Simple Poverty Scorecard® Poverty-Assessment Tool India

Mark Schreiner

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Abstract

The Simple Poverty Scorecard-brand poverty-assessment tool uses ten low-cost indicators from India's 2003 Socio-Economic Survey to estimate the likelihood that a household has expenditure below a given poverty line. Field workers can collect responses in about ten minutes. The scorecard's accuracy is reported for a range of poverty lines. The scorecard is a practical way for pro-poor programs in India to measure poverty rates, to track changes in poverty rates over time, and to segment clients for targeted services.

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Simple Poverty Scorecard® Poverty-Assessment Tool

Interview ID:			**Name**	**Identifier**
Interview date:		Participant:		
Country:	IND	Field agent:		
Scorecard:	001	Service point:		
Sampling wgt.:			Number of household members:	

Indicator	Response	Points	Score
1. How many members ages 0 to 17 are in the household?	A. Five or more	0	
	B. Four	8	
	C. Three	11	
	D. Two	17	
	E. One	22	
	F. None	31	
2. What is the household's primary energy source for cooking?	A. Firewood and chips, charcoal, or none	0	
	B. Other	8	
3. Does the household own a television?	A. No	0	
	B. Yes	4	
4. How many hectares of land does the household own?	A. Urban (any amount)	0	
	B. Rural (0 to 0.4)	4	
	C. Rural (0.41 to 2)	7	
	D. Rural (more than 2)	10	
5. What is the principal occupation of the household?	A. Agricultural labours	0	
	B. Operators and labourers, bricklayers, or construction workers	6	
	C. Cultivators, farmers, fishers, hunters, loggers, or no data	8	
	D. Sales workers, service workers, transport-equipment operators	11	
	E. Professional, technical, clerical, administrative, managerial, executive, or teachers	13	
6. How many *almirah*/dressing tables does the household own?	A. None	0	
	B. One	2	
	C. Two or more	9	
7. Is the residence all *pucca* (burnt bricks, stone, cement, concrete, jackboard/cement-plastered reeds, timber, tiles, galvanised tin or asbestos cement sheets)?	A. No	0	
	B. Yes	5	
8. Does the household own a pressure cooker or pressure pan?	A. No	0	
	B. Yes	5	
9. Does the household own a sewing machine?	A. No	0	
	B. Yes	6	
10. How many electric fans does the household own?	A. None	0	
	B. One or two	5	
	C. Three or more	10	

Score:

Simple Poverty Scorecard® Poverty-Assessment Tool India

1. Introduction

The Simple Poverty Scorecard poverty-assessment tool is a low-cost way for development programs in India to target services, track changes in poverty over time, and report clients' poverty rates.

Rather than asking for hours on end about all possible consumption items ("How many carrots did your household eat last week? If you bought the carrots, what price did you pay? If you grew the carrots yourself, what price would they have fetched in the market? Now then, how many cabbages did your household eat last week? . . ."), the scorecard uses 10 simple indicators (such as "Does the household own a television?" or "What is the floor of the house made of?") to produce a score that is highly correlated with poverty status as measured by the exhaustive expenditure survey.

Indicators in the scorecard come from an analysis of 41,013 households in Schedule 1.0 of the 59th Round (2003) of India's Social-Economic Survey (National Sample Survey Organisation, 2005). Indicators were selected to be:

- Inexpensive to collect, easy to answer quickly, and simple to verify
- Strongly correlated with poverty
- Liable to change over time as poverty status changes

All scorecard weights are positive integers, and scores range from 0 (most-likely "poor") to 100 (least-likely "poor"). Field workers can compute scores on paper.

A participant's score corresponds to a "poverty likelihood", that is, the probability of being "poor". In a group, the share of clients who are "poor" is the average poverty likelihood. For a group over time, progress is the change in average poverty likelihood.

A scorecard was constructed for use in all of India. Schreiner (2006) tests rural and urban scorecards, but the added complexity improves accuracy only slightly.

The scorecard can also be used to classify clients as "very poor" (poorest half in poverty), "poor" (top half in poverty), and "non-poor".

The scorecard accurately and objectively estimates the likelihood that Indian households have expenditure below $1/person/day. It should be certifiable as a "poverty tool" for the reporting required of USAID's microenterprise partners. In particular, the scorecard is quite accurate. With 90-percent confidence, a household's estimated poverty likelihood is accurate within ±2.7 percentage points, and a group's estimated overall poverty rate is accurate within ±0.7 percentage points.

2. Data

The scorecard was constructed using a one-half random sample of the 41,013 households in Schedule 1.0 of the 59th Round (2003) of India's Socio-Economic Survey (NSSO, 2005). The average surveyed household represented about 24,000 people. Sixteen households who each represented more than 500,000 people were omitted because they led to the breakdown of some bootstrap estimates (see Singh, 1998).

In addition to the one-half sample used in scorecard construction, one-fourth of the sample was used to associate scores with poverty likelihoods. The final one-fourth of the sample was used to test the accuracy of the scorecard's estimates. Figure 1 shows the number of households surveyed, the number of people represented, and the poverty rates for the three samples.

3. Poverty lines

Depending on the poverty line, India has 200 to 900 million poor people, more than any other country. There is an entire literature (but little agreement) about Indian poverty lines (Deaton and Kozel, 2005). Commonly used ones include:

- $1/person/day (Rs14.91 at purchasing power parity in 2003, see Sillers, 2003)
- Official all-India lines (Rs11.51 rural, Rs16.79 urban)
- Official state-wise and rural/urban lines, adjusted for cost-of-living
- Official state-wise and rural/urban lines adjusted for cost-of-living by Deaton (2003)

The state-wise lines are better because they adjust for cost-of-living. In turn, Deaton's (2003) adjustments are better because they account for what households actually buy.

The official lines were originally based on caloric benchmarks (2400/day for adult males in rural areas, 2100 in urban). Over time, the line has fallen behind the cost of food, and of course poverty is more than just lack of calories. Taking a "basic needs" approach, Abraham (2005) estimates a poverty rate of 90 percent. In contrast, Deaton

(2004) and Aiyar (2003) argue that mechanization has decreased caloric requirements and that food quality—and nutrient density—has improved with time.

Officially, about one in four Indians are poor. But more than half usually eat less than three meals per day, suggesting that the official lines are too low.

The scorecard here uses the $1/day poverty line, adjusted for state-wise and rural/urban cost-of-living using Deaton (2003). This is the international benchmark, and it is higher than the official lines (although probably still not high enough). The Appendix describes the details, and Figures 2 and 3 show the poverty lines. By the official line, 23.6 percent of all Indians are poor; by the Deaton-adjusted $1/day line, the figure is 37.4 percent. Rural poverty is more prevalent than urban.

4. Scorecard construction

About 400 potential poverty indicators were prepared, including:

- Household characteristics (such as cooking fuel and caste)
- Individual characteristics (such as age and number of meals usually taken)
- Household consumption (such as milk and toothbrushes)
- Household durable goods (such as electric fans and pressure cookers)

How well each indicator predicts poverty (by the $1/day adjusted line) was tested first with the entropy-based "uncertainty coefficient" (Goodman and Kruskal, 1979), with about 120 indicators selected for further analysis. Figure 4 lists the top 50, ranked by the uncertainty coefficient. They are worded as they would be in an actual scorecard, with responses ordered by the strength of their association with poverty.

Many indicators in Figure 4 are similar in terms of their association with poverty. For example, most households who own electric fans also use electricity for lighting. If a scorecard already includes "ownership of electric fans", then "source of energy for lighting" is superfluous. Thus, many indicators strongly associated with poverty are not in the scorecard because similar indicators are already included.

The scorecard also aims to measure *changes* in poverty through time. Thus, some powerful indicators (such as education of the female head) that are unlikely to change as poverty changes were omitted in favor of slightly less-powerful indicators that are more likely to change (such as ownership of electric fans).

In addition, some powerful indicators were not selected because they are difficult to collect ("How many chairs, stools, benches, and tables does the household own?") or too sensitive ("In the past 30 days, did the household use any sanitary napkins?").

The scorecard itself was constructed using Logit regression. Indicator selection combined statistics with the judgment of an analyst with expertise in scoring and development. Starting with a scorecard with no indicators, each candidate indicator was added, one-by-one, to a one-indicator scorecard, using Logit to derive weights. The improvement in accuracy was recorded using the "c" statistic.[1]

[1] "c" is a measure of a scorecard's ability to rank-order households. It is equivalent to the area under an ROC curve that plots the share of poor households (vertical axis) versus the share of all households ranked by score (horizontal axis). "c" can also be seen

After all indicators had been tested, one was selected based on several factors (Schreiner *et al.*, 2004; Zeller, 2004). These included the improvement in accuracy, the likelihood of acceptance by users (determined by simplicity, cost of collection, and "face validity" in terms of experience, theory, and common sense), the ability of the indicator to change values as poverty status changes, variety vis-à-vis other indicators already in the scorecard, and observability/verifiability.

The selected indicator was then added to the scorecard, and the previous steps were repeated until 10 indicators were selected. Finally, the Logit coefficients were transformed into non-negative integers such that the lowest possible score is 0 (most likely poor) and the highest is 100.

The statistical algorithm is the Logit analogue to the stepwise "MAXR" in, for example, Zeller, Alcaraz and Johannsen (2005) and IRIS (2005a and 2005b). Like R^2 in a least-squares regression on expenditure, "c" is a good general measure of general accuracy in a Logit regression on poor/non-poor status. The procedure here diverges from naïve stepwise in that expert judgment and non-statistical criteria were used to select from the most-predictive indicators. This improves robustness and, more importantly, helps ensure that the indicators are simple and sensible and so likely to be accepted by users.

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as the share of all possible pairs of poor and non-poor households in which the poor household has a lower score.

5. Scorecard use

As explained in Schreiner (2005), the main goal is not to maximize accuracy but to maximize the likelihood of programs' using scoring appropriately. When scoring projects fail, the culprit is usually not inaccuracy but rather the failure of users to accept scoring and to use it properly (Schreiner, 2002). The challenge is not technical but human and organizational, not statistics but change management. "Accuracy" is easier—and less important—than "practicality".

The scorecard here was designed to help users to understand and trust it (and thus use it properly). While accuracy matters, it must be balanced against simplicity, ease-of-use, and "face validity". In particular, programs are more likely to collect data, compute scores, and pay attention to the results if, in their view, scoring avoids creating "extra" work and if the whole process in general seems to make sense.

This "practicality" focus naturally leads to a one-page scorecard (Figure 5) that allows field workers to score households by hand in real time because it features:

- Only 10 indicators
- Only categorical indicators ("electric fans owned", not "value of all assets")
- User-friendly weights (non-negative integers, no arithmetic beyond simple addition)

Among other things, this simplicity enables "rapid targeting", such as determining (in a day) who in a village qualifies for, say, work-for-food, or ration cards.

The scorecard in Figure 5 could be photocopied for immediate use. It can also serve as a template for data-entry screens with database software that records indicators, indicator values, scores, and poverty likelihoods.

A field agent collecting data and computing scores on paper would:

- Read each question off the scorecard
- Circle the response and the corresponding points
- Write the points in the far-right column
- Add up the points to get the total score
- Implement program policy based on the score

5.1 Scores and poverty likelihoods

A score is not a poverty likelihood (that is, the estimated probability of being poor), but each score is associated with a poverty likelihood via a simple table (Figure 6). For example, scores of 0–4 correspond to a poverty likelihood of 88.5 percent.

Scores (sums of scorecard weights) are associated with poverty likelihoods (estimated probabilities of being poor) via the "bootstrap" (Efron and Tibshirani, 1993):

- From the first one-fourth hold-out sample, draw a new sample of the same size *with replacement*
- For each score range, compute the share of people with the score who are poor
- Repeat the previous two steps 10,000 times
- For a given score range, define the poverty likelihood as the average of the shares of people who are poor across the 10,000 samples

These resulting poverty likelihoods are objective, that is, based on data. This process would produce objective poverty likelihoods *even if the scorecards were constructed without data*. In fact, scorecards of objective, proven accuracy are often constructed *only* with qualitative judgment (Fuller, 2006; Caire, 2004; Schreiner *et al.*, 2004). Of course, the scorecard here used data. Some parties have misunderstood the significance of the fact that some choices in scorecard construction—as in any statistical analysis—are informed by the analyst's judgment. That the use of this judgment is explicitly acknowledged in no way impunes the objectivity of the poverty likelihoods, which depends on using data to associate scores with poverty likelihoods, not on whether only data was used to construct scorecards.

Figure 7 depicts the precision of estimated poverty likelihoods as point estimates with 90-, 95-, and 99-percent confidence intervals. Confidence intervals are the standard way to measure accuracy, and it is widely understood by lay people.

For example, the average poverty rate across bootstrap samples for people with scores of 30–34 (the poverty likelihood) was 52.8 percent. In 90 percent of the 10,000 samples, the share was between 49.7–56.0 percent. In 95 percent of samples, the share was 49.1–56.7; in 99 percent of samples, the share was 48.0–57.8.

Weighting by the people in each score range, the average 90-percent confidence interval is ±±2.7 percentage points, the 95-percent interval is ±3.2, and the 99-percent interval is ±4.2.

For estimated and true poverty likelihoods, Figure 8 depicts mean absolute differences and confidence intervals from 10,000 bootstrap samples on the second one-fourth hold-out sample. Weighting by the people in a score range, the mean absolute difference is 3.6 percentage points, with a 90-percent interval of ±2.6 percentage points, a 95-percent interval of ±3.1, and a 99-percent interval of ±4.1.

This discussion so far looks at whether estimated poverty likelihoods are close to true poverty likelihoods. There is another aspect of accuracy: how well the poor are concentrated in low scores and the non-poor in high scores. A perfect scorecard would assign all the lowest scores to poor people and all the highest scores to non-poor people. In reality, no scorecard is perfect, so some non-poor have low scores, and vice versa.

ROC curves are standard tools for showing how well scorecards concentrate the poor among lower scores (Baulch, 2003; Wodon, 1997). They plot the share of poor and non-poor households against the share of all households ranked by score.

What does the ROC curve for India in Figure 9 mean? Suppose a program sets a cut-off so as to target the lowest-scoring x percent of potential participants. The ROC curve then shows the share of the poor and non-poor who would be targeted. Greater ability to rank-order—with less leakage and less undercoverage—is signified by curves that are closer to the northwest and southeast corners of the graph.

In Figure 9, the two northwest (southeast) curves depict accuracy among the poor (non-poor). As a benchmark, the external trapezoid shows the accuracy of a hypothetical perfect scorecard that assigns all of the lowest scores to poor people.

The inner lines represent the actual India scorecard. They show, for example, that targeting the 20 percent of cases with the lowest scores would target 42 percent of all the poor and 7 percent of all the non-poor.

Figure 9 also reports two other common measures of ability to rank-order. The first is the Kolmogorov-Smirnov statistic, the maximum distance between the poor and non-poor curves (here 51.9). The second is the ratio of the area inside the ROC curves to the area inside the trapezoid of a hypothetical perfect scorecard (here 68.3).

Is this scorecard accurate enough for targeting? The author believes that targeting errors due to scorecard inaccuracy are probably small relative to errors due to other sources (such as mistakes in data collection or fraud) and relative to the accuracy of other feasible targeting tools.

5.2 Estimates of overall poverty rates

The estimated overall poverty rate is the average of the estimated poverty likelihoods of individuals.

For example, suppose a program had three participants on Jan. 1, 2006 who had scores of 20, 30, and 40, corresponding to poverty likelihoods of 73.6, 52.8, and 36.3 percent (Figure 5). The poverty rate is the participants' average poverty likelihood, that is, $(73.6 + 52.8 + 36.3) \div 3 = 54.2$ percent.

As a test, the scorecard was applied to 10,000 bootstrap replicates from the second one-fourth hold-out sample, comparing the estimated overall poverty rates with the true values. The mean difference was 2.00 percentage points, with a standard deviation of 0.39. The 90-percent confidence interval around the mean was ± 0.7 percentage points, the 95-percent interval was ± 0.8 percentage points, and the 99-percent interval was ± 1.0 percentage points.

In practice, this means that subtracting 2.00 percentage points from a group's average poverty likelihood would produce an unbiased estimate that, in 99 of 100 cases, would be within ± 1.0 percentage points of the true overall poverty rate.

5.3 Change through time

For a given group, change over time is estimated as the change in average poverty likelihood.

Continuing the previous example, suppose that on Jan. 1, 2007, the same three people (some of whom may no longer be participants) have scores of 25, 35, and 60 (poverty likelihoods of 60.6, 39.0, and 6.8 percent). Their average poverty likelihood is now 35.5 percent, an improvement of 54.2 – 35.5 = 18.7 percentage points in one year.

In a large group, this means that about 19 of every 100 progressed out of poverty. Given that 54.2 percent were poor in the first place, one in three (18.7 ÷ 54.4 = 34.3 percent) of those who were poor left poverty.

Of course, this does not mean that program participation *caused* the progress; the scorecard just measures what happened, regardless of cause.

6. Setting targeting cut-offs

Potential participants with scores at or below a targeting cut-off are labeled *targeted* and treated—for program purposes—as if they were poor. Those with higher scores are *non-targeted* and treated—for program purposes—as if they were non-poor.

Poverty status (expenditure below a poverty line) is distinct from *targeting status* (score below a cut-off). Poverty status is a fact whose determination requires an expensive expenditure survey. In contrast, targeting status is a policy choice whose determination requires a cut-off and an inexpensive estimate of poverty likelihood. Indeed, the purpose of scoring is to infer poverty status without incurring the high cost of directly measuring expenditure.

No scorecard is perfect, so some of the truly poor may not be targeted, and some of the truly non-poor may be targeted. Targeting is accurate to the extent that poverty status matches targeting status. Accuracy in turn depends in part on the targeting cut-offs; some cut-offs are more accurate for the poor, others for the non-poor.

Setting a cut-off requires trading off accuracy for the poor versus non-poor. The standard technique uses a *classification matrix* and a *net-benefit matrix* (SAS, 2004; SPSS, 2003; Adams and Hand, 2000; Salford Systems, 2000; Hoadley and Oliver, 1998; Greene, 1993).

6.1 Classification matrix

Given a targeting cut-off, there are four possible classification results:

A.	Truly poor	correctly	targeted	(score at or below the cut-off)
B.	Truly poor	mistakenly	non-targeted	(score above cut-off)
C.	Truly non-poor	mistakenly	targeted	(score at or below cut-off)
D.	Truly non-poor	correctly	non-targeted	(score above cut-off)

These four possibilities can be shown as a general classification matrix (Figure 10). Accuracy improves as there are more cases in A and D and fewer in B and C.

Figure 11 shows the number of Indians in each classification by score in the second one-fourth hold-out sample. For example, with a cut-off of 20–24, there are:

A. 16.5	truly poor	correctly	targeted
B. 22.2	truly poor	mistakenly	non-targeted
C. 4.5	truly non-poor	mistakenly	targeted
D. 56.9	truly non-poor	correctly	non-targeted

Targeting accuracy (and errors of undercoverage and leakage) depends on the cut-off. For example, if the cut-off were increased to 25–29, more poor (but less non-poor) are correctly targeted:

A. 23.1	truly poor	correctly	targeted
B. 15.6	truly poor	mistakenly	non-targeted
C. 8.7	truly non-poor	mistakenly	targeted
D. 52.6	truly non-poor	correctly	non-targeted

Whether a cut-off of 20–24 is preferred to 25–29 depends on net benefit.

6.2 Net-benefit matrix

Each of the four classification results is associated with a net benefit (Figure 12):

α. Benefit	truly poor	correctly	targeted
β. Cost (negative net benefit)	truly poor	mistakenly	non-targeted
γ. Cost (negative net benefit)	truly non-poor	mistakenly	targeted
δ. Benefit	truly non-poor	correctly	non-targeted

Given a net-benefit matrix and a classification matrix, total net benefit is:

$$\text{Total net benefit} = \alpha\cdot A + \beta\cdot B + \gamma\cdot C + \delta\cdot D.$$

To set an optimal cut-off, a program would:

- Select a net-benefit matrix based on its values and mission
- Compute total net benefits for each cut-off with the net-benefit matrix and Figure 11
- Select the cut-off with the highest total net benefit

The only non-trivial step is selecting a net-benefit matrix. Some common net-benefit matrices are discussed below. In general, however, each program should thoughtfully decide for itself how much it values successful targeting versus errors of undercoverage and leakage. Of course, any program that targets already uses (if only implicitly) a net-benefit matrix. It is healthy to go through a process of thinking explicitly and intentionally about the value of possible targeting outcomes.

6.2.1 "Total Accuracy"

As an example net-benefit matrix, suppose a program selects the net-benefit matrix that corresponds to the "Total Accuracy" criterion (Figure 13, IRIS, 2005b). With this criterion, total net benefit is the number of people correctly classified:

$$\begin{aligned}\text{Total net benefit} &= 1\cdot A + 0\cdot B + 0\cdot C + 1\cdot D,\\ &= A + D.\end{aligned}$$

Grootaert and Braithwaite (1998) and Zeller, Alcaraz, y Johannsen (2005) use "Total Accuracy" to evaluate the accuracy of poverty-assessment tools.

Figure 14 shows "Total Accuracy" for all cut-offs of the Indian scorecard. Total net benefit is greatest (76.2) for a cut-off of 30–34; at that point, poverty segment matches poverty status for about three in four Indians.

"Total Accuracy" weighs correct classifications of the poor and non-poor equally. If most potential participants are non-poor and/or if a scorecard is more accurate for the non-poor, then "Total Accuracy" might be high even if very few poor people are correctly classified. Programs targeting the poor, however, probably value correct classification more for the poor than the non-poor.

A simple, transparent way to reflect this valuation is to increase the relative net benefit of correctly classifying the poor. For example, if a program values correctly targeting the poor twice as much as correctly not targeting the non-poor, then α should be set twice as high as β in the net-benefit matrix. Then the new optimal cut-off is 40–44, the cut-off point where 2.A + D is highest.

6.2.2 "Poverty Accuracy"

A criterion that emphasizes solely the importance of correctly classifying the poor is "Poverty Accuracy" (Figure 15, IRIS, 2005b), which counts only counts correct classifications of the poor:

$$\begin{aligned}\text{Total net benefit} \quad &= 1 \cdot A + 0 \cdot B + 0 \cdot C + 0 \cdot D, \\ &= A.\end{aligned}$$

Of course, correctly targeting the poor is rarely the sole criteria. In fact, Figure 14 shows that "Poverty Accuracy" is greatest with a cut-off of 95–100. While targeting everyone does ensure that all poor people are targeted and so minimizes *undercoverage* of the poor (second-to-last column of Figure 14), it also targets all the non-poor and so maximizes *leakage* (the final column of Figure 14). A universal program may or may not be appropriate; the point here is to make explicit the implications of "Poverty Accuracy" as a criterion for choosing a targeting cut-off.

6.2.3 "Non-poverty Accuracy"

"Non-poverty Accuracy" counts only correct classifications of the non-poor (total net benefit is D). This is maximized by setting a cut-off of 0–4 and thus not targeting anyone (minimum leakage but maximum undercoverage).

6.2.4 "BPAC"

IRIS (2005b) proposes a new measure of accuracy called the "Balanced Poverty Accuracy Criterion". BPAC balances two goals:

- Accuracy of the estimated overall poverty rate
- "Poverty Accuracy"

According to IRIS (2005b), the first goal of the overall poverty rate is optimized when undercoverage B is balanced by leakage C. The second goal of "Poverty Accuracy" is optimized by maximizing A. If B > C, then Figure 16 is BPAC's net-benefit matrix. Thus, BPAC maximizes A while making B as close to C as possible:

$$\begin{aligned} \text{Total net benefit} \quad &= 1\cdot\text{A} + 1\cdot\text{B} + (-1)\cdot\text{C} + 0\cdot\text{D}, \\ &= \text{A} + (\text{B} - \text{C}). \end{aligned}$$

If C > B, then total net benefit under BPAC is A + (C – B).

BPAC was invented because IRIS does not estimate poverty likelihoods. Instead, IRIS estimates expenditure and then labels as poor those households with estimated expenditure less than the poverty line. In this set-up, the overall poverty rate is estimated as the share of people targeted, and this estimate is most accurate (that is, it matches the true value) when undercoverage B equals leakage C.

For a scorecard (like the one here) that estimates poverty likelihoods, however, BPAC is not meaningful. This is because the estimated overall poverty rate is the average of participants' estimated poverty likelihoods. These estimates are independent of whatever targeting cut-off a program might set. In contrast, the targeting errors of undercoverage B and leakage C depend directly on the cut-off chosen. Thus, for scorecards that estimate poverty likelihoods, getting B close to C is not related to optimizing the accuracy of the estimated overall poverty rate and so is not related to the goals of BPAC.

7. Training, quality-control, and MIS

The technical aspects of scorecard construction and accuracy just discussed are important, but gaining the trust and acceptance of managers and field workers are even more important (Schreiner, 2002).

In particular, the field workers who collect indicators must be trained. If they put garbage in, the scorecards will put garbage out. To prevent abuse, on-going quality control of data is required.

Programs should record in their MIS at least the poverty likelihood along with an identifier for each client. Ideally, they would also record the score, the indicators, and the values of the indicators. This will allow quick computation of average poverty likelihoods (as well as other analyses), both for a point in time and for changes through time (Matul and Kline, 2003).

8. Calibrating the scorecard for the very poor

The scorecard in Figure 4 can be used to track outreach not only to the poor but also to the *very poor*, that is, the poorest half of the poor.

8.1 Poverty likelihoods

As before, scores are associated with the probability of being very poor by bootstrapping 10,000 samples from the first one-fourth hold-out sample. The poverty likelihood for a given score is then taken as the average of the shares of people with that score who are very poor across the 10,000 samples.

Columns 2–4 in Figure 17 are the poverty likelihoods for the three classes for all scores. For example, if a potential participant has a score of 0–4, the probability of being very poor is 82.2 percent, the probability of being poor is 6.2 percent, and the probability of being non-poor is 11.5 percent.

Columns 5–7 in Figure 17 are the share of targeted participants by poverty status and by cut-off. For example, for a cut-off of 25–29, 45.0 percent of those targeted would be very poor, 27.5 percent would be poor, and 27.5 percent would be non-poor.

Each person is associated with three poverty likelihoods. For example, a person with a score of 12 may be targeted as very poor, but the likelihood of truly being very poor is not 100 percent but rather 61.2 percent (from Figure 17). The same person has a 20.5-percent likelihood of being truly poor, and an 18-percent likelihood of being truly non-poor. Each person has one targeting status (for program purposes), one true poverty status (in reality), and three estimated poverty likelihoods (one for each possible poverty status).

As before, these poverty likelihoods are objective, that is, based on data. They are valid even though the scorecard was not constructed originally to predict the likelihood of being very poor. It works because the likelihood of being very poor is highly correlated with having a low score (high likelihood) of being poor. A scorecard could be built specifically for the very poor, but it would add cost and complexity.

Figure 18 shows the precision of estimated poverty likelihoods for being very poor as point estimates with 90-, 95-, and 99-percent confidence intervals. For example, the average poverty rate (the poverty likelihood) across bootstrap samples for people with scores of 25–29 was 32.9 percent. In 90 percent of 10,000 samples from the first one-fourth hold-out, the share was between 30.3–35.6 percent. In 95 percent of samples, the share was between 29.8–36.0, and in 99 percent of samples, the share was between

28.8–36.9. Weighting by the people in each score range, the average 90-percent confidence interval is ±2.1 percentage points, the 95-percent interval is ±2.4, and the 99-percent interval is ±3.2.

For estimated and true poverty likelihoods, Figure 19 depicts mean absolute differences and confidence intervals from 10,000 bootstrap samples on the second one-fourth hold-out sample. Weighting by the people in a score range, the mean absolute difference is 3.0 percentage points, with a 90-percent interval of ±2.4 percentage points, a 95-percent interval of ±2.9, and a 99-percent interval of ±3.7.

The other aspect of accuracy is how well the very poor are concentrated in low scores. An ROC curve is a useful way to look at this.

Figure 20 plots the share of the very poor against the share of the not very poor, ranked by score. For example, targeting the 20 percent of cases with the lowest scores would target 55 percent of all the very poor and 12 percent of all the not very poor.

In terms of the Kolmogorov-Smirnov statistic, the maximum distance between the curves is 53.2. In terms of the ratio of the area inside the scorecard curves to the area inside the trapezoid of a hypothetical perfect scorecard, the value is 68.7.

All in all, Figures 18–20 suggest that the estimated likelihoods of being very poor are estimated both accurately and precisely.

8.2 Overall poverty rates for the very poor

The average of estimated poverty likelihoods for a group is their estimated overall (very poor) poverty rate. To measure the accuracy and precision of this estimate, the scorecard was applied to 10,000 bootstrap replicates from the second one-fourth hold-out sample, and then the estimated overall poverty rates were compared with the true values. The mean difference was 1.07 percentage points, with a standard deviation of 0.33. The 90-percent confidence interval around the mean was ±0.6 percentage points, the 95-percent interval was ±0.7 percentage points, and the 99-percent interval was ±0.9 percentage points.

Thus, subtracting 1.07 percentage points from a group's average poverty likelihood would produce an unbiased estimate that, in 99 of 100 cases, would be within ±0.9 percentage points of the true overall (very poor) poverty rate. This estimate is both very accurate and precise.

8.3 Targeting the very poor

As before, targeting involves using a classification matrix and a net-benefit matrix to select a cut-off. The wrinkle is that there are now three poverty statuses:

- Very poor: Poorest half of those with expenditure at or below the poverty line
- Poor: Least-poor half of those with expenditure at or below poverty
- Non-poor: Expenditure above poverty

There are also three targeting segments:

- Very poor: Score at or below the very poor/poor cut-off
- Poor: Score above the very poor/poor cut-off and at or below the poor/non-poor cut-off
- Non-poor: Score above the poor/non-poor cut-off

There are two cut-offs (very poor/poor and poor/non-poor) and 9 classification results (Figure 21):

A. Truly very poor correctly classified as very poor

B. Truly very poor incorrectly classified as poor

C. Truly very poor incorrectly classified as non-poor

D. Truly poor incorrectly classified as very poor

E. Truly poor correctly classified as poor

F. Truly poor incorrectly classified as non-poor

G. Truly non-poor incorrectly classified as very poor

H. Truly non-poor incorrectly classified as poor

I. Truly non-poor correctly classified as non-poor

The general classification matrix (Figure 21) and the net-benefit matrix (Figure 22) are combined to define total net benefit:

Total net benefit $= \alpha \cdot A + \beta \cdot B + \gamma \cdot C + \delta \cdot D + \varepsilon \cdot E + \zeta \cdot F + \eta \cdot G + \theta \cdot H + \iota \cdot I$.

Figure 23 shows classification results for all possible pairs of cut-off scores in the second one-fourth hold-out sample from the 59^{th} Round of India's Socio-Economic Survey. For example, suppose a program defined the following:

- Very poor/poor cut-off of 15–19 (so scores of 0–19 are targeted as very poor)
- Poor/non-poor cut-off of 30–34 (so scores of 20–34 are targeted as poor, and scores of 35–100 are targeted as non-poor)

As with any scorecard and cut-offs, there is both successful targeting and errors. For the example cut-offs of 15–19 and 30–34, targeting would be correct for 34 percent of the very poor, 50 percent of the poor, and 78 percent of the non-poor (Figure 24).

The program chooses a set of cut-offs to optimize the benefits of correct classifications, net of the costs (negative benefits) of incorrect classifications. For example, suppose the net-benefit matrix is Figure 25, representing one way to reflect:

- Greater importance of correctly targeting the very poor and poor
- Greater cost of gross errors such as targeting the truly very poor as non-poor

Given the classification results in Figure 24 and net benefits in Figure 25, total net benefit (+676) for the cut-off pair of 15–19 and 30–34 are computed in Figure 26.

Is this the best pair of cut-offs? The answer requires applying the net-benefit matrix to the classification results for all 190 possible pairs of cut-offs (Figure 23). It turns out that total net benefit is highest (+694) for cut-offs of 15–19 and 25–29. Of course, this implies that only people with scores of 20–24 are targeted as poor, so another set of cut-offs (such as 15–19 and 30–34) may be preferred for this reason.

9. Conclusion

India has more poor people than any other country. An easy-to-use, inexpensive tool for identifying the poor could improve targeting and speed progress out of poverty. This paper presents the scorecard as a way to estimate the likelihood that a person has expenditure of less than $1/person/day.

The scorecard is built and tested using data from Schedule 1.0 of the 59th Round of India Socio-Economic Survey. The scorecard is calibrated to estimate the likelihood of being poor (expenditure less than $1/day) or very poor (poorest half of the poor).

Out-of-sample bootstrap tests show that the estimates are both accurate and precise. For individual poverty likelihoods (whether poor or very poor), estimates are within 6 percentage points of the true value with 90-percent confidence. For a group's overall poverty rate (again, whether poor or very poor), estimates are within 1 percentage point of the true value with 99-percent confidence.

For targeting, programs can use the classification results reported here to select the best choice of cut-off according to their values and mission.

Accuracy is important, but ease-of-use is even more important; a perfectly accurate scorecard is worthless if programs feel daunted by its complexity and so never even try to use it. For this reason, the scorecard here is kept simple, using 10 indicators that are inexpensive to collect and that are straightforward to observe and verify. Indicator weights are all zeros or positive integers, and scores range from 0 (most likely poor) to 100 (least likely poor). Scores are related to poverty likelihoods via a simple look-up table, and targeting cut-offs are also simple to apply. Thus, field workers not only can understand the scorecard, but they can also use it to compute scores in the field, by hand, in real time.

Overall, the scorecard can help Indian development programs to target services to the poor, track participants' progress out of poverty through time, and report on participants' overall poverty rate.

Appendix:
Adjusting the $1PPP Poverty Line for Cost-of-Living

Poverty lines were constructed using the following criteria:

- Follow the World Bank's $1/person/day (purchasing-power parity) line, as the poverty rates implied by India's official poverty line are unrealistically low (27.0 percent in urban India, and 23.5 percent in rural), and those of Deaton (2003) are even lower (9.5 percent urban, 21.6 percent rural)
- Account for rural/urban and state-wise cost-of-living
- Match the average of the rural and urban $1PPP lines to the all-India $1PPP line
- Match the ratio of rural to urban $1PPP lines to that same ratio for Deaton's lines

Basic inputs to the calculation include:

- $1PPP/person/day for all-India in 2003 is Rs453.65/person/month
- In 2003, 74.82 percent of the population was rural, and 25.18 percent was urban
- Deaton's (2003) all-urban poverty line for 2000 is Rs354.11/person/month for urban and Rs309.32 for rural

The population-weighted average of rural and urban $1PPP lines should match the all-India $1PPP line:

$$\text{Rs453.90} = (0.7482 \text{ x Rural \$1PPP line}) + (0.2518 \text{ x Urban \$1PPP line}).$$

Furthermore, the ratio of the two lines should match the ratio of Deaton's lines:

$$(\text{Rural \$1PPP line} \div \text{Urban \$1PPP line}) = \text{Rs309.32} \div \text{Rs354.11}.$$

Solving the algebra gives:

- Rural $1PPP line of Rs437.93/person/month
- Urban $1PPP line of Rs501.35/person/month

To account for cost-of-living, Deaton's (2003) state-wise lines for 2000 are then adjusted by the ratio of the rural or urban $1PPP line to Deaton's corresponding line. For both rural and urban areas, the adjustment factor is 1.41578.

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Figure 1: Households surveyed, people represented, and overall poverty rates

		All	
	Households	**People**	**% poor**
Constructing scorecards	20,345	488,499,660	37.7
Associating scores with likelihoods	10,387	250,311,643	37.6
Testing accuracy	10,265	242,156,618	36.7
Total:	40,997	980,967,921	37.4

Source: Calculations based on Schedule 1.0 of the 59th (2003) Rounds of India Socio-Economic Survey by the National Sample Survey Organization.

16 households were omitted because their very high weights (greater than 500,000 persons each) caused them to dominate some of the bootstrap tests. See Singh (1998).

Figure 2: Rural poverty lines (Rs/person/month), 2003

State	Official state-wise	Deaton-adjusted	$1/day adjusted
Andhra Pradesh	280.93	330.80	438.35
Assam	390.43	363.19	481.28
Bihar	355.86	317.18	420.30
Gujarat	340.76	360.39	477.57
Haryana	387.63	332.03	439.98
Himachal Pradesh	392.59	386.06	511.58
Karnataka	330.77	344.67	456.73
Kerala	400.43	399.52	529.42
Madhya Pradesh	332.64	308.65	409.00
Maharashtra	340.43	341.73	452.84
Orissa	346.08	320.88	425.22
Punjab	387.49	338.14	448.08
Rajasthan	367.57	346.08	458.60
Tamil Nadu	328.69	359.54	476.44
Uttar Pradesh	359.93	299.68	397.11
West Bengal	374.13	327.83	434.42

Source: Calculations based on Schedule 1.0 of the 59th (2003) Rounds of India Socio-Economic Survey by the National Sample Survey Organization.

The first two columns come from Table 5 in Deaton (2003), scaled by 1.068403 for rural price increases from 2000 to 2003. The last column is the Deaton-adjusted line scaled by 1.41578 (see Appendix). As in Deaton and Tarozzi (2000), the poverty line for Jammu and Kashmir is taken as that of Himachal Pradesh; Chandigarh is taken as Punjab; Uttaranchal as Uttar Pradesh; Dehli as Haryana; Sikkim, Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura, and Meghalaya to Assam; Jharkhand as Bihar; Chhattisgarh as Madhya Pradesh; Daman and Diu, Dadra and Nagar Haveli, and Goa as Maharashtra; Lakshadweep as Kerala; and Pondicherry and the Andaman and Nicobar Islands as Tamil Nadu.

Figure 3: Urban poverty lines (Rs/person/month), 2003

State	Official state-wise	Deaton-adjusted	$1/day adjusted
Andhra Pradesh	514.45	387.76	488.10
Assam	386.89	426.26	536.57
Bihar	427.14	361.75	455.37
Gujarat	533.58	415.43	522.93
Haryana	472.61	403.08	507.39
Himachal Pradesh	472.61	424.75	534.67
Karnataka	575.23	413.02	519.90
Kerala	536.55	434.40	546.82
Madhya Pradesh	541.72	361.36	454.88
Maharashtra	607.02	433.42	545.58
Orissa	532.13	351.29	442.20
Punjab	436.56	394.25	496.27
Rajasthan	524.03	397.19	499.98
Tamil Nadu	534.92	411.74	518.29
Uttar Pradesh	468.21	360.38	453.64
West Bengal	460.26	386.35	486.33
Delhi	568.49	450.37	566.92

Source: Calculations based on Schedule 1.0 of the 59th (2003) Rounds of India Socio-Economic Survey by the National Sample Survey Organization.

The first two columns are derived from Table 5 in Deaton (2003), scaled by 1.1247165 for urban price increases from 2000 to 2003. The last column is the Deaton-adjusted line scaled by 1.41578 (see Appendix).

Figure 4: Poverty indicators ranked by uncertainty coefficient

Uncertainty coefficient		Indicator (Responses ordered starting from the one most-closely linked with poverty)
1.	120	How many electric fans does the household own? (0; 1; 2; 3 or more)
2.	104	Does the household own a television? (No; Yes)
3.	96	In the past 30 days, did anyone in the household spend anything on telephone charges? (No; Yes)
4.	93	What is the highest grade completed by any household member? (Primary or less; Middle; Secondary; Higher secondary; More than higher secondary)
5.	91	How many *almirah* (dressing tables) does the household own? (0; 1; 2 or more)
6.	91	How many pressure cookers or pressure pans does the household own? (0; 1; 2 or more)
7.	90	How many young children aged 0 to 14 are in the household? (4 or more; 3; 2; 1; 0)
8.	87	What is the principle occupation of the household? (Agricultural labourers; Operators and labourers, bricklayers, and construction workers; Cultivators, farmers, fishers, hunters, loggers, or unknown; Sales workers, service workers, and transport-equipment operators; Professional, technical, clerical, administrative, managerial, executive, and teachers)
9.	85	What is the household's principle type of employment? (Agricultural labor; Non-ag labour; Self-employed, others, or unknown)
10.	85	How many children aged 0 to 17 are in the household? (4 or more; 3; 2; 1; 0)
11.	75	What is the household's primary energy source for cooking? (Firewood and chips, charcoal, dung cake, or no cooking arrangement; Electricity, coke, or coal; Kerosene, *gobar* gas, others, or unknown; LPG)
12.	70	Is the residence all pucca (burnt bricks, stone, cement, concrete, jackboard/cement-plastered reeds, timber, tiles, galvanised tin or asbestos cement sheets)? (No; Yes)
13.	70	Does the household own a refrigerator? (No; Yes)
14.	69	What is the household's primary energy source for lighting? (Kerosene, oil other than kerosene, candles, no lighting arrangement, or unknown; Electricity, gas, or others)
15.	67	Does the household own a stove? (No; Yes)
16.	67	What is the highest grade completed by the male head/spouse? (Not literate or unknown; Literate but primary or less; Middle or greater)
17.	66	Does the household own a motorcycle or scooter? (No; Yes)
18.	66	In the past 30 days, did anyone in the household buy any petrol? (No; Yes)
19.	64	What is the highest grade completed by the female head/spouse? (Not literate, literate without formal schooling, or unknown; Literate and with formal schooling of any level)
20.	63	In the past 12 months, did anyone in the household buy a newspaper or periodical? (No; Yes)
21.	61	In the past 30 days, did anyone in the household consume any liquid milk or *ghee*? (No; Yes)
22.	58	In the past 12 months, did anyone in the household buy leather boots or shoes? (No; Yes)
23.	57	What is the employment status of the male head/spouse? (Casual laborer; Self-employed; Unemployed, unpaid family worker, or no male head/spouse present; Salaried/wage employee)
24.	56	In the past 30 days, did anyone in the household buy a toothbrush, toothpaste, etc.? (No; Yes)
25.	54	In the past 30 days, did anyone in the household consume an apple? (No; Yes)

Source: Computed from Schedule 1.0 of the 59th Round of India's Socio-Economic Survey.

Figure 4 (cont.): Poverty indicators ranked by uncertainty coefficient

Uncertainty coefficient		Indicator (Responses ordered starting from the one most-closely linked with poverty)
26.	51	What is the social group (caste) of the household? (Scheduled tribe; Scheduled caste; Other backward class; Others)
27.	49	Does the household own any tape recorders or CD players? (No; Yes)
28.	49	How many children aged 6 to 17 attend school? (Not all children attend school; There are no children; All children attend school)
29.	47	How many hectares of land does the household own? (Urban, any amount; Rural, 0 to 0.4; Rural, 0.41 to 2; Rural, >2)
30.	46	How many chairs, stools, benches, and tables does the household own? (0; 1 or 2; 3 or 4; 5 or more)
31.	44	Does the household own a sewing machine? (No; Yes)
32.	42	What is the sector of the usual principle activity of the male head/spouse? (Agriculture, hunting, forestry, fishing, mining, or construction; Manufacturing, wholesale and retail trade, transport, storage, communications, other, unknown, or no male head/spouse present; Education, health, social work, public administration and defense)
33.	39	In the past 30 days, did anyone in the household spend anything on conveyance (Bus/tram, taxi, auto-rickshaw, hand-drawn or cycle rickshaw, horse-cart, school bus/van)? (No; Yes)
34.	38	In the past 30 days, did anyone in the household consume a banana? (No; Yes)
35.	37	Does anyone in the household have salaried employment? (No; Yes)
36.	37	In what type of area does the household reside? (Rural; urban)
37.	37	In the past 30 days, did anyone in the household spend anything on entertainment (Cinema, theatre, *mela*, fair, picnic, sports goods, toys, clubs fees, goods for recreation, hobbies, photography, video cassette/V.C.R. (hire), and other entertainment)? (No; Yes)
38.	34	Does the household own an air conditioner or air cooler? (No; Yes)
39.	31	In the past 30 days, did the household consume any lemons? (No; Yes)
40.	30	In the past 30 days, did the household consume any *suji* or *rawa*? (No; Yes)
41.	28	In the past 30 days, did the household consume any *moong*? (No; Yes)
42.	28	In the past 30 days, did the household buy any bread from a bakery? (No; Yes)
43.	28	In the past 30 days, did the household consume any tea (leaf)? (No; Yes)
44.	25	In the past 30 days, did the household use any sanitary napkins? (No; Yes)
45.	24	In the past 30 days, did the household consume any tomatoes? (No; Yes)
46.	22	What is the household's tenancy of its dwelling? (Owned, others or no dwelling unit; Hired)
47.	21	In the past 30 days, did the household consume any *gram* (whole or split)? (No; Yes)
48.	22	In the past 30 days, did the household consume any *besan*? (No; Yes)
49.	18	In the past 12 months, did the household buy any bed sheets or bed covers? (No; Yes)
50.	7	In the past 30 days, did the household pay for the services of a doctor or surgeon? (No; Yes)

Source: Computed from Schedule 1.0 of the 59th Round of India's Socio-Economic Survey.

Figure 5: Scorecard

Indicator		Values						Points
1.	How many children aged 0 to 17 are in the household?	≥5	4	3	2	1	Zero	
		0	8	11	17	22	31	
2.	What is the household's primary energy source for cooking?				Firewood and chips, charcoal, or none		Any other fuel	
					0		8	
3.	Does the household own a television?					No	Yes	
						0	4	
4.	How many hectares of land does the household own?			Urban, any amount	Rural, 0 to 0.4	Rural, 0.41 to 2	Rural, >2	
				0	4	7	10	
5.	What is the principal occupation of the household?		Agricultural labourers	Operators and labourers, bricklayers, construction workers	Cultivators, farmers, fishers, hunters, loggers, unknown	Sales workers, service workers, transport-equipment operators	Professional, technical, clerical, administrative, managerial, executive, teachers	
			0	6	8	11	13	
6.	How many almirah/dressing tables does the household own?				None	One	Two or more	
					0	2	9	
7.	Is the residence all pucca (burnt bricks, stone, cement, concrete, jackboard/cement-plastered reeds, timber, tiles, galvanised tin or asbestos cement sheets)?					No	Yes	
						0	5	
8.	Does the household own a pressure cooker or pressure pan?					No	Yes	
						0	5	
9.	Does the household own a sewing machine?					No	Yes	
						0	6	
10.	How many electric fans does the household own?				None	One or two	Three or more	
					0	5	10	
Source: Calculations based on Schedule 1.0 of the 59th Round (2003) of India's Socio-Economic Survey (NSSO, 2005).							Total:	

Figure 6: Scores and poverty likelihoods

Score	Poverty likelihood for people with score in range (%)	% of people <=score who are poor	% of people >score who are non-poor
0-4	88.5	88.5	61.8
5-9	96.3	91.8	62.2
10-14	81.7	85.7	63.4
15-19	82.0	83.5	66.8
20-24	73.6	78.7	71.9
25-29	60.6	72.5	77.1
30-34	52.8	67.9	82.1
35-39	39.0	62.2	86.5
40-44	36.3	58.3	92.0
45-49	22.1	54.0	95.6
50-54	5.2	49.5	95.9
55-59	6.6	46.1	96.8
60-64	6.8	44.1	98.1
65-69	3.6	42.1	99.0
70-74	2.8	40.8	100.0
75-79	0.0	39.8	100.0
80-84	0.0	39.1	100.0
85-89	0.0	38.8	100.0
90-94	0.0	38.7	100.0
95-100	0.0	38.7	0.0

Surveyed cases weighted to represent all India.
Source: Calculations based on Schedule 1.0 of the 59th Round (2003) of India's Socio-Economic Survey (NSSO, 2005).

Figure 7: Confidence intervals for estimated poverty likelihoods associated with scores

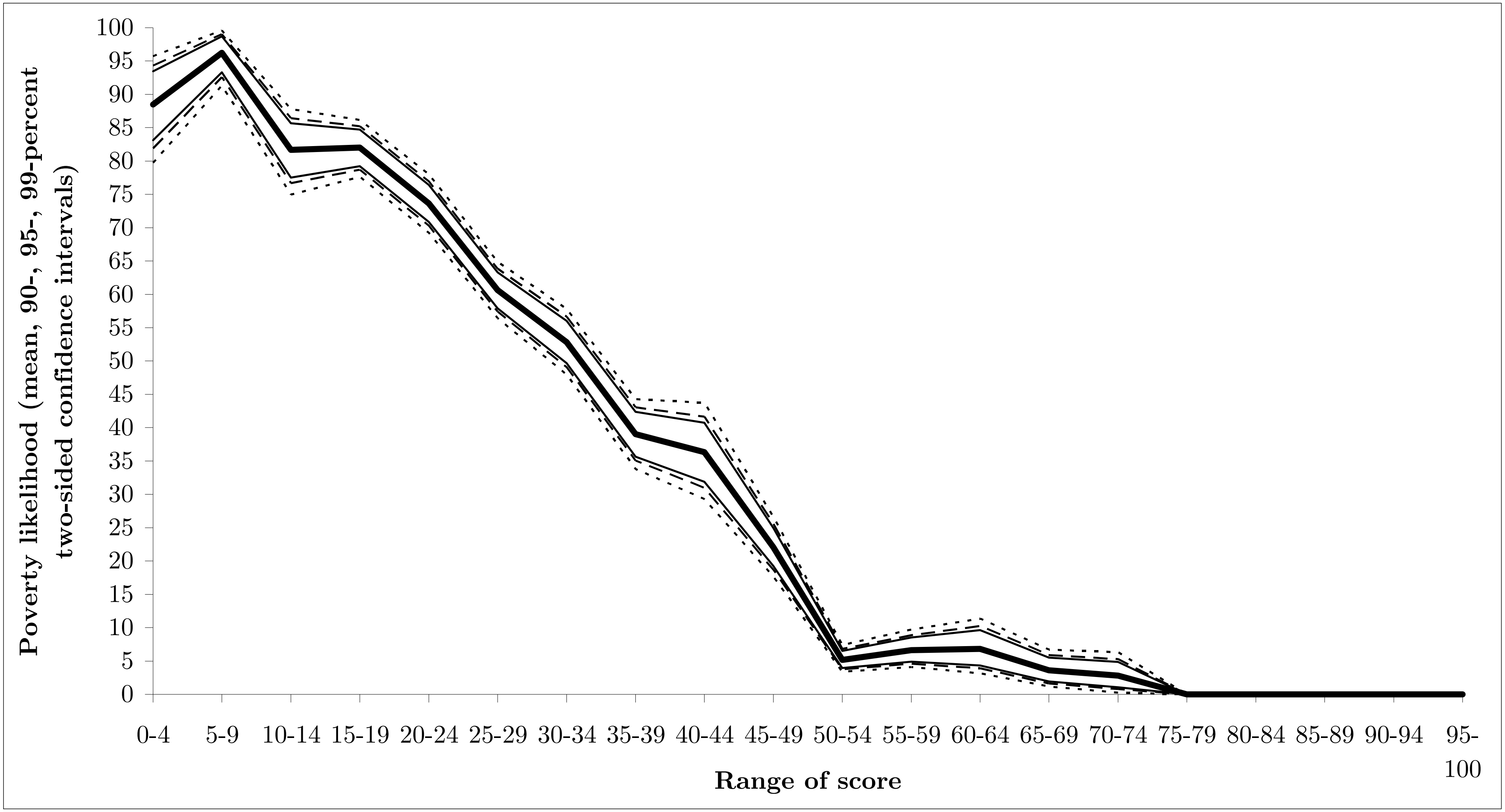

Figure 8: Differences between estimated and true poverty likelihoods

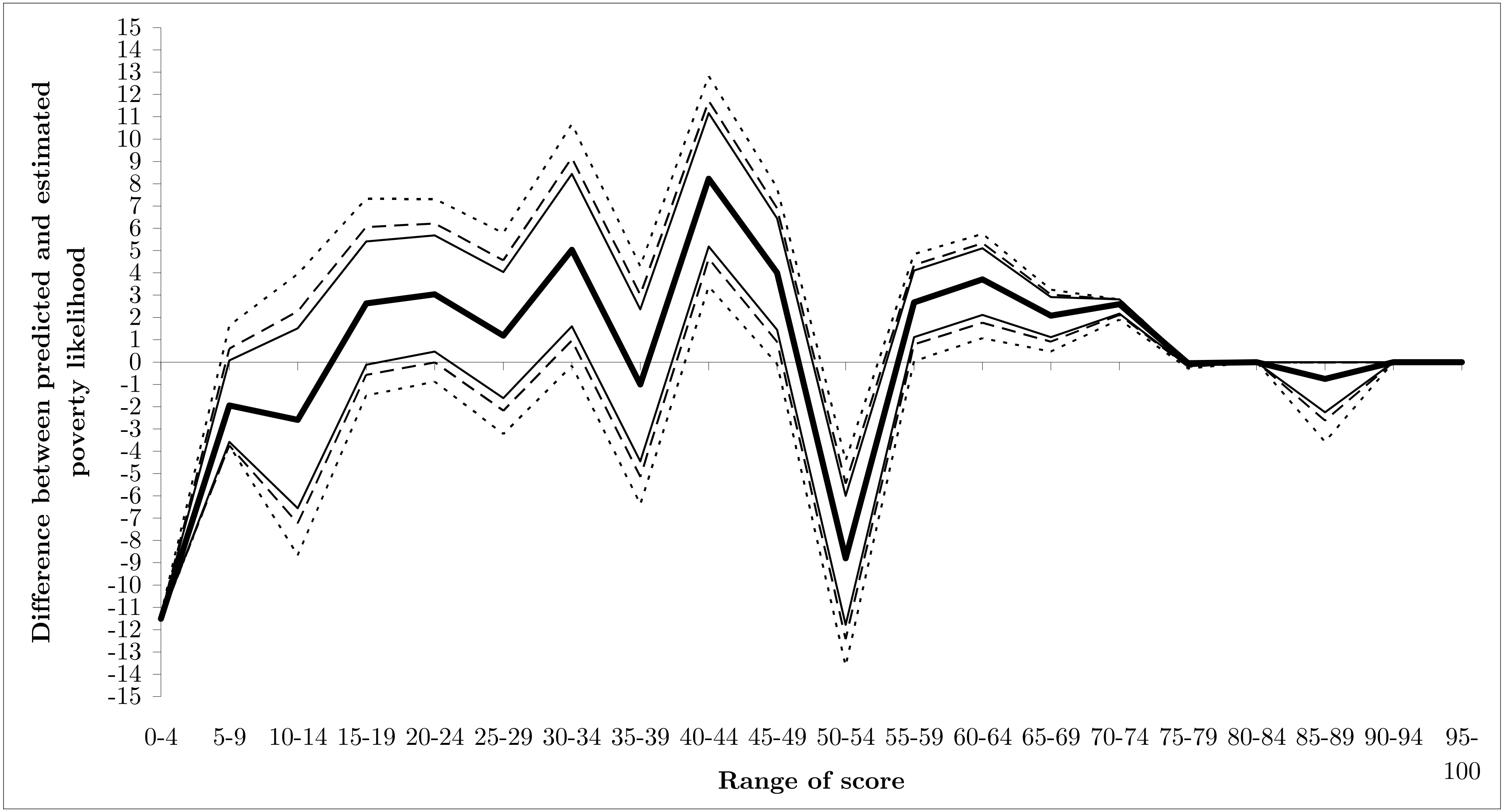

Figure 9: ROC curve of ability to rank-order households by poverty status

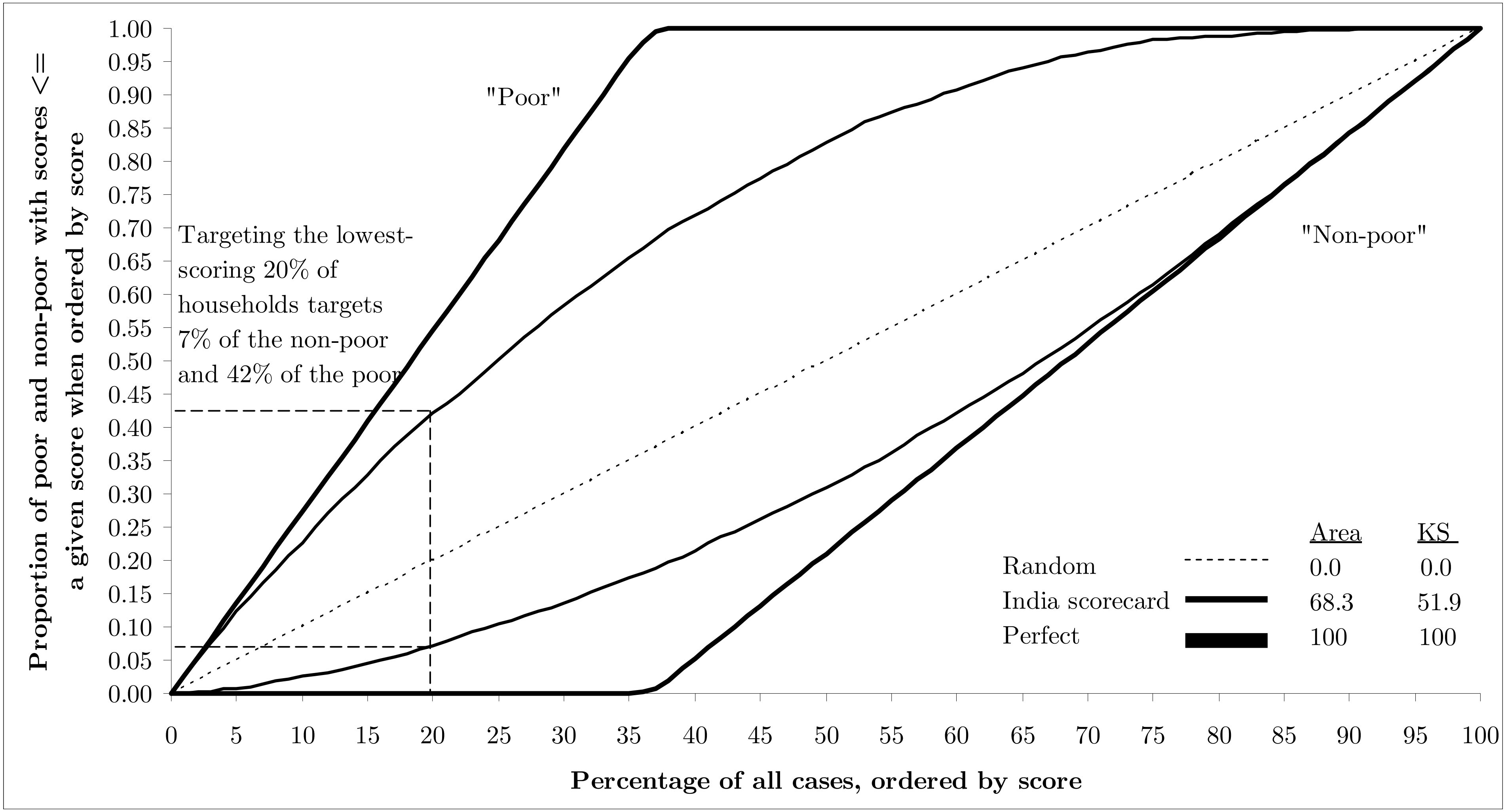

Figure 10: General classification matrix

		Targeting segment	
		Targeted	**Non-targeted**
True poverty status	**Poor**	**A.** Truly poor correctly targeted	**B.** Truly poor mistakenly non-targeted
	Non-poor	**C.** Truly non-poor mistakenly targeted	**D.** Truly non-poor correctly non-targeted

Figure 11: People by targeting classification and score

Score	A. Truly poor correctly targeted	B. Truly poor mistakenly non-targeted	C. Truly non-poor mistakenly targeted	D. Truly non-poor correctly non-targeted
0-4	0.9	37.8	0.1	61.2
5-9	1.5	37.1	0.1	61.2
10-14	3.7	35.0	0.6	60.7
15-19	9.0	29.7	1.8	59.5
20-24	16.5	22.2	4.5	56.9
25-29	23.1	15.6	8.7	52.6
30-34	28.2	10.5	13.3	48.0
35-39	32.2	6.5	19.5	41.8
40-44	35.5	3.1	25.4	35.9
45-49	37.3	1.3	31.7	29.6
50-54	37.7	1.0	38.4	22.9
55-59	38.1	0.5	44.6	16.7
60-64	38.4	0.3	48.6	12.7
65-69	38.6	0.1	53.1	8.3
70-74	38.7	0.0	56.0	5.3
75-79	38.7	0.0	58.6	2.7
80-84	38.7	0.0	60.2	1.2
85-89	38.7	0.0	61.0	0.4
90-94	38.7	0.0	61.3	0.0
95-100	38.7	0.0	61.3	0.0

Figures normalized to sum to 100.

Source: Calculations based on Schedule 1.0 of the 59th Round (2003) of India's Socio-Economic Survey (NSSO, 2005).

Figure 12: General net-benefit matrix

True poverty status	Targeting segment: Targeted	Targeting segment: Non-targeted
Poor	α	β
Non-poor	γ	δ

Figure 13: "Total Accuracy" net-benefit matrix

True poverty status	Targeting segment: Targeted	Targeting segment: Non-targeted
Poor	1	0
Non-poor	0	1

Figure 14: Total net benefit for some common net-benefit matrices

	Total Accuracy (A + B)		Poverty Accuracy 100*A / (A+B)		Non-poverty Accuracy 100*D / (C+D)		Undercoverage 100*B / (A+B)		Leakage 100*C / (A+C)	
	1	0	1	0	0	0	0	-1	0	0
Score	0	1	0	0	0	1	0	0	-1	0
0-4	62.1		2.2		99.8		97.8		11.5	
5-9	62.7		4.0		99.8		96.0		8.2	
10-14	64.4		9.5		99.0		90.5		14.3	
15-19	68.6		23.3		97.1		76.7		16.5	
20-24	73.4		42.7		92.7		57.3		21.3	
25-29	75.7		59.7		85.8		40.3		27.5	
30-34	76.2		72.9		78.3		27.1		32.1	
35-39	74.0		83.2		68.1		16.8		37.8	
40-44	71.4		91.9		58.5		8.1		41.7	
45-49	66.9		96.5		48.3		3.5		46.0	
50-54	60.6		97.5		37.4		2.5		50.5	
55-59	54.9		98.6		27.3		1.4		53.9	
60-64	51.1		99.3		20.7		0.7		55.9	
65-69	46.8		99.8		13.5		0.2		57.9	
70-74	44.0		100.0		8.7		0.0		59.2	
75-79	41.4		100.0		4.5		0.0		60.2	
80-84	39.8		100.0		1.9		0.0		60.9	
85-89	39.0		100.0		0.6		0.0		61.2	
90-94	38.7		100.0		0.0		0.0		61.3	
95-100	38.7		100.0		0.0		0.0		61.3	

All figures in percentage units.

Figure 15: “Poverty Accuracy” net-benefit matrix

		Targeting segment	
		Targeted	Non-targeted
True poverty status	Poor	1	0
	Non-poor	0	0

Figure 16: Net-benefit matrix for BPAC

True poverty status	Targeting segment: Targeted	Targeting segment: Non-targeted
Poor	1	1
Non-poor	-1	0

Figure 17: Poverty likelihoods for the very poor, poor, and non-poor by score

	Poverty likelihood in score range			Share of cases <= score		
Score	**Very Poor**	**Poor**	**Non-poor**	**Very Poor**	**Poor**	**Non-poor**
0-4	82.2	6.2	11.5	82.2	6.2	11.5
5-9	67.5	28.8	3.8	75.9	15.9	8.2
10-14	61.2	20.5	18.3	67.0	18.7	14.3
15-19	60.4	21.6	18.0	63.0	20.4	16.5
20-24	38.8	34.8	26.4	51.3	27.4	21.3
25-29	32.9	27.7	39.4	45.0	27.5	27.5
30-34	23.9	28.9	47.2	40.1	27.8	32.1
35-39	18.4	20.7	61.0	35.8	26.4	37.8
40-44	6.9	29.5	63.7	31.4	26.9	41.7
45-49	6.7	15.4	77.9	28.5	25.5	46.0
50-54	1.1	4.1	94.8	26.0	23.5	50.5
55-59	0.5	6.1	93.4	23.9	22.1	53.9
60-64	0.2	6.6	93.2	22.8	21.4	55.9
65-69	0.0	3.6	96.4	21.6	20.5	57.9
70-74	0.0	2.8	97.2	20.9	19.9	59.2
75-79	0.0	0.0	100.0	20.4	19.4	60.2
80-84	0.0	0.0	100.0	20.0	19.1	60.9
85-89	0.0	0.0	100.0	19.9	18.9	61.2
90-94	0.0	0.0	100.0	19.8	18.9	61.3
95-100	0.0	0.0	100.0	19.8	18.9	61.3

Figure 18: Confidence intervals for estimated poverty likelihoods for being very poor associated with scores

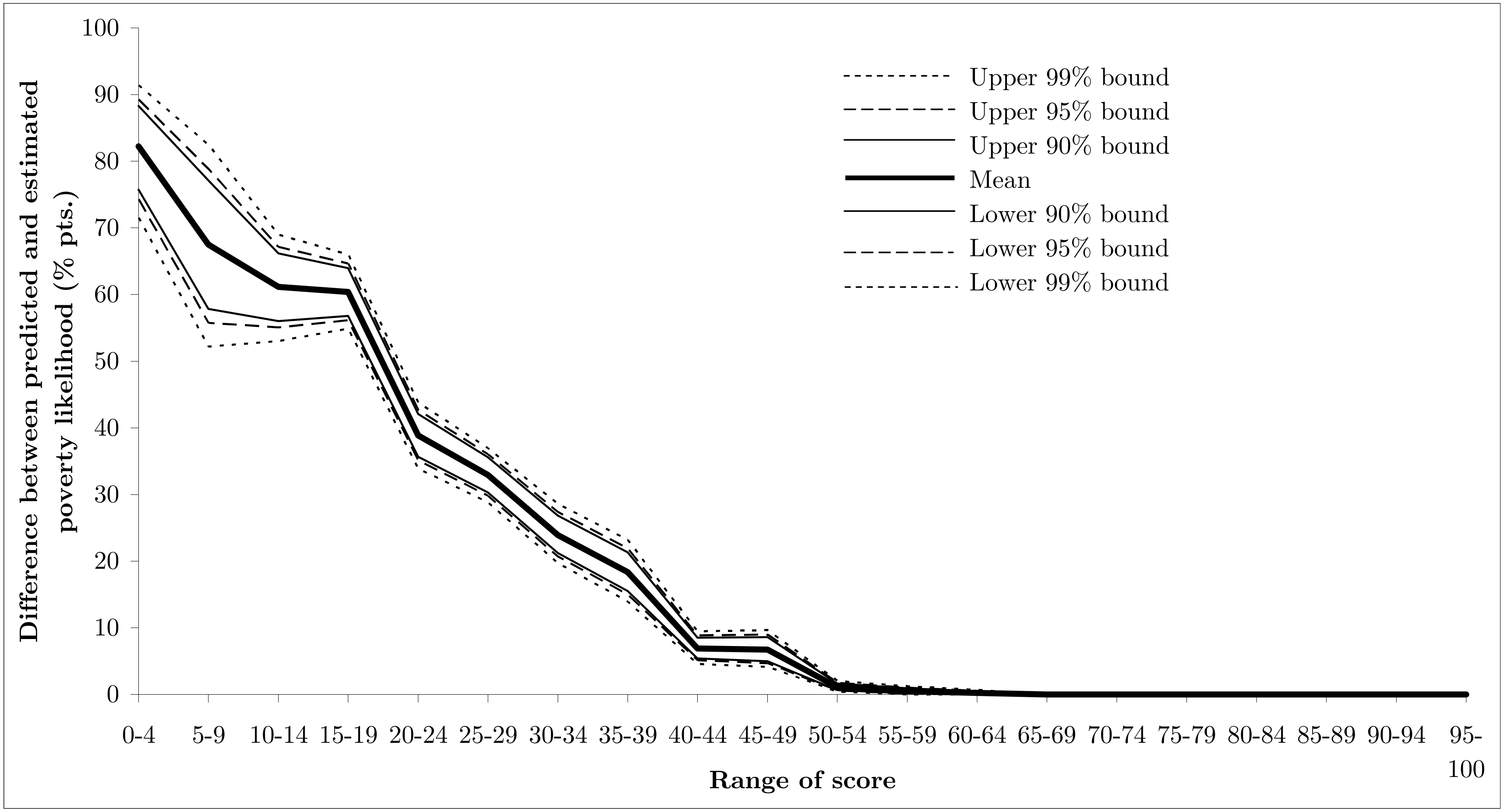

Figure 19: Differences between estimated and true poverty likelihoods for the very poor

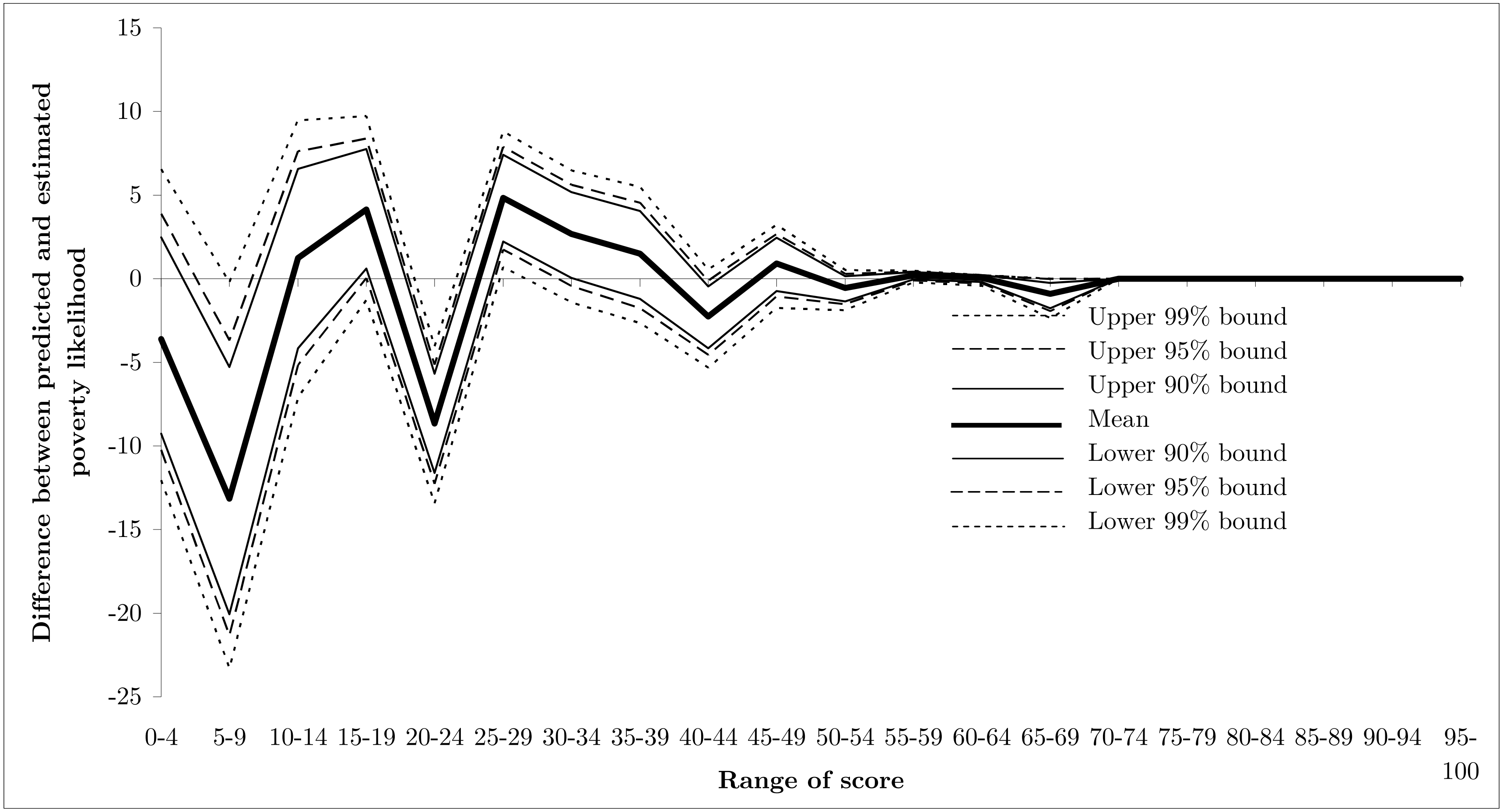

Figure 20: ROC curve of ability to rank-order households by very poor versus not very poor poverty status

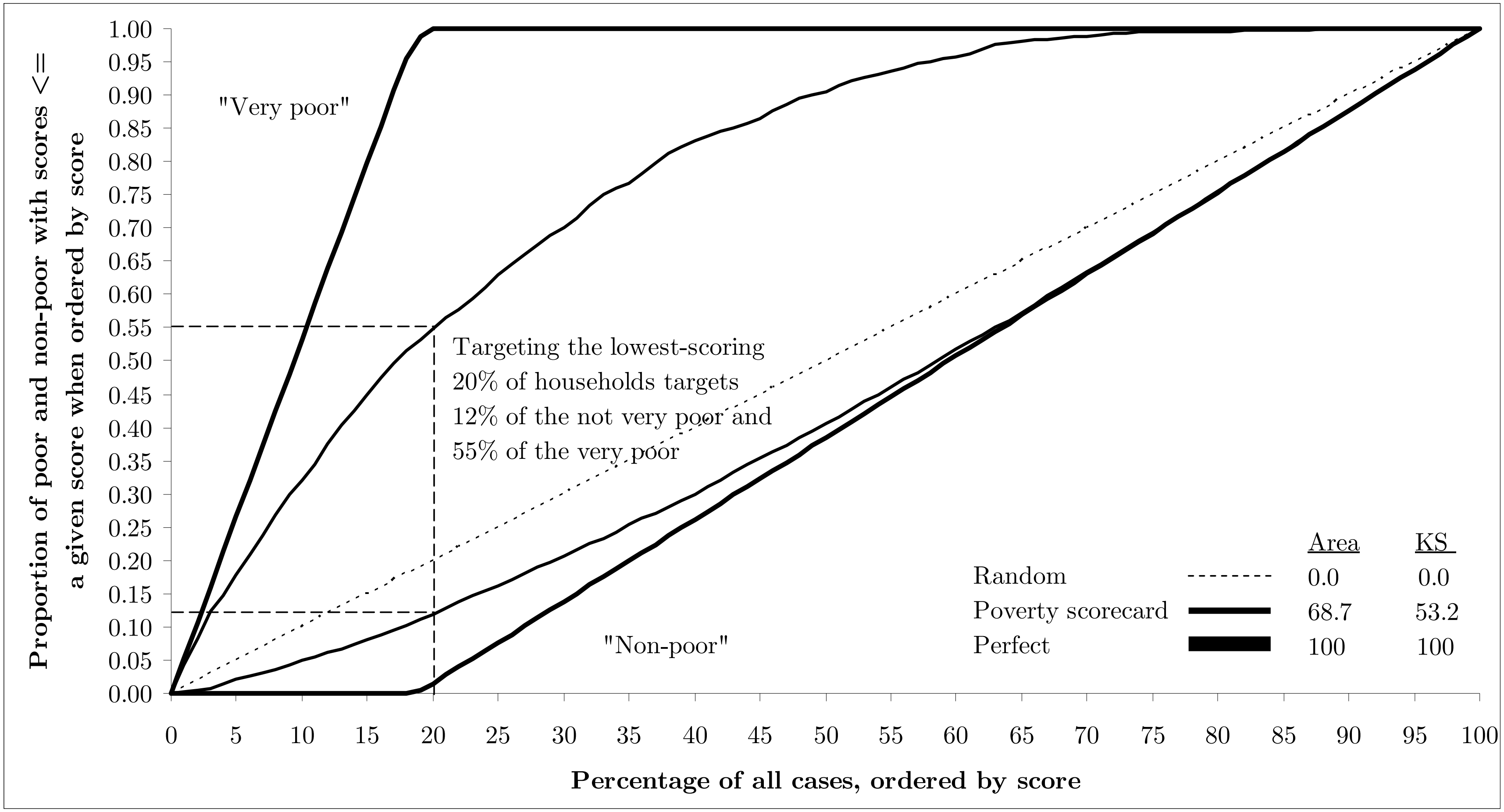

Figure 21: Classification matrix, three segments

True poverty status	Targeting segment: Very Poor	Targeting segment: Poor	Targeting segment: Non-poor
Very Poor	A. Truly very poor correctly targeted as very poor	B. Truly very poor incorrectly targeted as poor	C. Truly very poor incorrectly targeted as non-poor
Poor	D. Truly poor incorrectly targeted as very poor	E. Truly poor correctly targeted as poor	F. Truly poor incorrectly targeted as non-poor
Non-poor	G. Truly non-poor incorrectly targeted as very poor	H. Truly non-poor incorrectly targeted as poor	I. Truly non-poor correctly targeted as poor

Figure 22: Net-benefit matrix, three segments

		Targeting segment		
		Very Poor	Poor	Non-poor
True poverty status	Very Poor	α	β	γ
	Poor	δ	ε	ζ
	Non-poor	η	θ	ι

Figure 23: Classification results, very poor/poor cut-offs from 0 to 44 and poor/non-poor cut-offs from 5 to 49

	Lower bound, non-poor segment								
Upper bound, very poor segment	**5-9**			**10-14**			**15-19**		
0-4	19	1	3	19	1	3	19	1	3
	0	0	0	12	5	1	50	18	12
	461	455	1,483	449	450	1,482	410	437	1,470
5-9				31	6	3	31	6	3
				0	0	0	39	13	12
				449	450	1,482	410	437	1,470
10-14							70	19	15
							0	0	0
							410	437	1,470
15-19									
20-24									
25-29									
30-34									
35-39									
40-44									
45-49									

	Lower bound, non-poor segment								
Upper bound, very poor segment	**20-24**			**25-29**			**30-34**		
0-4	19	1	3	19	1	3	19	1	3
	146	52	41	241	138	105	328	210	209
	315	403	1,442	219	317	1,377	133	245	1,274
5-9	31	6	3	31	6	3	31	6	3
	134	47	40	229	133	105	316	205	208
	315	403	1,442	219	317	1,377	133	245	1,274
10-14	70	19	15	70	19	15	70	19	15
	95	34	28	191	120	93	277	192	197
	315	403	1,442	219	317	1,377	133	245	1,274
15-19	165	53	43	165	53	43	165	53	43
	0	0	0	96	86	65	182	158	168
	315	403	1,442	219	317	1,377	133	245	1,274
20-24				260	139	108	260	139	108
				0	0	0	86	73	103
				219	317	1,377	133	245	1,274
25-29							347	212	212
							0	0	0
							133	245	1,274
30-34									
35-39									
40-44									
45-49									

	Lower bound, non-poor segment								
Upper bound, very poor segment	**35-39**			**40-44**			**45-49**		
0-4	19	1	3	19	1	3	19	1	3
	384	278	319	429	329	471	445	395	614
	77	177	1,163	31	126	1,012	16	60	869
5-9	31	6	3	31	6	3	31	6	3
	372	273	319	417	324	470	433	390	613
	77	177	1,163	31	126	1,012	16	60	869
10-14	70	19	15	70	19	15	70	19	15
	333	260	307	379	311	458	394	377	601
	77	177	1,163	31	126	1,012	16	60	869
15-19	165	53	43	165	53	43	165	53	43
	238	226	279	284	277	430	299	343	573
	77	177	1,163	31	126	1,012	16	60	869
20-24	260	139	108	260	139	108	260	139	108
	142	140	214	188	192	365	203	258	508
	77	177	1,163	31	126	1,012	16	60	869
25-29	347	212	212	347	212	212	347	212	212
	56	68	110	102	119	262	117	185	405
	77	177	1,163	31	126	1,012	16	60	869
30-34	403	280	322	403	280	322	403	280	322
	0	0	0	46	51	151	61	117	294
	77	177	1,163	31	126	1,012	16	60	869
35-39				448	331	473	448	331	473
				0	0	0	15	66	143
				31	126	1,012	16	60	869
40-44							464	397	616
							0	0	0
							16	60	869
45-49									

Figure 23 (cont.): Classification results, very poor/poor cut-offs from 0 to 49 and poor/non-poor cut-offs from 50 to 100

Upper bound, very poor segment	Lower bound, non-poor segment														
	50-54			55-59			60-64			65-69			70-74		
0-4	19	1	3	19	1	3	19	1	3	19	1	3	19	1	3
	458	425	766	460	432	928	460	442	1,077	461	449	1,174	461	453	1,283
	3	30	717	1	23	555	0	13	405	0	6	308	0	2	200
5-9	31	6	3	31	6	3	31	6	3	31	6	3	31	6	3
	446	420	765	448	427	927	449	437	1,076	449	444	1,174	449	448	1,282
	3	30	717	1	23	555	0	13	405	0	6	308	0	2	200
10-14	70	19	15	70	19	15	70	19	15	70	19	15	70	19	15
	407	407	754	409	414	916	410	424	1,065	410	431	1,162	410	435	1,270
	3	30	717	1	23	555	0	13	405	0	6	308	0	2	200
15-19	165	53	43	165	53	43	165	53	43	165	53	43	165	53	43
	312	373	725	314	380	887	315	390	1,037	315	397	1,134	315	401	1,242
	3	30	717	1	23	555	0	13	405	0	6	308	0	2	200
20-24	260	139	108	260	139	108	260	139	108	260	139	108	260	139	108
	217	288	660	218	295	822	219	304	972	219	311	1,069	219	315	1,177
	3	30	717	1	23	555	0	13	405	0	6	308	0	2	200
25-29	347	212	212	347	212	212	347	212	212	347	212	212	347	212	212
	130	215	557	132	222	719	133	232	868	133	239	965	133	243	1,074
	3	30	717	1	23	555	0	13	405	0	6	308	0	2	200
30-34	403	280	322	403	280	322	403	280	322	403	280	322	403	280	322
	74	147	446	76	154	608	77	164	758	77	171	855	77	175	963
	3	30	717	1	23	555	0	13	405	0	6	308	0	2	200
35-39	448	331	473	448	331	473	448	331	473	448	331	473	448	331	473
	29	96	295	30	103	457	31	113	606	31	120	704	31	124	812
	3	30	717	1	23	555	0	13	405	0	6	308	0	2	200
40-44	464	397	616	464	397	616	464	397	616	464	397	616	464	397	616
	13	30	152	15	37	314	16	47	464	16	54	561	16	58	669
	3	30	717	1	23	555	0	13	405	0	6	308	0	2	200
45-49	477	427	768	477	427	768	477	427	768	477	427	768	477	427	768
	0	0	0	2	7	162	3	17	311	3	24	409	3	28	517
	3	30	717	1	23	555	0	13	405	0	6	308	0	2	200

Upper bound, very poor segment	Lower bound, non-poor segment														
	75-79			80-84			85-89			90-94			95-100		
0-4	19	1	3	19	1	3	19	1	3	19	1	3	19	1	3
	461	455	1,354	461	455	1,416	461	455	1,455	461	455	1,473	461	455	1,482
	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
5-9	31	6	3	31	6	3	31	6	3	31	6	3	31	6	3
	449	450	1,353	449	450	1,416	449	450	1,454	449	450	1,473	449	450	1,481
	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
10-14	70	19	15	70	19	15	70	19	15	70	19	15	70	19	15
	410	437	1,341	410	437	1,404	410	437	1,442	410	437	1,461	410	437	1,470
	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
15-19	165	53	43	165	53	43	165	53	43	165	53	43	165	53	43
	315	403	1,313	315	403	1,376	315	403	1,414	315	403	1,433	315	403	1,441
	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
20-24	260	139	108	260	139	108	260	139	108	260	139	108	260	139	108
	219	317	1,248	219	317	1,311	219	317	1,349	219	317	1,368	219	317	1,376
	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
25-29	347	212	212	347	212	212	347	212	212	347	212	212	347	212	212
	133	245	1,145	133	245	1,207	133	245	1,246	133	245	1,265	133	245	1,273
	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
30-34	403	280	322	403	280	322	403	280	322	403	280	322	403	280	322
	77	177	1,034	77	177	1,097	77	177	1,135	77	177	1,154	77	177	1,163
	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
35-39	448	331	473	448	331	473	448	331	473	448	331	473	448	331	473
	31	126	883	31	126	946	31	126	984	31	126	1,003	31	126	1,011
	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
40-44	464	397	616	464	397	616	464	397	616	464	397	616	464	397	616
	16	60	740	16	60	803	16	60	841	16	60	860	16	60	868
	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
45-49	477	427	768	477	427	768	477	427	768	477	427	768	477	427	768
	3	30	588	3	30	651	3	30	689	3	30	708	3	30	716
	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1

Figure 23 (cont.): Classification results, very poor/poor cut-offs from 50 to 94 and poor/non-poor cut-offs from 55 to 100

Upper bound, very poor segment / Lower bound, non-poor segment	55-59			60-64			65-69			70-74			75-79			80-84			85-89			90-94			95-100		
50-54	479	434	930	479	434	930	479	434	930	479	434	930	479	434	930	479	434	930	479	434	930	479	434	930	479	434	930
	0	0	0	1	10	149	1	17	247	1	21	355	1	23	426	1	23	488	1	23	527	1	23	546	1	23	554
	1	23	555	0	13	405	0	6	308	0	2	200	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
55-59				480	444	1,080	480	444	1,080	480	444	1,080	480	444	1,080	480	444	1,080	480	444	1,080	480	444	1,080	480	444	1,080
				0	0	0	0	7	97	0	11	206	0	13	276	0	13	339	0	13	378	0	13	396	0	13	405
				0	13	405	0	6	308	0	2	200	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
60-64							480	450	1,177	480	450	1,177	480	450	1,177	480	450	1,177	480	450	1,177	480	450	1,177	480	450	1,177
							0	0	0	0	4	108	0	6	179	0	6	242	0	6	280	0	6	299	0	6	308
							0	6	308	0	2	200	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
65-69										480	455	1,285	480	455	1,285	480	455	1,285	480	455	1,285	480	455	1,285	480	455	1,285
										0	0	0	0	2	71	0	2	134	0	2	172	0	2	191	0	2	199
										0	2	200	0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
70-74													480	457	1,356	480	457	1,356	480	457	1,356	480	457	1,356	480	457	1,356
													0	0	0	0	0	63	0	0	101	0	0	120	0	0	128
													0	0	129	0	0	66	0	0	28	0	0	9	0	0	1
75-79																480	457	1,419	480	457	1,419	480	457	1,419	480	457	1,419
																0	0	0	0	0	38	0	0	57	0	0	66
																0	0	66	0	0	28	0	0	9	0	0	1
80-84																			480	457	1,457	480	457	1,457	480	457	1,457
																			0	0	0	0	0	19	0	0	27
																			0	0	28	0	0	9	0	0	1
85-89																						480	457	1,476	480	457	1,476
																						0	0	0	0	0	8
																						0	0	9	0	0	1
90-94																									480	457	1,485
																									0	0	0
																									0	0	1

Figure 24: Classification results, very poor 0–19, poor 20–34, and non-poor 35–100

Targeting Segment	Score	Very Poor		Poor		Non-poor	
Very poor 0-19	0-4	**165** **34%**	19	**53** **12%**	1	**44** **3%**	3
	5-9		12		5		1
	10-14		39		13		12
	15-19		95		34		28
Poor 20-34	20-24	**238** **50%**	96	**227** **50%**	86	**278** **18%**	65
	25-29		86		73		103
	30-34		56		68		110
Non-poor 35-100	35-39	**77** **16%**	46	**177** **39%**	51	**1,162** **78%**	151
	40-44		15		66		143
	45-49		13		30		152
	50-54		2		7		162
	55-59		1		10		149
	60-64		0		7		97
	65-69		0		4		108
	70-74		0		2		71
	75-79		0		0		63
	80-84		0		0		38
	85-89		0		0		19
	90-94		0		0		8
	95-100		0		0		1
	Total:	480		457		1,485	

People with score in range (column group heading).

Note: Figures in units of 100,000 people

Figure 25: An example net-benefit matrix reflecting common values

True poverty status	Targeting segment: Very Poor	Targeting segment: Poor	Targeting segment: Non-poor
Very Poor	+3	-2	-6
Poor	-1	+2	-2
Non-poor	-2	-1	+1

Note: This is an example. Each program should define its own net-benefit matrix.

Figure 26: Computation of total net benefit for a cut-off pair of 15–19 and 30–34

Cell			Persons	Net benefit/person	Net benefit
A.	Truly very poor	as very poor	165	+3	+495
B.	Truly very poor	as poor	238	–1	–238
C.	Truly very poor	as non-poor	77	–2	–154
D.	Truly poor	as very poor	53	–2	–106
E.	Truly poor	as poor	227	+2	+454
F.	Truly poor	as non-poor	117	–1	–117
G.	Truly non-poor	as very poor	44	–6	–264
H.	Truly non-poor	as poor	278	–2	–556
I.	Truly non-poor	as non-poor	1,162	+1	+1,162
				Total net benefit:	+676

Note: Persons are counted in units of 100,000.