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Targeting the Poor Using ROC Curves

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Summary. — This paper compares the performance of targeting indicators to identify the poor. If the ROC curve of one indicator lies above that of another, the first indicator dominates the second for all social welfare functions based on the two types of errors involved in targeting. The method is applied to Bangladesh. Fifteen indicators are used, including location, land ownership, education, occupation, demographics, age, family structure, and housing. The analysis is applied at the national, urban, and rural levels with two poverty lines. Education dominates land ownership in urban areas. The ranking is reversed in most cases in rural areas. © 1997 Elsevier Science Ltd. All rights reserved.

Key words — Asia, Bangladesh, ROC curve, poverty, targeting, policy

1. INTRODUCTION

Targeting plays a crucial role in policies designed to alleviate poverty in developing countries. It enables policy makers to focus programs directly on the poor, and thereby to maximize the effectiveness of limited resources. The principles of targeting, its cost, and the political economy constraints for its implementation have been discussed (e.g., Besley and Kanbur, 1993; Grosch, 1995; Sen, 1995). In empirical work, various household characteristics taken as proxies for poverty as well as self-targeted programs have been proposed to reach the poor. Geographical location is among the most common (Ravallion, 1993; Baker and Grosch, 1994), but to cite only a few alternatives, land ownership (Ravallion, 1989; Ravallion and Sen, 1994), public works (Ravallion and Datt, 1995), and food subsidies (Cornia and Stewart, 1995) have also been used.

Two of the recurrent themes in the literature on targeting concern the objective function to be optimized and the targeting indicator to be chosen. Most empirical studies do not consider these two questions together. Researchers tend to consider only one targeting indicator at a time, which they use to optimize a given objective function. In contrast, this paper uses a simple tool to identify the condition (neglecting costs) under which an indicator is better than alternative indicators for the class of objective functions based on the two types of errors which can be committed in targeting, namely identifying as poor a non-poor household, and identifying as non-poor a poor household.

The paper uses ROC (Relative Operating Characteristics) analysis, a technique pioneered in the 1940s as a device for the detection and recognition of signals affected by noise (Egan, 1975; Green and Swets, 1974). The technique has been used for the analysis and performance evaluation of vision, memory, weather forecasting, polygraph lie detection, medical imaging for brain lesions, radiography in dental care, etc. In this paper, we focus on the simplest tool of ROC analysis, the ROC curve which, to our knowledge, has not yet been applied to poverty analysis. Using the unit level data of the 1991–92 Household Expenditure Survey of the Bangladesh Bureau of Statistics (1995), we assess the performance of 15 indicators, including geographical location, land ownership, education, occupation, age, demographics, family structure, and housing variables. The analysis is applied at the national, urban, and rural levels with two alternative poverty lines. Some of the main results are as follows:

— Education, occupation, and location have the best record in identifying the poor nationally.

— In urban areas, education is always a better targeting indicator than land ownership, while in most but not all cases considered, land ownership is better than education in rural areas.

— Housing variables such as the sanitary system and wall material also perform well.

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2. ROC CURVES

Consider a household with per capita consumption y and characteristics X, where X is a $mx1$ vector. Denote the poverty line by z, define $y^* = z - y$, and assume that consumption is determined by the model $y^* = \beta X + \varepsilon$, where β is a $1xm$ vector of returns to characteristics and ε is an error term with zero mean. With a representative sample of the population, X can be used to predict poverty. When we run a probit or logit of y^* on X, we pretend not to observe the y^*'s. We act as if we only observed a dummy variable h which takes the value 1 if $y^* > 0$ and 0 if $y^* < 0$. The probability that a household is poor is $\text{Prob}[h = 1] = \text{Prob}[\varepsilon > -\beta X] = 1 - F(-\beta X)$ where F is the cumulative distribution. The parameter vector β can be estimated by maximum likelihood. For a probit, $\text{Prob}[h = 1] = \Phi(\beta X)$, where Φ is the cumulative normal density. For a logit, $\text{Prob}[h = 1] = \exp(-\beta X)/[1 + \exp(-\beta X)]$.

Once this model has been estimated, it can be used for targeting provided we have a cut-off point. In comparing actual versus predicted outcomes, statistical packages use the standard cut-off point of one half. That is, denoting by b the estimate of β, if bX is greater than one half, the program bets that the household is poor, while if bX is less than one half, it bets that the household is non-poor. But we may also choose another cut-off point, such as one-third or two-thirds. Denoting the cut-off point by c, which is bounded by zero and one, we say that a positive outcome is observed for observation i if bX is larger than c. A negative outcome is observed if bX is smaller than c. Using ROC terminology, we say that sensitivity SE is the fraction of households with observed positive outcomes that are correctly classified as poor. Denoting by P, P^-, and P^+ the number of the poor, negative outcomes, and positive outcomes among the poor, $SE = P^+/(P^- + P^+) = P^+/P$. Specificity SP is the fraction of households with observed negative outcomes which are correctly classified as non-poor. Denoting the non-poor by NP, $SP = NP^-/(NP^- + NP^+) = NP^-/NP$. In econometric terminology, the probability of Type I error is one minus SP, and that of Type II error is one minus SE.

Table 1. *Sensitivity, specificity, and Type I and Type II errors*[a]

	Nonpoor	Poor
Predicted Nonpoor	$SP = NP^-/NP$	$1 - SE = P^-/P$
Predicted Poor	$1 - SP = NP^+/NP$	$SE = P^+/P$

[a] SP specificity; SE sensitivity; P number of the poor; NP number of the nonpoor; P^+ number of the poor classified as poor; P^- number of the poor classified as nonpoor; NP^+ number of the nonpoor classified as nonpoor; and NP^- number of the nonpoor classified as poor.

In what follows, we refer to SP and SE errors instead of Type I and Type II errors (Table 1).

When the cut-off point is increased, fewer households will be predicted as poor, SP will increase, and the probability of SP error will be reduced. On the other hand, SE will be reduced and the probability of SE error will increase. When the cut-off point is reduced, more households will be predicted as poor, SE will increase, the probability of SE error will drop, but the probability of SP error will increase. As will be discussed in Section 3, the choice of the cut-off point should be determined by the relative costs associated with the SP and SE errors. It may depend on the specific policy to be implemented to reduce poverty. What about the choice of the model used for predictions? Different models based on different sets of indicators X can be used. For each model, a ROC curve summarizes the SP and SE errors obtained along a continuum of cut-off points.

Figure 1 shows two ROC curves corresponding to two models which will be discussed in Section 4. Each ROC curve plots one minus SP on the horizontal axis, and SE on the vertical axis for all values of the cut-off c. At the origin of the graph (0,0), corresponding to $c = 1$, SE is equal to zero and SP is equal to one. Remember that with $c = 1$, nobody is ever classified as poor, and the probability that a non-poor person be classified as poor is zero. Hence the probability of SP error must be equal to zero. Moreover, with $c = 1$, the probability that a poor household will be classified as non-poor is equal to one. The probability of SE error must be equal to one. In contrast, at the upper right corner of the graph (1,1), SE is equal to one, and SP is equal to zero. This corresponds to $c = 0$, a probability of SP error of zero, and a probability of SE error of one. Between these extremes, the ROC curve plots the probabilities of the two types of errors for various values of c.

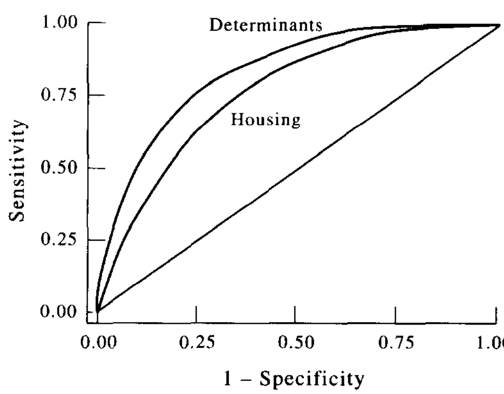

Figure 1. *ROC curves for determinants of poverty and housing models.*

While the two curves in Figure 1 are monotonically increasing, their shapes depend on the performance of the underlying model used to predict the poverty status of the households. On the 45° degree line, SE, the probability that a poor household will be classified as poor, is equal to $1 - SP$, the probability that a non-poor household will be classified as poor. The 45° degree line can thus be assimilated to a model with no predictive power. The better the model predicts the true status of the households, the more its ROC curve will be bowed toward the upper left corner of the graph. The area under a ROC curve is a measure of the accuracy of the predictions of the underlying model. Whenever the area is greater than 0.5, the curve lies above the 45° degree line and the model has some predictive ability. If a model were to predict poverty perfectly, its ROC curve would go through (0,1) and the area under the ROC curve would be equal to one.

3. CHOICE OF THE CUT-OFF POINT AND INDICATOR

In Figure 1, one model ("determinants of poverty") has a ROC curve that lies everywhere above the curve of the other model ("housing"), implying that the first model dominates the second. Whatever the choice of the cut-off point, the first model has lower probabilities of SP and SE errors than the second model. Imagine by contrast a case in which the two curves were to intersect, with the ROC curve of model (1) being above that of model (2) in the bottom part of the graph only. The bottom part of the graph corresponds to high values of the cut-off point, low probabilities of SP errors, and high probabilities of SE errors. If policy makers were relatively more lenient on the risk of identifying as non-poor a household who is poor, they would chose model (1). If they where more lenient on the risk of identifying as poor a household who is non-poor, they would choose model (2). None of the models would dominate the other over the whole range of cut-off points.

Given an indicator X, the choice of cut-off point can be formalized as follows. Assume that society's objective function W can be written in terms of SE and $1 - SP$, with $\partial W/\partial SE$ positive, $\partial W/(1 - \partial SP)$ negative, $\partial^2 W/\partial SE^2$ negative, and $\partial^2 W/\partial(1 - SP)^2$ positive. Although this is a simplified structure for measuring society's welfare, SP and SE errors are used in practice for program evaluation. For example, Cornia and Stewart (1995) evaluate food subsidies programs using a valuation of the form $W = c_1 NP^+ + c_2 P^-$, where NP^+ is the number of well-nourished households with access to the food subsidies, and P^- is the number of malnourished households without access to the subsidy. The cost parameter c_1 represents the unit monetary value of the subsidy which is considered wasted when available to well-nourished households. The parameter c_2 accounts not only for the immediate welfare loss of the malnourished households, but also for the loss of productivity at work for the adults, and the future loss of productivity for the children, due to their lack of calories and proteins. Such linear structures for W can be readily transformed into functions of $1 - SP$ and SE. Denoting $d_0 = c_2 P$ (which is a constant since P is exogenously given whatever the cut-off point) and $d_1 = c_1 NP$, we have $W = d_0 + d_1(1 - SP) - d_0 SE$ which can be maximized. In the more general case, society maximizes $W(SE, 1 - SP)$ subject to the ROC curve constraint represented by $g_X\ (1 - SP) = SE$:

$$\text{Max } W(SE, 1 - SP) \text{ subject to } g_X(1 - SP) = SE \quad (1)$$

At the highest achievable welfare level W^*, the first order tangency conditions yield:

$$-\frac{dW/dSE}{dW/d(1 - SP)}\Big|_{W^*} = \frac{\partial W/\partial(1 - SP)}{\partial W/\partial SE} = -\partial g_X/\partial(1 - SP) \quad (2)$$

As noted in the previous section, the ROC curve g_X is specific to the indicator vector X. Yet, for any X, when SP is zero, $g_X\ (1 - SP)$ must be equal to one. When SP is one, $g_X\ (1 - SP)$ must be equal to zero. Moreover, $\partial g_X/\partial(1 - SP) \geq 0$ and $\partial^2 g_X/[\partial(1 - SP)]^2 \leq 0$. Equation 2 states the optimal trade off between achieving more sensitivity, and allowing for more SP error in so doing. This tradeoff defines a unique value of the cut-off point c which is used to identify the households who should benefit from the program (any household with $bX \geq c$ will be given access to the targeted program).

The welfare level corresponding to the best cut-off point for X can be denoted as $v(g_X) = \text{Max}\{W(SE, 1 - SP) | g_X(1 - SP) = SE\}$. Now, if society can choose its indicator within a set of indicators $G = \{g_{X1}, ..., g_{XN}\}$, we can find the optimal cut-off point for each indicator, compute its indirect social utility, and chose the indicator yielding the highest welfare. The best indicator is:

$$g^*_{X_j} = argMax\ \{v^*(g_{X1}), ..., v^*(g_{XN})\}. \quad (3)$$

If there exists within the set G an indicator $g_{X_j}{}^*$, such that $g_{X_j}{}^*$ (.) is at least equal to g_{Xi} (.) for all values of $1 - SP$ and for all $i = 1, ..., N$, this indicator would yield the optimal welfare level for any objective function of the class $W(SE, 1 - SP)$. As long as there is no satiation in SE and SP in the social welfare function, that is as long as $\partial W/\partial SE$ is positive, $\partial W/\partial(1 - SP)$ is negative, and we have at least one strict inequality, society will be better off on the highest feasible ROC curve. This is the sense in which a ROC curve $g_{X_j}*$ can be said to dominate all the other g_{X_i}'s in the set G.

Note finally that ROC analysis can still be used when additional constraints are considered in the formulation (1), such as a budget constraint. The budget constraint can include the cost of finding from households the necessary information in order to implement the various targeting indicators in competition. Moreover, the dual problem of minimizing budget outlays subject to the ROC curve constraint and the achievement of a given level of welfare can be analyzed in order to identify how much savings can be achieved with the choice of one indicator versus another.

4. MULTIVARIATE INDICATORS

Elsewhere (Wodon, 1996, 1998), I used the 1991–92 Household Expenditure Survey unit level data of the Bangladesh Bureau of Statistics (1995) to analyze the determinants of poverty in Bangladesh. The survey provides detailed information on the consumption and characteristics of 5,760 households. In order to predict poverty according to real rather than nominal standards of living, it is necessary to estimate poverty lines which may vary by geographical areas, much as price indices do. In this section, the methodology followed to estimate the poverty lines is briefly outlined, and two alternative models are proposed for the prediction of the poverty status of households.

When using the cost of basic needs method, normative poverty lines are typically anchored in the evaluation of the cost of a food bundle deemed necessary to fulfill nutritional requirements. Three steps are followed in practice. First, the food bundle corresponding to minimum nutritional requirements is defined. Second, the cost of this food bundle is estimated. Third, an allowance for non-food items is computed. In accordance with the FAO standard for South Asian countries, and following a number of other studies, we defined a food bundle meeting the minimum requirement of 2,112 calories and 58 gm of protein per day per person. To assess the cost of this food bundle, we took into account the fact that observed food prices may vary not only with the geographical location of the households, but also with their characteristics. Households with higher levels of income, wealth, or education tend to buy higher quality goods. Following Chen and Ravallion (1996), we used regressions to estimate regional prices for each food item in the normative bundle after controlling for household characteristics. Finally, to determine a reasonable allowance for the non-food component of the poverty line, we measured the share of their income spent by households near the food poverty line on non-food items. Following Ravallion (1994), two cases were considered. In the first case, we computed the amount of resources spent on non-food items by the households whose total consumption was close to the cost of the food bundle. We then added this amount to the cost of the normative food bundle to determine a "lower" poverty line. In the second case, we computed the amount of resources spent on non-food items by the households whose food consumption was close to the cost of the normative food bundle, and added this amount to the cost of the normative bundle to obtain the "upper" poverty line. The upper poverty lines for the various geographical areas turned out to be about 25% higher than the lower ones. It is because poverty lines are subject to debate that it is interesting to consider a lower and an upper poverty lines for an assessment of the robustness of the performance of indicators to the choice of poverty lines.

Given the above poverty lines, two models were first estimated. For the first model, the following household characteristics were used as regressors: the geographical location of the household (along 14 areas represented below by the vector of dummy variables GL); the religion and the demographic characteristics of the household such as the number of babies, children, and adults, as well as the square of the number of babies, children, and adults (DM); the family structure of the household, such as a single person without children, a couple with or without children, and a male or a female single head with or without children (FS); the age of the household head and of his spouse and the square of both ages (AG); the education level of the household head (EH), of his spouse (ES), and of other members of the household (ED); the household head's main occupation or field of employment (OH); and the household's amount of land owned along four categories (LO). Denoting $y* = y - z$, we estimated with a logistic specification for the error[1]:

$$y* = \beta_0 + \beta_1 GL + \beta_2 DM + \beta_3 AG + \beta_4 FS + \beta_5 EH + \beta_6 ES + \beta_7 ED + \beta_8 OH + \beta_9 LO + \varepsilon \quad (4)$$
$$y = 1 \text{ if } y* \leq 0 \text{ and } y = 0 \text{ if } y* > 0$$

We will refer to this model as the "determinants of poverty model." Another source of information in the survey of the Bangladesh Bureau of Statis-

Table 2. *Areas under ROC curve for the two basic models*

Sample and poverty line	Determinants of poverty model	Housing model
National, lower poverty line	.857	.793
National, upper poverty line	.841	.767
Urban, lower poverty line	.883	.836
Urban, upper poverty line	.863	.807
Rural, lower poverty line	.841	.755
Rural, upper poverty line	.833	.732

Source: Own calculations from HES unit level data.

tics is related to the housing characteristics of households. We included the wall (*WALL*) and roof (*ROOF*) material of the house, the number of bedrooms and their size (*BEDS*), and the sanitary (*SAN*) and water (*WATER*) systems in a logistic regression to estimate the probability of being poor for a "housing model":

$$y* = \gamma_0 + \gamma_1 GL + \gamma_2 WALL + \gamma_3 ROOF + \gamma_4 BEDS + \gamma_5 SAN + \gamma_6 WATER + \varepsilon \quad (5)$$

$$y = 1 \text{ if } y* \leq 0 \text{ and } y = 0 \text{ if } y* > 0$$

Both models were estimated for our lower and upper poverty lines, each time for three different samples to include, respectively, the national, urban, and rural households. The results of the 12 regressions are not shown here, but they are available upon request. To each of the 12 regressions corresponds a ROC curve. Table 2 provides the measures of the areas under these curves. In all six combinations of poverty lines and samples, the determinants of poverty model performs better than the housing model on the basis of the area under the ROC curve criterium. The ROC curves of the determinants of poverty model also lie above those of the housing model in all combinations of poverty lines and samples. The curves for the national sample and the lower poverty line were those shown in Figure 1. In short, the determinants of poverty model dominates for targeting the housing model for all cut-off points and the class of objective functions $W(SE, 1 - SP)$.

If we were willing and able to use a complex combination of indicators to assess the poverty status of households, we could compute the score bX of households under the determinants of poverty model, and chose the optimal cut-off point c corresponding to the particular specification of $W(SE, 1 - SP)$. While the predictions would be good and W would be large, it is unlikely that we would have the necessary information to use the determinants of poverty model in practice. Even if we did, the implementation of a policy under such a complex set of indicators might be too difficult. Still, the preceding exercise is not fruitless as we can now use the predictive power of the two basic models as benchmarks against which to compare the performance of subsets of indicators.

5. UNIVARIATE INDICATORS

The performance of the two basic models described in the previous section can be used as benchmarks to assess the predictive power of subsets of indicators. We can simplify Equations 4 and 5 to take into account one set of indicators at a time. That is, we can estimate Equation 4 with the area dummies only, the demographic variables only, and so on, and do the same for Equation 5. To each

Table 3. *Areas under ROC curve for subsets of indicators (determinants of poverty)*[a]

Subsets of Indicators	National, Lower Line		National, Upper Line		Urban, Lower Line		Urban, Upper Line		Rural, Lower Line		Rural, Upper Line	
Education head	.706	1	.71	1	.758	1	.753	1	.651	5	.660	4
Occupation head	.701	2	.701	2	.684	4	.702	3	.700	1	.694	2
Geographical area	.695	3	.637	6	.644	5	.582	6	.652	4	.606	6
Demographics	.676	4	.679	3	.707	3	.693	4	.665	3	.669	3
Education spouse	.663	5	.666	4	.708	2	.715	2	.616	6	.617	5
Land owned	.629	6	.643	5	.592	6	.595	5	.700	1	.706	1
Age	.562	7	.559	7	.565	7	.540	9	.584	7	.582	7
Family Structure	.543	8	.544	8	.554	8	.541	8	.547	9	.549	8
Education others	.534	9	.534	9	.551	9	.570	7	.559	8	.545	9
All indicators	.857	—	.841	—	.883	—	.863	—	.841	—	.833	—

Source: Own calculations from HES unit level data. [a] The first number is the area under the ROC curve, and the second number is the rank of the indicator according to the area under the curve.

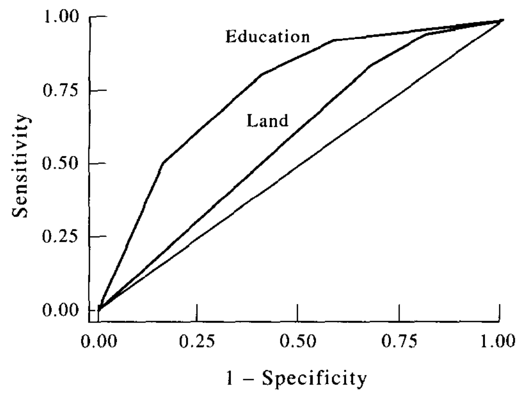

Figure 2. *ROC curves for education and land—urban areas.*

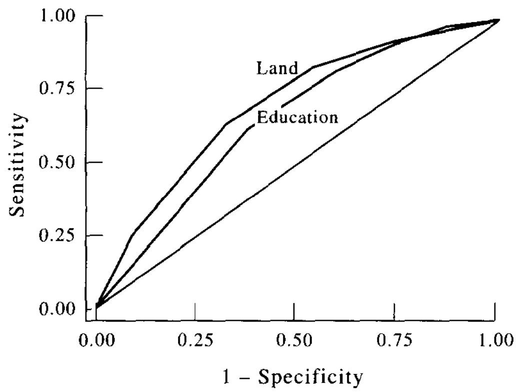

Figure 3. *ROC curves for education and land—rural areas.*

simplified model based on a subset of indicators corresponds a ROC curve[2].

Table 3 illustrates the impact of the choice of the poverty line on the performance of various subsets of indicators from the determinants of poverty model. At the national level, the area under the ROC curve for the geographical area indicators drops from 0.695 with the lower poverty line to 0.637 with the higher poverty line. By contrast, the areas under the ROC curves of the education and occupation indicators are similar for both poverty lines. The geographical indicators are more sensitive to the choice of the poverty line than the education and occupation indicators. As the poverty line is increased, the differences in poverty among areas are phased out more rapidly than the differences in poverty by education level or occupation status (this is because poverty lines are area-specific, see Wodon, 1996). Table 3 also illustrates the impact of the sampling universe on the performance of the indicators. The area under the ROC curves indicates that in urban areas, the education of the household head is a good indicator. In rural areas, land ownership is better.

Does any subset of indicators dominate all the others nationally, in the urban, or in the rural sector? By looking at the areas under the ROC curves, we might be led to believe that education is unambiguously the best indicator in the urban areas, and that land is unambiguously the best indicator in the rural areas. But these areas are only summary measures. To check if the performance of these indicators is the highest for all possible values of the cut-off point, we must look at the ROC curves themselves. It turns out that no indicator dominates all others nationally or in either the rural or the urban sector. At the national level for example, occupation is a better indicator for low values of the cut-off point, education is better for high values of the cut-off point, and geographical area is better for a small range of medium values of the cut-off point. At the sectoral level, as shown in Figures 2 and 3, education dominates land ownership in the urban areas, but land ownership does not dominate education in the rural areas. There are a few values of the cut-off point for which education is a better indicator than land ownership in rural areas.

Table 4 gives the performance of subsets of indicators from the housing model for the two poverty lines and the three sampling universes.

Table 4. *Area under ROC curve for subsets of indicators (housing)*[a]

Subsets of Indicators	National, Lower Line		National, Upper Line		Urban, Lower Line		Urban, Upper Line		Rural, Lower Line		Rural, Upper Line	
Sanitary system	.703	1	.689	1	.745	1	.722	3	.636	2	.629	4
Wall material	.684	2	.686	2	.742	2	.736	1	.631	4	.635	2
Roof material	.677	3	.679	3	.730	3	.723	2	.632	3	.634	3
Bedrooms space	.642	4	.647	4	.668	4	.672	4	.644	1	.642	1
Bedrooms number	.603	5	.607	5	.637	5	.637	5	.576	5	.578	5
Water system	.563	6	.566	6	.634	6	.633	6	.510	6	.510	6
All indicators	.793	—	.767	—	.836	—	.807	—	.755	—	.732	—

Source: Own calculations from HES unit level data. [a] The first number is the area under the ROC curve, and the second number is the rank of the indicator according to the area under the curve.

Again, the choices of the poverty line and of the sampling area matter. Moreover, some subsets of indicators from the housing model perform as well or better than many subsets of indicators from the determinants of poverty model. In urban areas for example, while not shown here, the sanitary indicators dominate the occupation indicators (while paradoxically the wall material indicators do not, even if the area under the curve is larger).

6. STRENGTHS AND LIMITS OF ROC ANALYSIS

As discussed in Section 3, ROC analysis is useful for the assessment of the performance of targeting indicators with welfare functions such as $W(SE, 1 - SP)$ which depend on the two types of errors involved in targeting. But how does ROC analysis compare with other methods traditionally used in the assessment of poverty policies? Two questions can be distinguished here. First, are there other methods which could provide the same information as ROC analysis does? Second, is the welfare rationale for ROC analysis adequate, or should other objective functions be considered?

For the first question, dominance analysis comes to mind. The technique was proposed by Atkinson (1987) in order to assess the sensitivity of poverty comparisons to the choice of alternative poverty lines and poverty measures. Consider a poverty comparison between households with two different levels of land ownership. The poverty incidence curves of, say, the landless (less than 0.05 acres of land) and near landless (between 0.05 and 0.50 acres of land) plot on the vertical axis the headcount indices of poverty in the two categories as functions, on the horizontal axis, of the poverty line. That is, the poverty incidence curves are graphs of the cumulative density functions of per capita consumption in both land categories. Then, for a given range of poverty lines, the near landless will be said to first-order dominate the landless if the poverty incidence curve of the near landless lies everywhere below that of the landless. First-order dominance implies not only that the headcount index of poverty, but also higher order poverty measures of the FGT (Foster *et al.*, 1984) class, will be lower in the near landless category than in the landless category. Moreover, one can check for higher order of dominance if first-order dominance is not obtained.

First-order dominance analysis can be used to retrieve part of the information needed to construct ROC curves when one categorical indicator is considered at a time, such as in the above example with land ownership categories. To see this, consider Figure 4, where rural poverty incidence curves are drawn for five groups of households classified by land ownership. The horizontal axis represents per capita consumption normalized by the lower poverty line. That is, Figure 4 plots the headcount indices of poverty in the various land categories as functions of

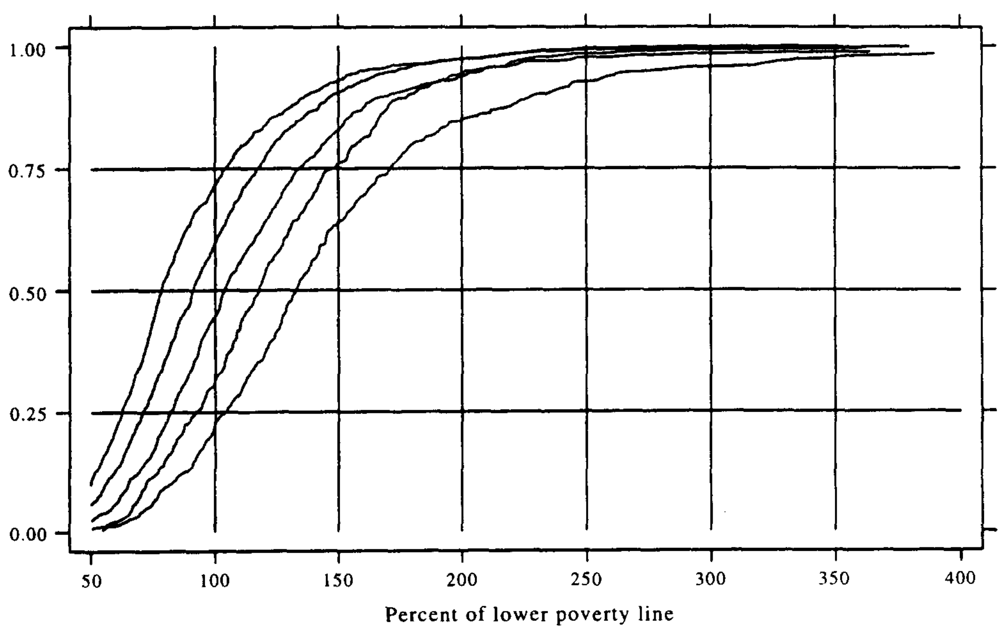

Figure 4. *Poverty incidence curves, lower poverty line, rural areas (groups with more land first-order dominate groups with little land).*

multiples of the lower poverty line. The headcounts by category can be found by the intersection of the various poverty incidence curves with the vertical line at 100% of the poverty line. If a policy intervention is targeted to the landless, the proportion SE of the poor benefiting from the intervention is simply the number of the poor among the landless (equal to the landless population times the percentage of the poor among the landless, the later being given by the poverty incidence curve), divided by the total number of the poor. To find SP, it is sufficient to know the number of the nonpoor among the landless and to divide it by the total number of the nonpoor. A similar procedure could be used to find SE and $1 - SP$ when additional land categories are chosen for targeting, or when another targeting indicator is used, such as education. In the end, after some computations and with some extra information, the ROC curves in Figure 3 comparing land and education indicators could thus be obtained from poverty incidence curves and dominance analysis.

It might seem that dominance and ROC analysis are just two different ways to present the same information. But that is not so: ROC analysis has two advantages over dominance analysis for analyzing sensitivity and specificity. First, when one considers a continuous rather than a categorical indicator, such as the exact amount of land owned by a household, dominance analysis does not work because there are too many poverty incidence curves to be drawn and too few households in the data for each value of the continuous indicator. But ROC curves can be drawn with continuous indicators, and the curves will be smooth (as in Figure 1, as opposed to the segmented ROC curves in Figures 2 and 3 obtained with categorical indicators). Second, and more importantly, when two or more sets of variables (e.g., land ownership and geographical location) are jointly used as indicator for targeting purposes, ROC analysis is better than dominance analysis for identifying sensitivity and specificity because it is based on a regression which optimizes the information provided by the two sets of variables in order to identify the poor. That is, the logistic regressions (4) and (5) estimate parameters, which are then used to compare the regression score of all households with any chosen cut-off point. When the two variables are categorical, dominance analysis can also be based on a joint indicator (combining five land categories with five education categories would result in an indicator with 25 values, with a corresponding poverty incidence curve for each of the 25 possible combinations of land ownership and education level), but this joint indicator is not obtained though an optimization procedure such as that involved in the estimation of the logistic regressions used to construct the ROC curves.

The second question outlined at the outset of this section is more substantive: is the welfare function $W(SE, 1 - SP)$ appropriate? Or should the success of a policy be measured by its contribution to poverty alleviation (noting that a reduction in poverty can easily be expressed graphically through dominance analysis but not through ROC curves)? With data from Bangladesh, Ravallion and Sen (1994) use an algorithm to compute the reduction in the squared poverty gap which could be achieved by taxing large landowners and providing transfers to the landless or near landless. The exercise could be replicated for another indicator such as geographical location. The reduction in poverty obtained with the two indicators could be compared, and the better one could be chosen. The question then is whether minimizing poverty is more appropriate than maximizing a welfare function of the type $W(SE, 1 - SP)$, for which another indicator could be found superior using ROC analysis. The answer to that question depends on the policy considered, and on the political economy context. Minimizing poverty makes sense when the focus is on cash transfers as in the case studied by Ravallion and Sen (1994). But their technique is less straightforward for choosing an indicator for in-kind transfers for which it may be difficult to estimate a cash equivalent. In addition, if the political economy landscape is such that taxpayers wish to prevent the nonpoor from benefiting from programs targeted to the poor, it is more natural to reason in terms of sensitivity and specificity than in terms of the minimization of a poverty measure. Of course, if highly targeted programs risk losing political support, then ROC analysis has limits. Judgment is thus called for to identify the appropriate welfare function, and hence the technique to be used for policy evaluation.

Another advantage of ROC analysis is its simplicity: the technique could be readily used by public agencies and NGOs. It should be no surprise that land ownership has in practice been used in Bangladesh by micro-credit organizations such as the Grameen Bank as the key targeting indicator to reach the poor. This is not only because land ownership can discriminate between the poor and the non poor, but also because the cost of identifying the landless is low: in a small village, everybody knows who owns what. The cost of identifying indicators should clearly be a consideration in the choice of the targeting indicator, but integrating this cost in the analysis is relatively straightforward, especially if the welfare function used for evaluation is linear.

7. CONCLUSION

This paper has proposed a simple methodology to assess the predictive power of targeting indicators in matters of poverty. The methodology is based on ROC analysis. A set of targeting indicators will be said to dominate another for the class of welfare functions $W(SE, 1 - SP)$ based on the two types of errors committed in targeting if, for all values of the cut-off point representing the tradeoff between the two types of errors, the probabilities of both errors associated with the first set of indicators can be made smaller than the probabilities of both errors associated with the second set of indicators. Graphically, this property will be obtained if the ROC curve of the first model lies everywhere above the ROC curve of the second model. Moreover, the areas under the ROC curve of both models will provide useful summary statistics of their respective predictive powers.

The method was applied to Bangladesh, where education, occupation and geographical location were found to be good indicators at the national level. But, the performance of geographical location is less robust to the choice of the poverty line than education and occupation because poverty lines are area-specific (with higher poverty lines, differences in poverty rates between areas vanish more rapidly). Education is better than land ownership in urban areas, while the reverse applies in most cases in rural areas. Some easily identifiable household characteristics related to housing also prove to be quite good targeting indicators, especially in urban areas. All these results can be useful for policy, even though actual policy applications are bound to be more complex than the simple framework used in this paper. For example, incentive effects and the cost of targeting using various indicators would have to be taken into account in the comparisons.

NOTES

1. The latent dependent variable y^* in Equations 4 and 5 is the difference between the per capita monthly poverty line and per capita monthly consumption. Per capita consumption corresponds to an equivalence scale of one when equivalent consumption is expressed as HY/HS^e, with HY as household consumption, HS as household size, and e as equivalence scale. Other equivalence scales (and poverty lines) could have been used, which would have resulted in different coefficient estimates, especially for demographic variables whose coefficient estimates are more sensitive to the choice of equivalence scale. Per capita consumption has been used in this paper because it is the standard metric used in Bangladesh, for example by the Bangladesh Bureau of Statistics.

2. Strictly speaking, we do not have a ROC curve for the categorical indicators (land and education) in Figures 2 and 3, but only a set of points. This is because with only dummy variables as regressors, the score βX of a household can take only a finite number of values. With five categories of land or education, we have four points to draw the ROC curve apart from the points (0,0) and (1,1). In practice, this means that small changes in the cut-off point in the neighborhood of these values have no effect on SP and SE, and therefore on the choice of the indicator. By contrast, in Figure 1, we do have 5,760 points to draw the figure, one for each household since the value of βX changes for every household (there may be a few tie-ins). See also the discussion in Section 6.

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