions across the two groups. Our emphasis is on recently developed techniques which estimate the point at which population distributions of participants and non-participants cross. These crossing points provide us with upper bounds on the income of those who have been (relatively speaking) excluded from the program. This approach has the advantage of detecting non-monotonicities in inclusion probabilities, even over small ranges of the income distribution under very general distributional assumptions. Empirical distributions functions are not new to the targeting literature. Ravallion (1991) uses these to evaluate targeting in the Employment Guarantee Scheme in Maharashtra, India. What is largely missing from the literature are tests of differences in these distributions and estimates of possible crossings. Our techniques are all based on existing results in nonparametric statistics and we see the main contribution of this paper as demonstrating that these methods can be used profitably to enrich debates on the impact of poverty alleviation programs.

Our data comes from a rapidly growing microfinance program in Central India. Professional Assistance for Development Action (PRADAN) is a non-government organization that has been promoting women's savings and credit groups in the state of Jharkhand in Central India since 1988. A major objective of the organization is to alleviate poverty by helping rural women obtain the credit and technical expertise required for profitable self employment. We use household survey data to compare the composition of newly formed microcredit groups to other randomly chosen households in the area. By restricting ourselves to villages in which PRADAN has recently formed microcredit groups, we are able to assess the economic condition of members *before* they received any benefits from the program. We combine survey data on a variety of standard of living indicators into an economic index and compare the distribution of this index for members and non-members of the program.

We find that new members of PRADAN's microfinance program are predominantly poor, judged by both national and international standards. This is largely a result of very high overall levels of poverty in the region which makes geographical targeting effective. We see no evidence of stochastic dominance of the distribution of non-members over that of program members. The two empirical distributions cross and our estimate of the crossing point is statistically significant. We also find the smaller proportion of members among the poorest households statistically significant using a sign test for quantiles. Based on the responses of these households to questions on levels of education, voting behavior, participation in local village organizations and on receipts of government subsidies, it seems that they are also excluded from village level activities and from government sponsored programs aimed at poverty alleviation.

Although much of our discussion and our empirical work refers to targeting in poverty alleviation programs, the methods proposed are of more general applicability. They can be usefully employed in a variety of situations where the crossing of population distributions is of interest. For example, students in some schools may come from the tails of an income distribution (because the school may admit you either if you are very wealthy or poor and intelligent) while others come from the middle. Some firms may hire some very able managers and low skill workers while others might hire employees of similar ability. Estimates and tests for crossing points can be useful in these situations to characterize different behaviors and thereby evaluate their effect on performance.

The next section describes the methods we use in some detail. Section 3 outlines PRADAN's microfinance program our sampling procedures. Section 4 contains estimates and test results on poverty targeting in the program and Section 5 concludes.

2 Methodology

2.1 Tests Based on Sample Means

A common procedure to test for differences in two populations is to use a test statistic based on the means from the two samples. In our context, if our samples of members and non-members constitute independent random samples from two normal populations with the same unknown variance, a likelihood ratio test could be used to test the null hypothesis of equal means. If the underlying distributions are not normal, but the samples are large, we could proceed along the same lines, by invoking a central limit theorem under which sample means would still be normally distributed.

We first compare mean values of a variety of standard of living indicators for members and non-members using likelihood ratio tests. We then combine the available indicators to arrive at an index, which is used as a proxy for income in the rest of the analysis, and test for differences in the mean of this index across our two groups. The fairly strong distributional assumptions under which these tests are valid, may not be appropriate in our context since there may be differences in the distributions of members and non-members which are reflected, not in their means, but rather in the tails of these distributions. The rich might be ineligible for rural anti-poverty programs and the poor might be excluded from them for a variety of social and economic reasons. We begin with these tests because they are so commonly used in the existing literature and their results in our case provide justification for the more elaborate methods which we advocate. Our focus is on methods that are based on estimates of the entire population distribution for members and non-members and which we describe below. Some of these tests have similar power to the means test when the latter is valid.

2.2 Nonparametric Tests for the Equality of Two Distributions

To estimate population distribution functions, we use the empirical distribution function which is given by

$$H_N(x) = \frac{1}{N}\sum_{i=1}^{N} I(X_i \leq x),$$

where $I(A)$ is the indicator function of the set A and N is the sample observations. $H_N(x)$ is a step function with jumps at the order statistics[2] of the sample. It is therefore enough to evaluate the empirical distribution function at the ordered observations. The Glivenko-Cantelli theorem (Fisz (1963)), establishes that the empirical distribution function converges uniformly to the population distribution function with probability one.

We denote the population distribution of the economic index by $F(x)$ for members in the microcredit program by $G(x)$ for non-members. Our two samples are denoted by $X_1, \ldots, X_n$ and $Y_1, \ldots, Y_m$ respectively.

We begin with commonly used tests for the equality of two distributions. The Kolmogorov-Smirnov is used to test the null hypothesis of equal distributions against the very general alternative that the distributions are unequal. The statistic is given by

$$KS = \sup_x |F_n(x) - G_m(x)|.$$

This is the maximum difference between the two empirical distribution functions and is distribution free for any continuous common population. Large values of the statistic are evidence against equal distributions and lead to the rejection of null hypothesis. The exact null probability distribution is available in tabulated form for small samples. We use critical values based on the asymptotic distribution, since our samples of both members and non-members are both sufficiently large. [3]

Kolmogrov tests are often used for preliminary studies of data since the alternatives involved are very general. To test the null hypothesis against the more specific alternative of stochastic dominance of the non-member distribution,

$$F(x) \geq G(x) \quad \text{for all} \quad x, F(x) > G(x) \quad \text{for some} \quad x,$$

[2]If $X_1, \ldots, X_N$ is a random sample from a continuous distribution $H(x)$, then

$$X_{(1)} < X_{(2)} < \ldots < X_{(N)}$$

are the **order statistics** of the sample.

[3]For the asymptotic distribution we have

$$\lim_{m,n \to \infty} P(\sqrt{\frac{mn}{m+n}} KS \leq d) = L(d)$$

where

$$L(d) = 1 - 2 \sum_{i=1}^{\infty} (-1)^{i-1} e^{-2i^2 d^2}$$

we use the more powerful Wilcoxon-Mann-Whitney test. The Mann-Whitney statistic is defined as the number of times an X precedes a Y in the combined ordered arrangement of the two independent random samples $X_1, X_2, \ldots, X_n$ and $Y_1, Y_2, \ldots, Y_m$ into a single sequence of $m + n = N$ variables, increasing in magnitude. The statistic is given by

$$W = \sum_{i=1}^{n} \sum_{j=1}^{m} I(X_i < Y_j).$$

The distribution of W under the null hypothesis is conceptually easy to compute and and is tabulated for small samples. We use critical values based on the asymptotic distribution of W under the null hypothesis. This has been shown to be normal with mean $\frac{mn}{2}$ and variance $\frac{mn(N+1)}{12}$. The null hypothesis is rejected for large values of the statistic. The test performs particularly well as a test for equality of means (or medians). The asymptotic relative efficiency (ARE) of the Wilcoxon Mann-Whitney test relative to the likelihood ratio test is never less than 0.864, and if the populations are normal the ARE is .955.[4]

2.3 Crossing Point Estimates

Our estimates of the distribution functions for members and non-members (described in the following section) as well as the results from the Wilcoxon Mann-Whitney test suggest that the two distributions cross with the very poor being largely outside the program. To arrive at an upper bound of the income group that is relatively neglected by the program, we estimate the point at which the two distributions cross. Hawkins and Kochar (1991) and Chen et al (2002) have considered point as well as interval estimation of the crossing point x^*. We derive estimates of the crossing point based on the methodology in Chen et al (2002) which we summarize here.

Suppose that in our sample $\lim_{N\to\infty} m/N = \gamma$ for some $\gamma \in (0, 1)$. Let $Z_1, \ldots, Z_N$ be the combined sample of $X's$ and $Y's$ and $Z_{(1)} < Z_{(2)} < \ldots, Z_{(N)}$ be the order statistics of this sample.

We wish to test

$$H_0 : F(x) = G(x)$$

against the alternative

[4]See Gibbons and Chakraborti (1992), chapter 7 for derivations and a more detailed discussion of these results.

$$H_1 : F(x) < G(x) \text{when } x < x^*, G(x) < F(x) \text{when } x > x^*.$$

Chen et al (2002) proposed the following supremum type criterion function for testing H_0 against H_1.

$$\lambda(x) = \sup_{t \leq x}(G(t) - F(t)) + \sup_{x \leq t}(F(t) - G(t)) - |F(x) - G(x)|.$$

They prove that under the null hypothesis $\lambda(x) = 0$ and under the alternative hypothesis the crossing point x^* is the unique maximizer of $\lambda(x)$. An estimate of $\lambda(x)$ is given by

$$\lambda_N(x) = \sup_{t \leq x}(G_n(t) - F_m(t)) + \sup_{x \leq t}(F_m(t) - G_n(t)) - |F_m(x) - G_n(x)|.$$

Since empirical distribution functions are step functions with jump points as order statistics, $\lambda_N(x)$ attains its maximum at some point $Z_{(j)}$. Hence

$$\sup_x \lambda_N(x) = \max_{0 \leq j \leq N} \lambda_N(Z_{(j)})$$

They propose the statistic

$$J_N = \sqrt{\frac{mn}{N}} \max_{0 \leq j \leq N} \lambda_N(Z_{(j)})$$

for testing H_0 against H_1. Critical values for small sample sizes have been tabulated in Chen et al. (1998)). The authors obtain asymptotic critical regions using Monte-Carlo simulation. Relevant asymptotic critical values are presented together with our results in Section 4.

Since the empirical distribution functions are only estimates of the population distribution functions, sampling error may result in multiple estimates, even if the population distributions exhibit a unique crossing point. When we encounter multiple crossing points, we use the smallest value as our estimate since this is our most conservative estimate the households who are excluded from the program.

2.4 Tolerance Intervals and Sign Tests

Finally, we test whether differences in the relative share of members and non-members in the tails of the distribution are statistically significant and therefore support the relative exclusion of the very poor and the very wealthy from the program. To do this, we first require an estimate of the relevant population quantiles of our economic index. We obtain these cutoffs by estimating a *tolerance interval.* This, like a confidence interval, has random endpoints, but instead of covering a population parameter with a certain probability, it covers a given fraction of the population with some prescribed probability. In other words, a tolerance interval for a continuous distribution with tolerance coefficient α, is a random interval such that with probability α, the area between the end points of the interval and under the probability density function is at least a preassigned number p. We set both p and α at .9, so our estimated interval covers 90% of the population households with probability .9. The end points of the tolerance interval are simply two ordered observations,say $Z_{(r)}$ and $Z_{(s)}$, and the difference, $s-r$ is chosen to satisfy

$$\alpha = 1 - \sum_{j=s-r}^{n} \binom{n}{j} p^j (1-p)^{n-j}.$$

These order statistics are then chosen based on what fraction of the population we would like to include in each tail. We choose values that exclude an estimated 5% in each tail.

The end points of the tolerance interval are used to test a set of hypotheses on the fraction of members and non-members in each of the tails. In particular, we are interested in whether 5% of the population in each of the two groups (members and non-members) lies below the lower end point $Z_{(r)}$, and 95% of the population in each of the two groups lies below the upper end point $Z_{(s)}$, of the interval.

We use a one-sided sign test, a popular non-parametric procedure to test for quantiles in one sample. We test the null hypotheses that $Z_{(r)}$ is a quantile of order $p = .05$, for members and non-members separately, and that $Z_{(s)}$ is a quantile of order $p = .95$. The tests are based on the number of observations (S_n) for each group that are below these cutoffs. S_n has a binomial distribution with parameters n and p and we use critical values based on the normal approximation. We present p-values for both the one-sided and two-sided alternatives. The one-sided hypotheses are constructed so that the share of members in both tails is less than 5% and the share of non-members is greater than 5%.[5]

[5] See Gibbons and Chakraborti (1992) and Sprent (1989) for more detailed discussions of tolerance intervals and the sign test.

3 The Data

3.1 PRADAN's Microfinance Program

PRADAN's microfinance program is concentrated in the state of Jharkhand in Central India. Jharkhand is among the poorest of the 27 Indian states, with over half its population below the national poverty line.[6] At the time of the last census in 2001, Jharkhand had a literacy rate of 54%, eleven percentage points below the national average. PRADAN works in 10 out of a total of 18 administrative districts which currently constitute Jharkhand[7] and has established microcredit groups in close to a thousand villages in these areas or about 3% of all villages in the state. An important aspect of PRADAN's strategy for expanding its activities has been to concentrate its programs in geographical clusters, partly for administrative ease, but also to enable beneficiaries in different villages to interact and learn from their combined experience.

Establishing a group usually begins with a PRADAN representative holding a meeting at some public place in a village, such as the primary school, where the details of the program are described. After a few such meetings, a group of between 10 and 20 women is formed. If a village is large, or interest in the program is widespread, multiple groups may be created. The group chooses a name for itself, agrees on a weekly meeting time and determines other group rules such as the minimum contributions per member at each meeting, the interest rate charged on loans that are given to group members, and fines for non-attendance or late payment. After a few months a savings account is opened at a commercial bank near the village, and usually after about a year, the either some or all members of the group take a loan from the bank for one of the income generating activities promoted by PRADAN.

There are now over 4,000 PRADAN-initiated groups in operation and about 57,000 women are involved. Between April 2001 and March 2002, these groups collectively mobilized about $200,000 (U.S. dollars) in savings and made loans that were about double this amount. During the same period, about 700 of these groups took bank loans totaling to $184,000. Bank credit was used for a variety of income generating activities, ranging from paddy processing, which requires an initial investment of about $40 per group, to cattle

[6] In 1993-1994, (the last year for which uncontroversial poverty estimates are available), 57% of the rural population in Jharkhand was below the national poverty line, compared to 33% for the whole country. Poverty estimates using standard international poverty lines are much higher. (Jharkhand figures are from Dubey and Gangopadhay (1998), p. 69, and the All-India figure is from Dreze and Sen (2002), Table A.3.

[7] These are Godda, Dumka, Bokaro, Hazaribag, Koderma, Lohardaga, Gumla, Ranchi, West Singhbhum and East Singhbhum.

trading which needs closer to \$400 per group. To put these figures in perspective, groups usually start with monthly contributions of \$0.50 per group member.

3.2 Survey Data

We use data from a household survey which we conducted over a period of two months, starting in the middle of August 2002. Only villages with newly formed groups were included in the sampling population since our objective was to examine PRADAN's success in targeting poor households, rather than in raising incomes through the microcredit program. The inclusion of members from previously formed groups might have contaminated our results if access to credit or other aspects of group membership changed the economic condition of the household. The survey population consisted of households in 149 new microcredit groups in 100 villages from 11 different administrative districts.[8]

We stratified the survey population into 4 geographical clusters: based on differences in demographic characteristics observed in census data. Villages in northeastern Jharkhand form region 1, those in central Jharkhand, region 2, villages in the southwest and the southeast form regions 3 and 4 respectively. The religious and social composition of these areas is quite different. Since this may affect the propensity for collective action and therefore the composition of microcredit groups, we used a stratified sampling strategy. This has the additional advantage of providing regional estimates of targeting.

For each cluster, a simple random sample of 6 villages was chosen from the set of all villages with at least one group formed during the period April 1st –June 30th, 2002. The principal reason for focusing on these villages is that very little lending takes place in the months immediately following the formation of the group, and yet membership is fairly stable. The villages with groups formed in July were left out, since membership tends to be unstable during the first month. New members come in as news of the group spreads in the village, and others leave as they learn more about the objectives, rules, restrictions and composition of the group.

A total of 24 respondents were surveyed from each of these villages- 6 of them were members of microcredit groups in the village and the remaining 18 were randomly selected non-members from the same village. The relative sample sizes of 1:3 for members and non-members were chosen based on our prior belief that the group of non-members is more

[8]One of these districts, Banka, is part of the state of Bihar and not Jharkhand. It was included in the study because it borders the Jharkhand villages in our study and comes within the region covered by one of the Jharkhand PRADAN teams.

heterogeneous than the group of members because PRADAN forms these groups in a similar fashion across the state and is therefore likely to attract similar sorts of households into the program. A pilot survey in early August found some very poor households who were not part of the program and this supported the assumption of greater heterogeneity among the non-members. Given these differences in the variance of economic well-being between the two groups, a larger sample size for non-members would provide estimates of similar accuracy for both groups.

A list of members in each group was available before the start of the survey and this was used to obtain a simple random sample of members in each region. For the non-members, sketches of maps of the sampled villages were made marking the location of all households. The number of households in the village (obtained through this process) was divided by 18, to arrive at the interval between the houses of non-members to be interviewed. A systematic sample of non-members was then chosen, starting from one end of the village. If a chosen non-member was not available, was unwilling to participate, or was a member of an older existing microcredit group in the village, the neighboring household was selected. Only 4% of the households originally selected had to be replaced with others for these reasons.[9]

Data was collected on a large number of economic indicators such as the quantity and type of food consumed, the size and condition of the household's main dwelling, land owned and cultivated and the possession of durable goods.[10] In addition, respondents were asked about household debt, contact with the government bureaucracy, benefits received from government sponsored development programs and the household's participation in elections and in informal organizations within the village. Responses to these questions allowed for an assessment of whether the households excluded from the program were also excluded from other official programs and from social networks within the village.

[9] In the Santhal Parganas (region 1), a large number of new groups have been formed and there were sampled villages without enough non-members to get the required sample size. In these cases, the non-member sample was augmented using households from neighboring villages.

[10] The section of the questionnaire on living standards was based on Henry et al (2000) with appropriate modifications made for local lifestyles.

4 Results

4.1 Differences in Group Means

Table 1 presents mean values of household characteristics for member and non-member households. The means for the two groups look similar for many indicators. Both groups are, on average, quite poor : 55% of the member households and 53% of the non-member households in the sample report themselves as being recorded as below the national poverty line, which is well below the international poverty line of $1/day. Roughly 40% of adults surveyed from both groups were literate and both groups spent very similar amounts on education.[11] There are a few notable, and at first sight intriguing, differences between the two groups. Households that were members of microcredit groups consumed more meals in the two days preceding the survey than non-members and they cultivated and owned more land while households with non-members were slightly more likely to be engaged in non-farm employment, have bigger houses and own more valuable durable goods. Differences in the mean levels were tested for five indicators of food consumption, eight indicators of the cost of the household's dwelling, thirteen different durable goods, ten major expenditure categories and three indicators of land ownership and cultivation. Of these, differences in means were statistically significant in only four cases. Moreover, based on these differences, it is hard to rank either group as being relatively poorer. Member households consumed more meals in the two days preceding the survey and cultivated more land than the non-member households, but showed, on average lower food grain consumption and were less likely to have toilets in their homes. From these initial results, it seemed plausible that the distribution of economic well-being for the two groups may be different in ways that would not be revealed through a comparison of means. If it is the case that only the very poor consume significantly fewer meals than the rest of the population, and the relatively better-off families (because of the economic backwardness of the area in which the survey was done) have toilets inside their homes, then one explanation for the above differences in mean values of these variables across the two groups would be that households at both extremes of the distribution of economic well-being have been excluded from the microcredit program. To be able to focus on estimates of the entire population distribution of economic well-being for members and non-members, the subsequent analysis is restricted to an economic index,

[11] Official poverty lines for urban and rural areas of different states can be found in Deaton (2001). For rural Bihar, the official poverty line in 1999-2000 was a monthly per capita consumption expenditure of Rs 333 which is equivalent to about $0.23 per day.

generated by combining available standard of living indicators.

4.2 An Economic Index

An economic index, constructed using principal component analysis is used in our subsequent analysis. The index is constructed using the following variables: meals consumed in the two days prior to the survey, the daily household consumption of food grains (in kilograms), annual household expenditure on clothing and footwear, the number of rooms in the dwelling, the quantity of land owned and the total value of livestock and durable goods owned by the household at the time of the survey. The choice of variables used in the analysis was based on what past studies have found to be important indicators of consumption and wealth, on our own judgement of what captures poverty in this region and on the share of total variance in the set which was accounted for by the first principal component, which we used as our index. To be comprehensive, at least one variable was chosen from each section of the survey to ensure that all aspects of the household's economic condition were considered. The variance of the first three principal components accounted for 72 per cent of the total variation in these variables and the first component accounted for 42 per cent of this variation. The weights used in the index for each of the six variables (known as scoring coefficients) are in Table 2a and the variance of each component and associated eigenvalues are in Table 2b. We use the first principal component as our index of economic well being. We also consider each of the individual components of the index individually, to insure that the behavior of the weighted average if not a result of offsetting influences from the different components. We find that estimated distribution functions for the annual household expenditure on clothing and footwear behave very much like the index as a whole. This is consistent with other studies that have used this methodology to measure standards of living (Henry, 2000).

Table 1: Mean Values of Selected Variables (Household Survey Data).

	members	non-members	p-values
household size	6.22	6.15	
fraction scheduled tribes	0.39	0.40	
literacy rate	0.39	0.41	
meals consumed in past 2 days	5.68	5.31	.0001
per capita food grain consumption in good months	0.61	0.67	.051
per capita food grain consumption in scarce times	0.34	0.37	
number of rooms in dwelling	3.06	3.35	
fraction with toilet in dwelling	0.006	0.032	.097
fraction with electricity in dwelling	0.15	0.15	
land owned (in hectares)	1.24	1.1	
land cultivated (in hectares)	1.03	.82	.059
fraction self-employed in non-farm employment	.14	.16	
fraction of households with bicycles	0.72	0.65	
fraction of households with motorcycles	0.05	0.05	
fraction of households with a radio/tape-recorder	0.24	0.28	
value of durable goods (Indian rupees)	1922	2703	
per capita expenditure on clothing & footwear	527	553	
per capita expenditure on education	78.6	76.8	
fraction below official poverty line	.55	.53	

Notes: Foodgrain consumption is recorded in kilograms per day per capita. Fraction self-employed in non-farm activities is calculated for each household and then average over all households in the relevant group. All expenditures are annual expenditures in Indian rupees (1 USD= 48 INR) . P-values are reported only for those variables where the differences in means are statistically significant at the 10% level using the a t-test for differences in means.

Table 2a: Scoring Coefficients for the First Principal Component

variable	scoring coefficient
number of meals consumed in the 2 days prior to survey	.16
average daily household consumption of food grains in good times	.43
annual household expenditure on clothing and footwear	.48
number of rooms in dwelling	.49
land owned by the household (in hectares)	.38
value of livestock and durable goods	.41

Notes: Livestock includes cattle, sheep, goats, pigs, poultry and pigeons. Durable goods include all vehicles, farm machinery and household durables such as appliances and brass utensils.

Table 2b: Eigenvalues and Variances of the Principal Components

Component	Eigenvalue	Cumulative Variance
1	2.54	0.42
2	.98	0.59
3	0.82	0.72
4	0.76	0.85
5	0.49	0.93
6	0.41	1.00

The distribution of the economic index for members and non-members were compared using a variety of parametric and nonparametric statistical tests. Mean values of the index, by region and by group membership, are given in Table 3, together with p-values from tests for differences in means. The null hypothesis of equal means cannot be rejected for the region as a whole and only in one of the regions (region 3) do we find the difference statistically significant at the 5% level.

Table 3: Mean Values of the Index, by Region.

	overall mean	members	non-members	t-test p-value
full sample	.00	-.021	.01	.85
region 1	.34	.29	.35	.86
region 2	.29	-.11	.43	.08
region 3	-.26	.22	-.42	.04
region 4	-.37	-.49	-.33	.49

If the microcredit program targets households in the middle of the distribution and excludes both tails, then an analysis of means is not very useful. Estimates of the entire population distribution for members and non-members are needed to identify the nature of targeting in the program. This is what we turn to now.

4.3 Nonparametric Tests of Targeting

The empirical distribution functions for the index for both groups can be seen in Figure 1.

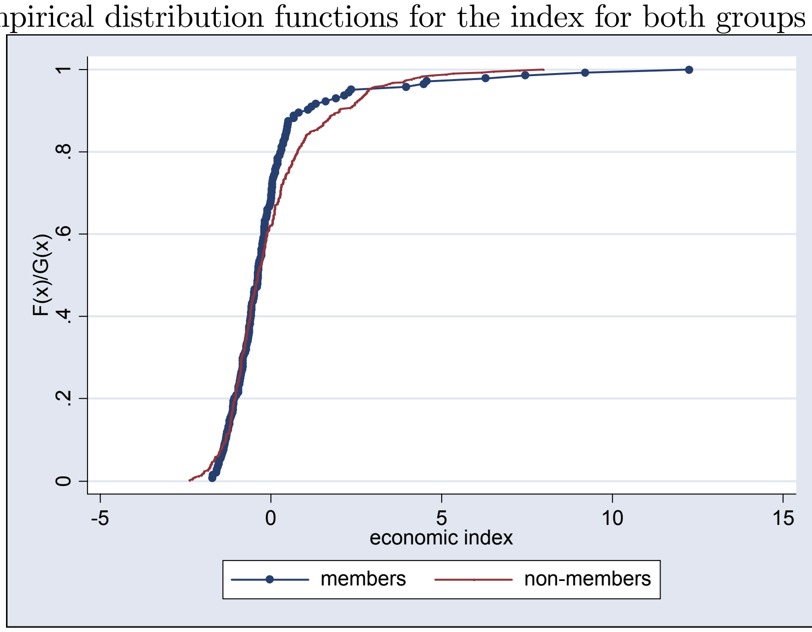

Figure 1: Empirical distribution functions for members and non-members.

The estimated functions are quite similar for large sections of the survey population. There are however some striking differences. The lowest value of the economic index (-2.38) is taken by a non-member household and 2% of sampled members and 5% of non-members are below the 5th percentile of the index (-1.58). The very poorest households in the survey are not part of the program, whether we look at the region as a whole, or at each of the sub-regions. In fact, among the poorest 3% of the sample, there is not a single member household!

Table 4 contains p-values from Kolmogorov Smirnov and Mann Whitney tests for the equality of the member and non-member distributions. The null hypothesis of equal distributions if rejected at the 5% level in the full sample and in region 2 by the Kolmogorov Smirnov test. The Mann-Whitney p-values do not indicate the stochastic dominance of the non-member distribution (evidence of poverty targeting) in any of the regions at the 5% level.

Table 4 : P-values from Kolmogorov-Smirnov and Mann-Whitney Tests

population	KS	W	observations
full sample	.05	.49	576
region 1	.91	.60	144
region 2	.03	.09	144
region 3	.24	.27	144
region 4	.51	.96	144

From the plots of the empirical distribution functions in Figure 1, it seems likely that the population distribution functions of the members and non-members cross. Using the methodology outlined in Section 2, we estimate of the crossing point x^*. The value of the economic index at the crossing point is -1.19 , which is in the 15th percentile of the distribution of the index for the whole sample. The estimate is statistically significant at the asymptotic critical levels tabulated by Chen et al (2002) and presented in Table 5.

Table 5: Estimated Crossing Points with Asymptotic Critical Levels.

	x^*	J_N
full sample	-1.19	1.756
$\alpha = .05$		1.529
$\alpha = .01$		1.796

Our estimated tolerance interval (which includes 90% of the population with probability .9) has terminal points (given by the 24th and the 552nd ordered observations of the economic index) -1.66 and 3.30. The p-values from the one sample sign test are given in Table 6. The proportion of members below the lower limit of our tolerance interval is statistically significant supporting our claim that the very poor have been left out of the program. We do not see any significant differences in the upper tails. This might be because these households, given the relative poverty of the area, are not rich enough to be excluded from the program.

Table 6: P-values from Sign Tests for Quantiles based on the Tolerance Interval.

	p-value (one-sided alternative)	p-value (two-sided alternative)
members below r (lower limit)	.02	.046
non-members below r	.55	.94
members below s (upper limit)	.47	.90
non-members below s	.84	.30

By definition, the share of both groups below the crossing point of their population distributions is equal. This is why the crossing point only provides us with an estimate of the upper bound on the economic condition of those neglected by the program. Crossing points of estimated density functions would, in some sense provide us with a better idea of exclusion from the program. The reason we do not rely on these is because we have available the estimation and inference procedures for the distribution functions and not for the densities. Estimated kernel densities for the economic index can however be used to get a better idea of the set of households that are relatively neglected by the program, and those that gain the most from it. Etimated kernel densities are presented in Figure 2.[12] When both densities are rising, the smallest value of the index at which they intersect is -1.72 and when both densities falling, the smallest value is 0.49. The households between these two cutoffs are therefore the ones targeted by the program. Based on these estimates, the program seems to focus on households between the fourth and forty-fifth percentile of the distribution of economic well-being. To get some idea of the economic condition of households in this targeted interval is, annual household expenditure on clothing and footwear for these households ranges between 515 and 2,695 Indian rupees, or between 11-56 U.S. dollars. The mean household size of six, the richest households in this interval spend about $9 per person per year on clothing and footwear. Further households comparisons are discussed in the following section.

[12] We use the Epanechnikov kernel and a bandwidth of .29 for non-members and .25 for members.

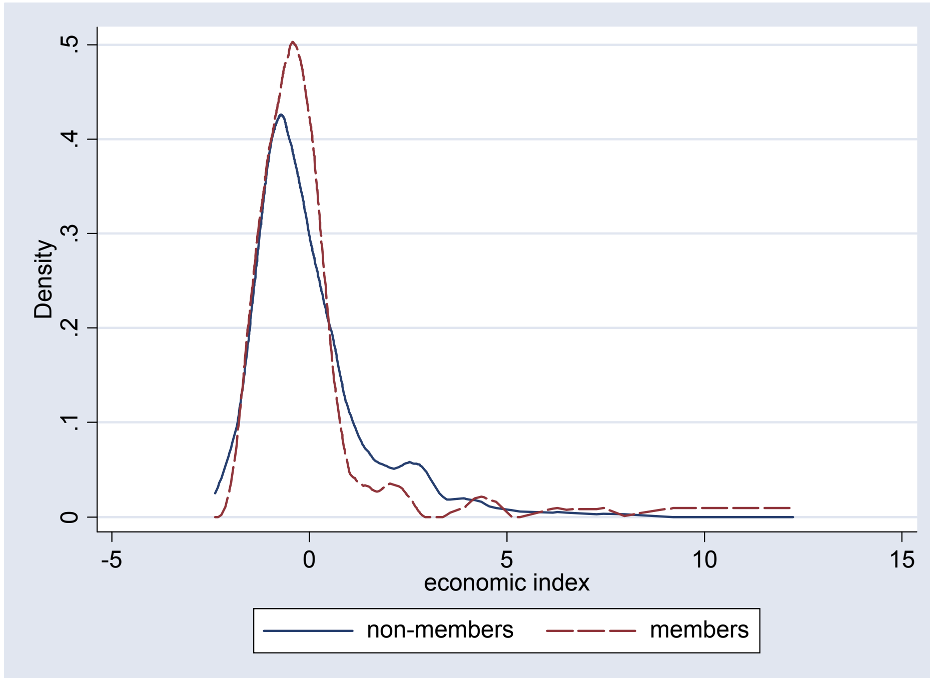

Figure 2: Estimated Kernel Densities of the Economic Index for Member and Non-member Households.

4.4 Profiles of the Excluded Households

How poor are the excluded households? Results from the sign test discussed above suggest that the microfinance program has not been able to successfully include the poorest 5% of households. This section translates the values of the economic index for these households back into commonly observed household characteristics in order to better understand the characteristics that might lead to their exclusion and also allow for their easy identification by policy makers and non-government organizations.

Table 7 presents mean values selected characteristics of the poorest 5% of households, the middle 90% and the top 5%. The poorest five per cent of surveyed households, based on the economic index used in this paper, have dramatically different lifestyles and consumption levels from the rest of the sampled households. Most of these households consume two or fewer meals per day and 71% of them live in one room dwellings. They consume between 25-30% less food grains (by weight) than the other households and significantly less high protein foods, such as fish and eggs. The mean value of their assets of livestock and durable goods is one-twentieth of the mean for other households.

The households that are difficult to involve in the microcredit program also seem to be excluded from other public programs and the political process more generally. Literacy rates among adults in these households are about half of those observed for households in the middle 90% of the distribution and one-third those in the upper tail. Only 34 % of the children below the age of 15 attend school compared to 61% of those in the top tail. Only 7% of these households have ever approached a government official as opposed to 28% of all other households. Their participation in local village organizations and in state and central government elections is also more limited.

Table 7: A Comparison of Mean Values of Selected Variables for the Poorest 5%, the Richest 5% and Other Households

	poorest 5%	middle 90%	richest 5%
meals in past 2 days	3.8	5.5	5.6
days/month not enough food	5.2	3.4	0.4
rooms in dwelling	1.2	3.1	9.2
toilet in dwelling	0	0.02	0.11
land owned (in hectares)	0.2	0.6	2.9
fraction owning a bicycle	0.2	0.6	1.4
fraction owning a radio / tape recorder	0.07	0.26	0.68
value of livestock and durables	495	7335	47601
per capita foodgrains - normal times (kg)	0.5	0.65	0.81
per capita grain consumption-difficult times(kg)	0.25	0.36	0.44
per capita annual expenditure on schooling	5	68	324
per capita annual expenditure on clothing/footwear	243	534	1076
share of literate adults in household	0.22	0.40	0.66
share of children attending school	0.34	0.48	0.61
share voting in parliamentary elections	0.93	0.99	1
participation in informal village organizations	1	1.3	1.5
share that has ever approached a government officer	0.07	0.27	0.46
number of months in village (per year)	10.8	11.1	10.6

Notes:

1. Literacy and school attendance rates, and the number of months in the village during the year are calculated for each household and averaged over all households in the relevant group.

2. All expenditures are annual expenditures in Indian rupees.

3. The figure for participation in village level organizations is a group average of the number of village level organizations in which the household participates

5 Conclusions

We present nonparametric methods to assess poverty targeting in public programs. These are especially appropriate when participation rates are not monotonic in income and the population distributions of participants and non-participants cross. Estimates of these crossing points provide upper bounds on the incomes of those who are neglected by the program or unable to participate for a variety of reasons.

We apply our methods to the PRADAN microcredit program in Central India. We find evidence that the population distributions of program members and non-members cross, with the poorest households excluded from the program. These households also appear to have limited access to public programs which are, in principle, designed for their benefit: they are no more likely to be on official poverty lists that other households in the area and their responses to questions on levels of education, voting behavior, participation in local village organizations and on receipts of government subsidies suggest that these households are also excluded from village level activities and from government-sponsored social programs. It is difficult, on the basis of the data collected, to assess the reasons for such exclusion. On average, members of these households do spend fewer months in the village than others in the sample. This may contribute to their difficulty in being a member of a regular savings group. It is however also possible that these families are socially excluded and discouraged from being members, or that they find it difficult to regularly save even the small amount required by the program.

References

[1] Atkinson, Anthony B. "On Targeting Social Security: Theory and Western Experience with Family Benefits " in van-de-Walle, Dominique and Kimberly Nead, ed. *Public Spending and the Poor: Theory and Evidence*, John Hopkins Press for the World Bank, 1995.

[2] Bartholomew, David, Fiona Steele, Irini Moustaki and Jane I. Galbraith, *The Analysis and Interpretation of Multivariate Data for Social Scientists*, Chapman and Hall, 2002.

[3] Castrol-Leal Florencia, Julia Dayton, Lionel Demery and Kalpana Mehra, "Public Social Spending in Africa: Do the Poor Benefit?", *World Bank Research Observer*, 14(1), February 1999.

[4] Census of India 1991, Data files available from the Registrar General of India.

[5] Census of India, 1991, *Union Primary Census Abstract for Scheduled Castes and Scheduled Tribes, Paper-1 of 1993*, Registrar General and Census Commissioner, India.

[6] Census of India 2001, *Provisional Population Totals*, Delhi, June 2001.

[7] Chen, G.J., J.H. Chen and Y.M. Chen, *Statistical inference on comparing two distribution functions with a possible crossing point*, Technical Report, Department of Mathematics, Anhui University.

[8] Chen, Guijing, Jiahua Chen and Yuming Chen, "Statistical inference on comparing two distribution functions with a possible crossing point", Statistics and Probability Letters, 60(2002), 329-341.

[9] Deaton, Angus, "Adjusted Poverty Estimates for 1999-2000", *Economic and Political Weekly, Volume XXXVIII, no 4*, January 25, 2003.

[10] Deaton, Angus: *Computing prices and poverty rates in India, 1999-2000*, Research Program in Development Studies, Princeton University, Working Paper, 2001.

[11] Dreze, Jean and Amartya Sen, *Development and Participation*, Oxford, 2002.

[12] Dubey, Amaresh and Shubhashis Gangopadhay, "Counting the Poor: Where are the Poor in India?", *Sarvekshana Analytical Report Number 1*, Department of Statistics, Government of India.

[13] Everitt, Brian S. and Graham Dunn, *Applied Multivariate Data Analysis*", Second Edition, Arnold Publishers, 2001.

[14] Fisher, Thomas and M.S. Sriram (ed.), *Beyond Micro-Credit: Putting Development Back into Micro-Finance*, Vistaar Publications, New Delhi, 2002.

[15] Fisz, Marek, *Probability Theory and Mathematical Statistics*, New York, Wiley, 1963.

[16] Gibbons, Jean Dickinson and Subhabrata Chakraborti, *Nonparametric statistical inferenc*e, M. Dekker, New York, 1992.

[17] Hawkins, D.L and Subhash Kochar, "Inference for the Crossing Point of Two Continuous CDF's", *The Annals of Statistics*, 19(3), September 1991, 1626-1638.

[18] Heckman, James J. and Jeffery A. Smith, "The Determinants of Participation in a Social Program: Evidence from a Prototypical Job Training Program", *NBER Working Paper* number 9818, July 2003.

[19] Henry, Carla, Manohar Sharma, Cecile Lapenu and Manfred Zeller, *Assessing the Relative Poverty of Microfinance Clients: A CGAP Operational Tool*, International Food Policy Research Institute, July 2000.

[20] Karmakar, K.G., *Rural Credit and Self-Help Groups: Micro-finance Needs and Concepts in India*, Sage Publications, New Delhi, 1999.

[21] Morduch, Jonathan, *Does Microfinance Really Help the Poor? New Evidence from Flagship Programs in Bangladesh*, working paper available at http://www.wws.princeton.edu/%7Erpds/Downloads/morduch_microfinance_poor.pdf

[22] Paxson, Christina and Norbert R. Schady, "The Allocation and Impact of Social Funds: Spending on School Infrastructure in Peru", *World Bank Economic Review,* 16(2), pages 297-319.

[23] PRADAN, *RBI and NABARD Guidelines on Linking Self Help Groups with Banks: A Compilation of Relevant Circular Issued by the Reserve Bank of India and the National Bank for Agriculture and Rural Development*, New Delhi, 1988.

[24] PRADAN, *PRADAN Annual Report, 2001-2002*, New Delhi, 2002.

[25] National Sample Survey Organization, *Consumption of Some Important Commodities in India, 1999-2000*, Report no. 461, July 2001.

[26] Ravallion, Martin, “Reaching the Rural Poor through Public Employment: Arguments, Evidence and Lessons from South Asia”, *World Bank Research Observer,* 6(2), July, 1991.

[27] Sprent, P. *Applied Nonparametric Statistical Methods*, Chapman and Hall, London, 1989.