Simple Poverty Scorecard® Poverty-Assessment Tool Philippines

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This document and related tools are at `SimplePovertyScorecard.com`

Abstract

The Simple Poverty Scorecard®-brand poverty-assessment tool uses ten low-cost indicators from the Philippines' 2002 Annual Poverty Indicators Survey to estimate the likelihood that a household has income 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 the Philippines to measure poverty rates, to track changes in poverty rates over time, and to segment clients for targeted services.

Version note

This version replaces that of April 27, 2007, which, due to an incorrect Purchase Power Parity conversion factor, used an incorrect $2/day line. The correct $2/day line turns out to be almost the same as the "very poor" line defining the poorest half below the national poverty line. The $3/day line, in turn, is almost exactly the national poverty line. Therefore, this version reports on the $4/day line. These changes affect Section 8 and Figures 26–29; everything else is unchanged. Organizations that have applied the scorecard here should simply discard their $2/day figures and associate their existing scores with the correct poverty likelihoods for $4/day, using Figure 26.

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Simple Poverty Scorecard® Poverty-Assessment Tool

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

Indicator	Response	Points	Score
1. How many people in the family are aged 0 to 17?	A. Five or more	0	
	B. Three, or four	7	
	C. One, or two	16	
	D. None	27	
2. Does the family own a gas stove or gas range?	A. No	0	
	B. Yes	13	
3. How many television sets does the family own?	A. None	0	
	B. One	9	
	C. Two or more	18	
4. What are the house's outer walls made of?	A. Light (*cogon*, *nipa*, or *sawali*, bamboo, *anahaw*)	0	
	B. Strong (iron, aluminum, tile, concrete, brick, stone, wood, asbestos)	4	
5. How many radios does the family own?	A. None	0	
	B. One	3	
	C. Two or more	10	
6. Does the family own a *sala* set?	A. No	0	
	B. Yes	9	
7. What is the house's roof made of?	A. Light materials (Salvaged, makeshift, *cogon*, *nipa*, or *anahaw*)	0	
	B. Strong materials (Galvanized iron, aluminum tile, concrete, brick, stone, or asbestos)	2	
8. What kind of toilet facility does the family have?	A. None, open pit, closed pit, or other	0	
	B. Water sealed	3	
9. Do all children in the family of ages 6 to 11 go to school?	A. No	0	
	B. Yes	4	
	C. No children ages 6 to 11	6	
10. Do any family members have salaried employment?	A. No	0	
	B. Yes	6	

SimplePovertyScorecard.com **Score:**

Simple Poverty Scorecard® Poverty-Assessment Tool Philippines

1. Introduction

This paper presents the Simple Poverty Scorecard®-brand poverty-assessment tool. Pro-poor programs in the Philippines can use it to estimate the likelihood that a household has income below a given poverty line, to measure groups' poverty rates at a point in time, to track changes in groups' poverty rates over time, and to segment clients for targeted services.

Indicators in the scorecard were derived from the 38,014 households surveyed in the 2002 Annual Poverty Indicators Survey (APIS). Selection criteria included:

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

All scorecard weights are positive integers, and scores range from 0 (most-likely "poor") to 100 (least-likely "poor"). The scorecard is easy to understand, and field workers can compute scores by hand, on paper, in real time.

A participant's score corresponds to a "poverty likelihood", that is, the probability of being poor. For a group, the overall poverty rate (the so-called "head-count index") is the average poverty likelihood of the individuals in the group. For a group over time, progress (or regress) is the change in its average poverty likelihood.

The scorecard qualifies for certification for the reporting required of USAID's microenterprise partners. In particular, the scorecard is highly practical to use. Also, it accurately and objectively estimates the likelihood of having income below the national poverty line. With 90-percent confidence, a household's estimated poverty likelihood is accurate within +/–6 percentage points, and a group's estimated overall poverty rate is accurate with 99-percent confidence to within +/–1 percentage points.

2. Data and poverty lines

The analysis uses the 38,014 households in the 2002 APIS from the Philippines' National Statistics Office. This is the best, most recent household survey available with income or expenditure data.

This paper divides the APIS households into three random samples (Figure 1), with one-half the households used for constructing the scorecard, one-fourth used for associating scores with estimated poverty likelihoods, and one-fourth used for measuring the accuracy of estimates derived from the scorecard.

APIS is fielded annually and measures income but not expenditure. The official poverty lines are in terms of income, and the Philippine government applies them only to a larger, more detailed survey, the triennial Family Income and Expenditure Survey (FIES). The 2003 FIES is not available, but Ericta (2005) reports that it gives a poverty rate of 30.4 percent.

This paper applies the official poverty lines to the income meaure in the 2002 APIS. While APIS uses different questions than FIES to measure income, the resulting overall poverty rate is 31.8 percent, remarkably close to FIES' 30.4 percent.

The rural poverty rate in APIS was 46.4 percent, while urban was 17.3 percent. This paper presents a single scorecard for use anywhere in the Philippines, as evidence from India and Mexico (Schreiner, 2006 and 2005a) suggests that there are only small returns to segmenting scorecards by rural and urban.

Figure 2 shows the official poverty lines by urban/rural for each province. It also shows the "half lines" that demarcate the very poor, that is, the poorest half of the poor. The second-to-last section of the paper looks at poverty by the $4/day-or-less standard.

3. Scorecard construction

About 500 potential poverty indicators were prepared, including:

- Household and housing characteristics (such as cooking fuel and type of floor)
- Individual characteristics (such as age and highest grade completed)
- Household consumption (such as spending on non-alcoholic drinks)
- Household durable goods (such as electric fans and telephones)

Each indicator's ability to predict poverty was tested first with the entropy-based "uncertainty coefficient" (Goodman and Kruskal, 1979). This resembles a correlation coefficient, but it is applied to categorical indicators (such as "type of floor") rather than continuous ones (such as "square meters of floor space"). About 120 indicators were then selected for further analysis. Figure 3 lists the top 50, ranked by uncertainty coefficient. Responses are ordered by strength of association with poverty.

Many indicators in Figure 3 are similar in terms of their link with poverty. For example, most households who have a television also have electricity. If a scorecard already includes "has a television", then "has electricity" is superfluous. Thus, many indicators strongly linked 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/spouse) that are unlikely to change as poverty changes were omitted in favor of slightly less-powerful indicators (such as the number of radios) that are more likely to change. All the indicators of consumption (such as "In the past six months, how much on average per week did the household spend on dairy products and eggs") were not selected because they cannot be directly observed nor verified.

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 for each indicator was recorded using the "c" statistic.[1]

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[1] Higher "c" indicates greater ability to rank households by poverty status. For a Logit regression with a categorical outcome (such as poor/not poor), "c" is a general measure of explanatory power, much like R^2 in a least-squares regression on a continuous

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 over time, variety vis-à-vis other indicators already in the scorecard, and ease of observation/verification.

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 final scorecard appears in Figure 4.

This statistical algorithm is the Logit analogue to the stepwise "MAXR" in, for example, Zeller, Alcaraz and Johannsen (2005) and IRIS (2005a and 2005b). The procedure here diverges from naïve stepwise in that expert judgment and non-statistical criteria were used to select from among the most-predictive indicators. This improves robustness and, more importantly, helps ensure that the indicators are simple and sensible, increasing the likelihood of acceptance by users.

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outcome. "c" is equal to the Mann-Whitney statistic (also known as the Wilcoxon rank-sum statistic) that indicates how much two distributions overlap (here, the distributions are of the estimated poverty likelihoods for poor and non-poor households). "c" is also equivalent to the area under an ROC curve—discussed in more detail later—that plots the share of poor and non-poor households versus all households ranked by score. Finally, "c" can also be seen as the share of all possible pairs of poor and non-poor households in which the poor household has a lower score. The more often the poor household has the lower score, the better the ranking by poverty status.

4. Scorecard use

As explained in Schreiner (2005b), the central challenge is not to maximize accuracy but rather 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 is 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 generally seems to make sense.

This practical focus naturally leads to a one-page scorecard (Figure 4) that allows field workers to score households by hand in real time because it features:

- Only 10 indicators
- Only observable, categorical indicators ("flooring material", not "value of house")
- 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 4 can 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

4.1 Scores and poverty likelihoods

A score is not a poverty likelihood (that is, the probability of being poor), but each score is associated with an estimated poverty likelihood via a simple table (Figure 5). For example, scores of 25–29 correspond to a poverty likelihood of 76.8 percent.

Scores (sums of weights) are associated with estimated poverty likelihoods (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 people in a given score range, compute the share 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 in that score range 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 themselves 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 uses data. While its construction—like any statistical analysis—was partially informed by the analyst's judgment, the explicit acknowledgment of this fact is irrelevant for the objectivity of the poverty likelihoods. After all, objectively depends on using data to associate scores with poverty likelihoods, not on pretending to avoid the use of judgment during scorecard construction.

Figure 6 depicts the precision of estimated poverty likelihoods as point estimates with 90-, 95-, and 99-percent confidence intervals. This is the standard way to measure accuracy, and it is widely understood by lay people. The confidence intervals here were derived empirically from the 10,000 bootstrap samples described above. For a given score, the lower (upper) bound on the x-percent confidence interval is the value less (greater) than (100–x)/2 percent ((100+x)/2 percent) of the bootstrapped likelihoods.

For example, the average poverty rate across bootstrap samples for people with scores of 25–29 is 76.8 percent (this is the poverty likelihood in Figure 5). In 90 percent of samples, the poverty rate is between 73.1–80.4 percent (Figure 6). In 95 percent of samples, the share is 72.4–81.0; in 99 percent of samples, the share is 70.8–82.3.

For estimated and true poverty likelihoods, Figure 7 depicts mean absolute differences and confidence intervals from bootstrapping the second one-fourth hold-out sample from the 2002 APIS. The mean absolute difference is 3.6 percentage points.

This discussion so far looks at whether estimated poverty likelihoods are close to true poverty likelihoods (and indeed they are). There is another aspect of accuracy, one associated with targeting: how well the poor are concentrated in low 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 poor people have high scores, and vice versa.

ROC curves are standard tools for showing how well the poor are concentrated in 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 in Figure 8 mean? Suppose a program sets a cut-off so as to target the lowest-scoring x percent of people. The ROC curve then shows the share of the poor (northwest curve) and non-poor (southwest curve) targeted. Greater ability to rank-order—with less leakage and less undercoverage—is shown by curves that are closer to the northwest and southeast corners of the graph.

In Figure 8, the northwest (southeast) curve depicts 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 diagonal line represents random targeting.

The curves for the scorecard show, for example, that targeting the 20 percent of households with the lowest scores would target 51 percent of all the poor and 6 percent of all the non-poor. In contrast, randomly targeting 20 percent of cases would target 20 percent of the poor and 20 percent of the non-poor.

Figure 8 also reports two other common measures of rank-ordering. The first is the Kolmogorov-Smirnov (KS) statistic, defined as the maximum distance between the poor and non-poor curves (here 59.2). Higher KS implies better rank-ordering.

The second measure is the ratio of the area inside the ROC curves to the area inside the trapezoid of a hypothetical perfect scorecard (here 75.5). Again, greater area within the curves implies better rank-ordering.

Is this scorecard accurate enough for 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. All in all, Figures 6–8 suggest that the estimated likelihoods of being poor are estimated both accurately and precisely.

4.2 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 has 3,000 participants on Jan. 1, 2006 and that 1,000 have scores of 20, 1,000 have scores of 30, and 1,000 have scores of 40. The poverty likelihoods that correspond to these scores are 77.6, 77.7 and 48.3 percent (Figure 5). The overall poverty rate is the participants' average poverty likelihood, that is, 1,000 x (77.6 + 77.7 + 48.3) ÷ 3,000 = 67.9 percent.

To test accuracy and precision, 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 0.1 percentage points, with a standard deviation of 0.37. 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 +/–1.0 percentage points. The estimated overall poverty rate is thus unbiased and highly precise.

4.3 Progress out of poverty over time

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

Continuing the previous example, suppose that on Jan. 1, 2007, the same 3,000 people (some of whom may no longer be participants) are now in groups of 500 with scores of 20, 25, 30, 35, 40, and 45 (by Figure 5, poverty likelihoods of 77.6, 76.8, 77.7, 48.6, 48.3, and 33.6 percent). Their average poverty likelihood is now 60.4 percent, an improvement of 67.9 – 60.4 = 7.5 percentage points. In other words, 7.5 of every 100 in this group left poverty. Among those who were poor to start with, one in nine (7.5 ÷ 67.9 = 11.1 percent) left poverty.

Of course, the scorecard does not indicate what *caused* progress; it just measures the change, regardless of cause.

5. Setting targeting cut-offs

How would the scorecard be used for targeting? 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—again, 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 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 cost of direct measurement.

No scorecard is perfect, so some of the truly poor will not be targeted, and some of the truly non-poor will be targeted. Targeting is accurate to the extent that poverty status matches targeting status. In turn, this depends on the selection of a targeting cut-offs and how it balances accuracy for the poor versus non-poor. The standard approach uses a *classification matrix* and a *net-benefit matrix* (SPSS, 2003; Adams and Hand, 2000; Salford Systems, 2000; Hoadley and Oliver, 1998; Greene, 1993).

5.1 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 9). Accuracy improves as there are more cases in A and D and fewer in B and C.

Figure 10 shows the number of people in each classification by score in the second one-fourth hold-out sample. For example, with a cut-off of 25–29, there are:

A. 12.4	truly poor	correctly	targeted
B. 19.7	truly poor	mistakenly	non-targeted
C. 2.2	truly non-poor	mistakenly	targeted
D. 65.7	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 39–34, more poor (but less non-poor) are correctly targeted:

A. 16.6	truly poor	correctly	targeted
B. 15.5	truly poor	mistakenly	non-targeted
C. 3.4	truly non-poor	mistakenly	targeted
D. 64.5	truly non-poor	correctly	non-targeted

Whether a cut-off of 40–44 is preferred to 45–49 depends on net benefit.

5.2 Net-benefit matrix

Each of the four classification results is associated with a net benefit (Figure 11):

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

Each net benefit α, β, γ, and δ corresponds to one of the quadrants in the general classification matrix in Figure 9. For example, α is the net benefit associated with each truly poor person who is correctly targeted (quadrant A), and β is the cost (negative net benefit) associated with each truly poor person incorrectly targeted (quadrant B).

Given a net-benefit matrix and a classification matrix, total net benefit is the sum of the net benefit per person in each quadrant multiplied by the number of people in the quadrant, summed across all four quadrants:

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

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 10
- 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.

For example, suppose a program places great importance on correctly targeting the poor, even at the cost of accidentally targeting more non-poor. It could reflect this valuation by increasing the weight on quadrant A (by increasing its net benefit α), and/or by decreasing the weight on quadrant B (by decreasing its net benefit β). The examples of net-benefit matrices discussed next represent different valuations of correctly/incorrectly targeting the poor/non-poor.

5.2.1 "Total Accuracy"

As an example, suppose a program selects the net-benefit matrix that corresponds to the "Total Accuracy" criterion (Figure 12, IRIS, 2005b). Then total net benefit is the number of people correctly classified:

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

This values correct classifications of the poor and non-poor equally. Grootaert and Braithwaite (1998) and Zeller, Alcaraz, y Johannsen (2005) use "Total Accuracy" to evaluate their poverty-assessment tools.

Figure 13 shows "Total Accuracy" for all cut-offs. Total net benefit is greatest (81.1) for a cut-off of 30–34; at that point, poverty segment matches poverty status for four out of five people.

"Total Accuracy" weighs the poor and non-poor the same. If most people are non-poor and/or if a poverty-assessment tool is more accurate for the non-poor, then "Total Accuracy" might look good even if few poor people are correctly classified. Development programs, however, probably value correct targeting more for the poor than for the non-poor.

A simple, transparent way to reflect this valuation is to increase the relative net benefit α 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 δ in the net-benefit matrix. Then the new optimal cut-off is 50–54, the cut-off point where $\alpha.A + \delta.D = 2.A + D$ is highest.

5.2.2 "Poverty Accuracy"

A criterion that values only correctly classifying the poor is "Poverty Accuracy" (Figure 14, IRIS, 2005b):

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

Of course, correctly targeting the poor is rarely the sole criteria. In fact, Figure 13 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 13), it also targets all the non-poor and so maximizes *leakage* (the last column of Figure 13).

5.2.3 "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).

5.2.4 "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 is optimized when undercoverage B is balanced by leakage C, and the second goal is optimized by maximizing A. If B > C, then BPAC's net-benefit matrix is Figure 15. In essence, BPAC maximizes A while making B and C as close to each other 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, closest to the true value) when undercoverage B equals leakage C.

But the scorecard estimates poverty likelihoods, however, so 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. 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 BPAC's goals.

6. 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 is even more important (Schreiner, 2002).

In particular, the field workers who collect indicators must be trained. If they put garbage in, the scorecard 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).

7. Calibrating the scorecard for the very poor

The scorecard 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 below the national poverty line. This is the relevant group for USAID certification.

7.1 Poverty likelihoods

As before, scores are associated with the probability of being very poor by bootstrapping 10,000 samples from first one-fourth hold-out sample from the 2002 APIS. 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 16 are the poverty likelihoods for the three classes for all scores. For example, if a potential participant has a score of 25–29, the probability of being very poor is 42.2 percent, the probability of being poor is 34.4 percent, and the probability of being non-poor is 23.2 percent.

Columns 5–7 in Figure 16 are the share of targeted participants by poverty status and by cut-off. For example, for a cut-off of 25–92, 58.3 percent of those targeted would be very poor, 26.4 percent would be poor, and 15.2 percent would be non-poor.

Each person is associated with three poverty likelihoods. For example, a person with a score of 25 may be targeted as very poor, but the likelihood of truly being very poor is not 100 percent but rather 42.4 percent (from Figure 16). The same person has a 34.4-percent likelihood of being truly poor, and a 23.2-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 17 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 42.4 percent. In 90 percent of 10,000 bootstraps from the second one-fourth hold-out sample, the share was between 38.2–46.7 percent. In 95 percent of samples, the share was between 37.3–47.7, and in 99 percent of samples, the share was between 35.9–49.3.

For estimated and true poverty likelihoods, Figure 18 depicts mean absolute differences and confidence intervals from 10,000 bootstraps on the second one-fourth hold-out sample. Weighting by the people in a score range, the mean absolute difference is 1.8 percentage points, with a 90-percent interval of +/–2.5 percentage points.

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

Figure 19 plots the share of the very poor against the share of the not very poor, ranked by score. For example, targeting the 30 percent of cases with the lowest scores would target 77 percent of all the very poor and 21 percent of all the not very poor.

In terms of the Kolmogorov-Smirnov statistic, the maximum distance between the curves is 56.0. 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 73.4.

All in all, Figures 17–19 suggest that the likelihoods of being very poor are estimated both accurately and precisely.

7.2 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 samples from the 2002 APIS, and then the estimated overall poverty rates were compared with the true values. The mean difference was 0.8 percentage points, with a standard deviation of 0.32. The 90-percent confidence interval around the mean was +/–0.5 percentage points, the 95-percent interval was +/–0.6 percentage points, and the 99-percent interval was +/–0.8 percentage points.

Thus, subtracting 0.8 percentage points to a group's average poverty likelihood would produce an unbiased estimate that, in 99 of 100 cases, would be within +/–0.8 percentage points of the true overall (very poor) poverty rate. This estimate is both quite accurate and quite precise.

7.3 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 20):

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
D.	Truly poor	incorrectly targeted as	very poor
E.	Truly poor	correctly targeted as	poor
F.	Truly poor	incorrectly targeted as	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	non-poor

The general classification matrix (Figure 20) and the net-benefit matrix (Figure 21) are combined as before to define total net benefit:

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

Figure 22 shows classification results for all possible pairs of cut-off scores in the second one-fourth hold-out sample. For example, suppose a program defined:

- Very poor/poor cut-off of 20–24 (so scores of 0–24 are targeted as very poor)
- Poor/non-poor cut-off of 30–34 (so scores of 25–34 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 20–24 and 30–34, targeting would be correct for 65 percent of the very poor, 39 percent of the poor, and 81 percent of the non-poor (Figure 23).

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 24, 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 23 and net benefits in Figure 24, total net benefit for the cut-off pair of 20–24 and 30–34 is +404 (Figure 25).

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 (Figure 22). It turns out that total net benefit is highest for cut-offs 30–34 and 50–54, giving a net benefit of 764.

8. Calibrating for $4/day-or-less poverty

The scorecard can be used to track outreach not only to the poor (the upper half of those under the national poverty line) and the very poor (the lower half of those under the national poverty line) but also the $4PPP/day poor, that is, those with incomes above the national poverty line but below the $4/day/person international benchmark at purchase-power parity. The Appendix describes the derivation of a

$4PPP poverty line that accounts for differences in cost-of-living across Filipino provinces and across rural and urban areas.

8.1 Poverty likelihoods

Scores are associated with the probability of being very poor by bootstrapping 1,000 samples from the first one-fourth hold-out sample from the 2002 APIS. The poverty likelihood for a given score is then taken as the average of the shares of people with that score who are $4/day-or-less poor across the 1,000 bootstrapped samples.

Columns 2–5 in Figure 26 are the poverty likelihoods for the four classes for all scores. For example, if a potential participant has a score of 25–29, the probability of being very poor is 42.2 percent, the probability of being poor is 34.4 percent, the probability of being $4/day poor is 14.4 percent, and the probability of being non-poor is 8.8 percent. The sum of the four poverty likelihoods is, of course, 100 percent.

Columns 6–9 in Figure 26 are the share of targeted participants by poverty status and by cut-off. For example, for a cut-off of 25–29, 58.3 percent of those targeted would be very poor, 26.4 percent would be poor, 9.5 percent would be $4/day poor, and 5.8 percent would be non-poor.

Each person's score is associated with four poverty likelihoods. For example, a person with a score of 25 may be targeted as very poor, but the likelihood of truly being very poor in this case is not 100 percent but rather 42.4 percent (from Figure 26). The same person has a 34.4-percent likelihood of being truly poor, a 14.4-percent likelihood of being $4/day poor, and an 8.8-percent likelihood of being truly non-poor. Each person has one targeting status (for program purposes), one true poverty status (in reality), and four estimated poverty likelihoods (one for each possible poverty status).

Figure 27 shows the precision of estimated poverty likelihoods for being $4/day-or-less poor as point estimates with 90-, 95-, and 99-percent confidence intervals. For example, the average $4/day-or-less poverty rate (the poverty likelihood) across bootstrap samples for people with scores of 25–29 was 91.2 percent. In 90 percent of 1,000 bootstraps from the second one-fourth hold-out sample, the share was between 88.7–93.6 percent. In 95 percent of samples, the share was between 88.1–94.0, and in 99 percent of samples, the share was between 86.9–94.4.

For estimated and true poverty likelihoods, Figure 28 depicts mean absolute differences and confidence intervals from 1,000 bootstraps on the second one-fourth hold-out sample. Weighting by the people in a score range, the mean absolute difference is 4.7 percentage points, with a 90-percent interval of +/–5.2 percentage points.

The other aspect of accuracy is how well the $4/day-or-less poor are concentrated in low scores. Once again, an ROC curve is a useful way to look at this.

Figure 29 plots the share of the $4/day-or-less poor against the share of the non-poor, ranked by score. For example, targeting the 20 percent of cases with the lowest scores would target 44 percent of all the $4/day-or-less poor and 4 percent of all the non-poor.

In terms of the Kolmogorov-Smirnov statistic, the maximum distance between the curves is 58.0. 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 74.3.

8.2 Overall poverty rates for the $4/day-or-less poor

The average of estimated poverty likelihoods for a group is their estimated overall ($4/day-or-less) poverty rate. To measure the accuracy and precision of this estimate, the scorecard was applied to 1,000 bootstrap replicates from the second one-fourth hold-out samples from the 2002 APIS, and then the estimated overall poverty rates were compared with the true values. The mean difference was 0.6 percentage points, with a standard deviation of 0.39. 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 +/–1.0 percentage points.

Thus, subtracting 0.6 percentage points to 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 ($4/day-or-less) poverty rate. This estimate is both quite accurate and quite precise.

9. Conclusion

Pro-poor programs in the Philippines can use the Simple Poverty Scorecard tool to segment clients for targeted services as well as to estimate:

- The likelihood that a household has income below a given poverty line
- The poverty rate of a population at a point in time
- The change in the poverty rate of a population between two points in time

The scorecard is built and tested using data on 38,014 households from the 2002 APIS. The scorecard is calibrated to estimate the likelihood of being poor (income below the official line), very poor (poorest half of the poor), $4/day poor (income above the official line but below the $4/day international benchmark), or non-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 points of the true value with 99-percent confidence.

For targeting, programs can use the classification results reported here to select the best cut-off for their particular 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 either 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, users can not only understand the scorecard, but they can also use it to compute scores in the field, by hand, in real time.

Scorecard can help 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 $4PPP Poverty Line for Cost-of-Living Differences

$4PPP poverty lines were constructed using the following criteria:

- Account for differences in cost-of-living by province and by rural/urban within each province
- Match the average of rural and urban $4PPP lines to the all-Philippines $4PPP line
- Match the ratio of rural to urban $4PPP lines to that same ratio for the official national lines

Basic inputs to the calculation include:

- $4PPP/person/day for all-Philippines in 2002 is 46.85 pesos/person/day
- In 2002, 50.16 percent of the population was rural
- The population-weighted official poverty line in 2002 was 38.49 pesos/person/day for urban areas and 31.59 pesos/person/day for rural areas

The population-weighted average of rural and urban $4PPP lines should match the all-Philippines $4PPP line:

$$46.85 = (0.5016 \text{ x Rural \$4PPP line}) + (0.4984 \text{ x Urban \$4PPP line}).$$

Furthermore, the ratio of the two lines should match the ratio of the official lines:

$$(\text{Rural \$4PPP line} \div \text{Urban \$4PPP line}) = 31.59 \div 38.49.$$

Solving the algebra gives:

- Rural $4PPP line of 42.25 pesos/person/day
- Urban $4PPP line of 51.48 pesos/person/day

To account for cost-of-living across provinces, the official lines for 2002 are then adjusted by their ratio with the rural or urban $4PPP line. For both rural and urban areas, the adjustment factor is 1.337. That is, the $4PPP poverty line is 33.7 percent higher than the national poverty line.

$2/day is about equal to the "very poor" line that defines the poorest half below the national poverty line, and $3/day is almost exactly the same as the national line.

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

Sub-sample	Households	People	% poor
Constructing scorecards	18,846	39,459,467	32.0
Associating scores with likelihoods	9,665	20,407,790	31.4
Testing accuracy	9,503	19,760,021	31.9
	38,014	79,627,278	31.8

Source: 2002 APIS.

Figure 2: Official poverty lines and “half” poverty lines, pesos/person/year

Province	Official line Urban	Official line Rural	"Half" line Urban	"Half" line Rural
NCR				
1st District	16,496	N/A	13,353	N/A
2nd District	16,007	N/A	12,875	N/A
3rd District	15,256	N/A	12,739	N/A
4th District	16,654	N/A	13,828	N/A
Region I				
Ilocos Norte	13,175	13,688	9,000	9,271
Ilocos Sur	12,768	14,368	9,746	8,375
La Union	13,415	13,183	10,118	7,667
Pangasinan	13,449	12,737	9,699	8,034
Region II				
Batanes	15,490	12,386	13,525	8,522
Cagayan	12,507	10,127	9,029	7,409
Isabela	14,883	11,317	10,364	7,500
Nueva Vizcaya	13,707	10,730	10,112	8,412
Quirino	12,072	10,670	9,464	6,885
Region III				
Bataan	13,344	11,706	10,411	10,200
Bulacan	14,822	13,265	13,526	8,521
Nueva Ecija	16,048	14,182	11,943	10,156
Pampanga	15,459	14,111	12,068	11,631
Tarlac	13994	12409	10099	8675

Province	Official line Urban	Official line Rural	"Half" line Urban	"Half" line Rural
Region IV				
Batangas	15,993	15,002	11,410	11,230
Cavite	14,851	16,240	11,992	12,480
Laguna	14,147	12,312	11,480	9,941
Marinduque	12,301	11,639	8,726	8,001
Occidental Mindoro	12,271	12,327	8,409	7,420
Oriental Mindoro	15,095	13,938	10,368	8,859
Palawan	13,541	10,729	9,017	7,520
Quezon	13,430	12,605	9,478	8,318
Rizal	14,264	13,561	10,870	10,192
Romblon	12,770	11,234	7,267	7,006
Aurora	12,121	11,469	7,304	7,379
Region V				
Albay	15,239	11,763	10,251	6,954
Camarines Norte	13,931	11,259	8,822	6,686
Camarines Sur	13,049	10,389	8,349	6,206
Catanduanes	13,523	10,653	9,541	6,292
Masbate	13,784	10,903	8,367	7,462
Sorsogon	13,551	11,264	8,098	7,366
Region VI				
Aklan	12,581	11,938	9,420	7,080
Antique	11,981	10,969	7,852	7,165
Capiz	12,354	10,781	8,280	8,446
Iloilo	12,948	12,328	9,750	8,110
Negros Occidental	11,507	11,463	8,057	9,345
Guimaras	12,293	11,469	7,379	8,443
Region VII				
Bohol	11,070	10,060	6,754	5,903
Cebu	10,950	9,817	8,100	6,498
Negros Oriental	11,587	8,358	8,057	8,345
Siquijor	11,823	9,361	7,283	5,553

Province	Official line Urban	Official line Rural	"Half" line Urban	"Half" line Rural
Region VIII				
Eastern Samar	10,617	9,690	6,658	6,461
Leyte	10,639	10,460	7,978	6,473
Northern Samar	9,726	9,503	6,751	6,045
Western Samar	10,868	10,523	8,320	6,799
Southern Leyte	11,033	9,921	8,515	6,795
Biliran	10,218	10,644	6,816	7,375
Region IX				
Basilan	11,891	9,350	8,984	7,604
Zamboanga del Norte	11,715	9,377	7,440	5,731
Zamboanga del Sur	10,676	9,385	7,374	4,772
Region X				
Bukidnon	11,125	9,649	6,890	6,140
Camiguin	14,228	11,943	8,854	6,959
Misamis Occidental	11,898	10,081	7,543	6,535
Misamis Oriental	12,649	11,508	8,121	7,239
Region XI				
Davao del Norte	11,648	11,401	8,596	7,551
Davao del Sur	12,457	9,912	8,750	6,529
Davao Oriental	12,624	10,289	10,089	7,652
South Cotabato	12,803	11,659	8,140	6,300
Saranggani	12,674	11,719	7,482	4,944

Province	Official line Urban	Official line Rural	"Half" line Urban	"Half" line Rural
Region XII				
Lanao del Norte	12,393	11,630	8,014	6,336
North Cotabato	11,172	9,761	7,680	6,185
Sultan Kudarat	11,940	10,565	7,444	6,893
CAR				
Abra	13,201	13,928	10,075	7,987
Benguet	15,300	13,309	12,976	8,363
Ifugao	13,353	12,330	8,581	5,780
Kalinga	12,128	11,469	8,070	6,688
Mt. Province	17,044	14,863	9,953	7,033
Apayao	11,030	11,200	6,688	7,593
ARMM				
Lanao del Sur	13,459	14,725	8,831	10,017
Maguindanao	14,247	11,996	9,427	7,022
Sulu	13,487	12,602	7,054	7,684
Tawi-tawi	13,192	13,259	11,057	10,097
Others				
Agusan del Norte	12,767	10,594	7,839	5,908
Agusan del Sur	12,355	11,104	8,433	6,000
Surigao del Norte	13,813	11,261	8,456	6,050
Surigao del Sur	12,422	10,694	8,356	6,663

Source: National Statistic Coordination Board (2004) and calculations based on the 2002 APIS.

Figure 3: Poverty indicators ranked by uncertainty coefficient

Uncertainty coefficient		Indicator (Value for those most likely “poor”; Value for those least likely “poor”)
1.	247	During the past six months, how much on average did the household spend per month on fuel, light, and water (charcoal, firewood, LPG, kerosene/gas, electricity, candles, oils, water, etc.) (<P83/person; ≥P83/person)
2.	214	During the past six months, how much on average did the household spend per week on meat and meat preparations (fresh chicken, beef, pork, carabeef, goat’s meat, corned beef, luncheon meat, meatloaf, Vienna sausage, longaniza, chorizo, hot dogs, tocino, tapa, etc.) (<P19/person; ≥P19/person)
3.	214	During the past six months, how much on average did the household spend per month on personal care and effects (cleansing cream, body deodorant, lotion, baby oil, toilet/bath soap, tissue paper, toothpaste, sanitary napkins, shampoo, jewelry, handbags, wallets, wristwatches, haircuts, manicure or pedicure, etc.) (<P30/person; ≥P30/person)
4.	195	During the past six months, how much on average did the household spend per month on transportation and communication (bus, jeepney, tricycle, air or water transport fare, gasoline/diesel, driver’s salary, telephone bills, postage stamps, telegrams, driving lessons, feeds for animals used for transport, etc.) (<P38/person; ≥P38/person)
5.	190	Does the family own a gas stove or gas range? (No; Yes)
6.	183	Does the family own a refrigerator? (No; Yes)
7.	181	How many television sets does the family own? (0; 1; 2 or more)
8.	162	During the past six months, how much on average did the household spend per week on non-alcoholic beverages (soft drinks, pineapple juice, orange juice, ice candy, ice drop, ice buko, etc.) (<P3/person; ≥P3/person)
9.	152	During the past six months, how much on average did the household spend per week on dairy products and eggs (milk, ice cream, butter, cheese, fresh eggs, balut, salted eggs) (<P6/person; ≥P6/person)
10.	145	How many telephones and/or cell phones does the family own? (0; 1; 2 or more)
11.	140	During the past six months, how much on average did the household spend per week on food regularly consumed outside the home (meals at school, place of work, restaurants, merienda or snacks, etc.) (<P11/person; ≥P11/person)
12.	136	Does the family own a sala set? (No; Yes)
13.	127	Does the family own a washing machine? (No; Yes)
14.	126	Is there any electricity in the building/house? (No; Yes)
15.	123	Does the family own a dining set? (No; Yes)
16.	121	During the past six months, how much did the household spend on clothing, footwear, and other wear (clothing and ready-made apparel, footwear, sewing materials, accessories, service fees, etc.) (<P200/person; ≥P200/person)
17.	113	What is the highest grade completed by a household member? (Graduated secondary or less; 1 or more years of post-secondary)
18.	105	What is the primary occupation of the male head/spouse? (Farmers and laborers; Clerks, trades, special occupations, and occupations not elsewhere classified; Clerks, and plant and machine operators; Technicians, and officials of government and special-interest organizations; Professionals)

Figure 3 (cont.): Poverty indicators ranked by uncertainty coefficient

Uncertainty coefficient		Indicator (Value for those most likely "poor"; Value for those least likely "poor")
19.	104	What is the house's main source of water supply? (Spring, river, stream, dug well, or rain; Peddler or others; Own-use or shared-use from a tubed/piped well or a community water system)
20.	102	Does the family have health insurance from Philhealth, a Health Maintenance Organization, a private health-insurance company, or a community or cooperative? (No; Yes)
21.	98	Does the family have health insurance with Philhealth? (No; Yes)
22.	95	On a ladder with 10 steps going from lowest/poorest to highest/richest, on which step would you be? (1; 2; 3; 4; 5; 6 or more)
23.	94	How many people in the family are aged 0 to 17? (5 or more; 4; 2 or 3; 0 or 1)
24.	89	What are the house's outer walls made of? (Salvaged or makeshift materials or all light or predominantly light materials such as cogon, nipa, or sawali, bamboo, or anahaw; All strong or predominantly strong materials such as iron, aluminum, tile, concrete, brick, stone, wood, or asbestos)
25.	86	What kind of toilet facility does the family have in the house? (None, open pit, or others; Closed pit; Water sealed)
26.	80	How many radios does the family own? (0; 1; 2 or more)
27.	78	What type of construction materials is the house's roof made of? (Salvaged or makeshift materials or all light or predominantly light materials such as cogon, nipa, or anahaw; All strong or predominantly strong materials such as galvanized iron, aluminum tile, concrete, brick, stone, or asbestos)
28.	77	What is the highest grade completed by the male head/spouse? (Grades I to V of elementary; Did not complete any grade; Grade VI of elementary to graduate of secondary; 1 or more years of post-secondary)
29.	77	How many people are there in the family from ages 0 to 17? (3 or more; 2; 1; 0)
30.	77	What is the highest grade completed by the female head/spouse? (I to V of elementary; None; VI of elementary to graduate of secondary; 1 or more years of post-secondary)
31.	69	What is the primary occupation of the female head/spouse? (Farmers and laborers; Clerks, trades, special occupations, and occupations not elsewhere classified; Clerks, and plant and machine operators; Technicians, and officials of government and special-interest organizations; Professionals)
32.	61	Does the family live in an urban area? (No; Yes)
33.	58	How many children are there aged 17 or younger per adult aged 18 or older? (1 or more; <1)
34.	58	Does the family engage in crop farming or gardening? (Yes; No)
35.	53	Does the family own a vehicle? (No; Yes)
36.	48	What is the floor area of house in square meters? (50 or less; ≥50)
37.	47	Does the household have some type of health insurance? (No; Yes)
38.	41	During the past six months, did the household regularly consume food outside the home (meals at school, place of work, restaurants, merienda or snacks, etc.)? (No; Yes)

Figure 3 (cont.): Poverty indicators ranked by uncertainty coefficient

Uncertainty coefficient		Indicator (Value for those most likely "poor"; Value for those least likely "poor")
39.	40	During the past six months, did the household buy non-alcoholic beverages (soft drinks, pineapple juice, orange juice, ice candy, ice drop, ice buko, etc.)? (No; Yes)
40.	39	How many children are there aged 11 or younger per adult aged 18 or older? (0.5 or more; <0.5)
41.	38	During the past six months, did the household make any deposits in banks? (No; Yes)
42.	35	During the past six months, did anyone in the family receive cash, gifts, support, or relief from abroad (including pensions retirement, workmen's compensation, dividends from investments, etc.)? (No; Yes)
43.	31	Is the male head/spouse self-employed? (No; Yes)
44.	22	During the past six months, did the household buy dairy products and eggs (milk, ice cream, butter, cheese, fresh eggs, balut, salted eggs)? (No; Yes)
45.	22	Do all children in the family of ages 6 to 11 go to school? (No; Yes)
46.	22	Do any family members assist in the family business? (No; Yes)
47.	21	During the past six months, did anyone in the family make a deposit in a bank, receive interest on savings, or make a withdrawal from a savings account? (No; Yes)
48.	21	Do any family members have salaried employment? (No; Yes)
49.	18	In the next 12 months, do you expect your household's economic conditions to worsen, stay the same, or improve? (Worsen; Stay the Same; Improve)
50.	17	Does the family have any income from entrepreneurial activities? (Yes; No)
51.	16	Is your household's situation at present compared with the last 12 months worse, about the same, or better? (Worse, About the same, Better)
52.	16	Are any household members involved with self-employment? (No; Yes)

Source: Based on 2002 APIS.

Figure 4: Scorecard for the Philippines

Indicator	Values				Points
1. How many people in the family are aged 0 to 17?	5 or more 0	3 or 4 7	1 or 2 16	Zero 27	
2. Does the family own a gas stove or gas range?			No 0	Yes 13	
3. How many television sets does the family own?		Zero 0	1 9	2 or more 18	
4. What are the house's outer walls made of?		Light (*cogon*, *nipa*, or *sawali*, bamboo, *anahaw*) 0		Strong (iron, aluminum, tile, concrete, brick, stone, wood, asbestos) 4	
5. How many radios does the family own?		Zero 0	1 3	2 or more 10	
6. Does the family own a *sala* set?			No 0	Yes 9	
7. What is the house's roof made of?		Light (Salvaged, makeshift, *cogon*, *nipa*, or *anahaw*) 0		Strong (Galvanized iron, aluminum tile, concrete, brick, stone, or asbestos) 2	
8. What kind of toilet facility does the family have?		None, open pit, closed pit, or other 0		Water sealed 3	
9. Do all children in the family of ages 6 to 11 go to school?		No 0	Yes 4	No children ages 6-11 6	
10. Do any family members have salaried employment?			No 0	Yes 6	
				Total:	

Source: Calculations based on the 2002 APIS.

Figure 5: 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	99.3	99.3	68.4
5-9	92.5	94.6	69.4
10-14	91.9	93.2	70.9
15-19	93.4	93.3	72.5
20-24	77.6	88.3	74.3
25-29	76.8	84.8	77.0
30-34	77.7	82.9	80.6
35-39	48.6	74.0	83.4
40-44	48.3	68.7	86.8
45-49	33.6	63.0	89.1
50-54	34.4	58.4	92.7
55-59	22.6	55.5	94.0
60-64	10.1	49.0	94.9
65-69	10.2	43.7	96.6
70-74	6.9	40.1	97.9
75-79	3.8	37.1	98.8
80-84	2.1	34.1	100.0
85-89	0.0	32.9	100.0
90-94	0.0	32.5	100.0
95-100	0.0	32.1	100.0

Surveyed cases weighted to represent the Filipino population.

Source: Based on the 2002 APIS.

Figure 6: Confidence intervals for estimated poverty likelihoods associated

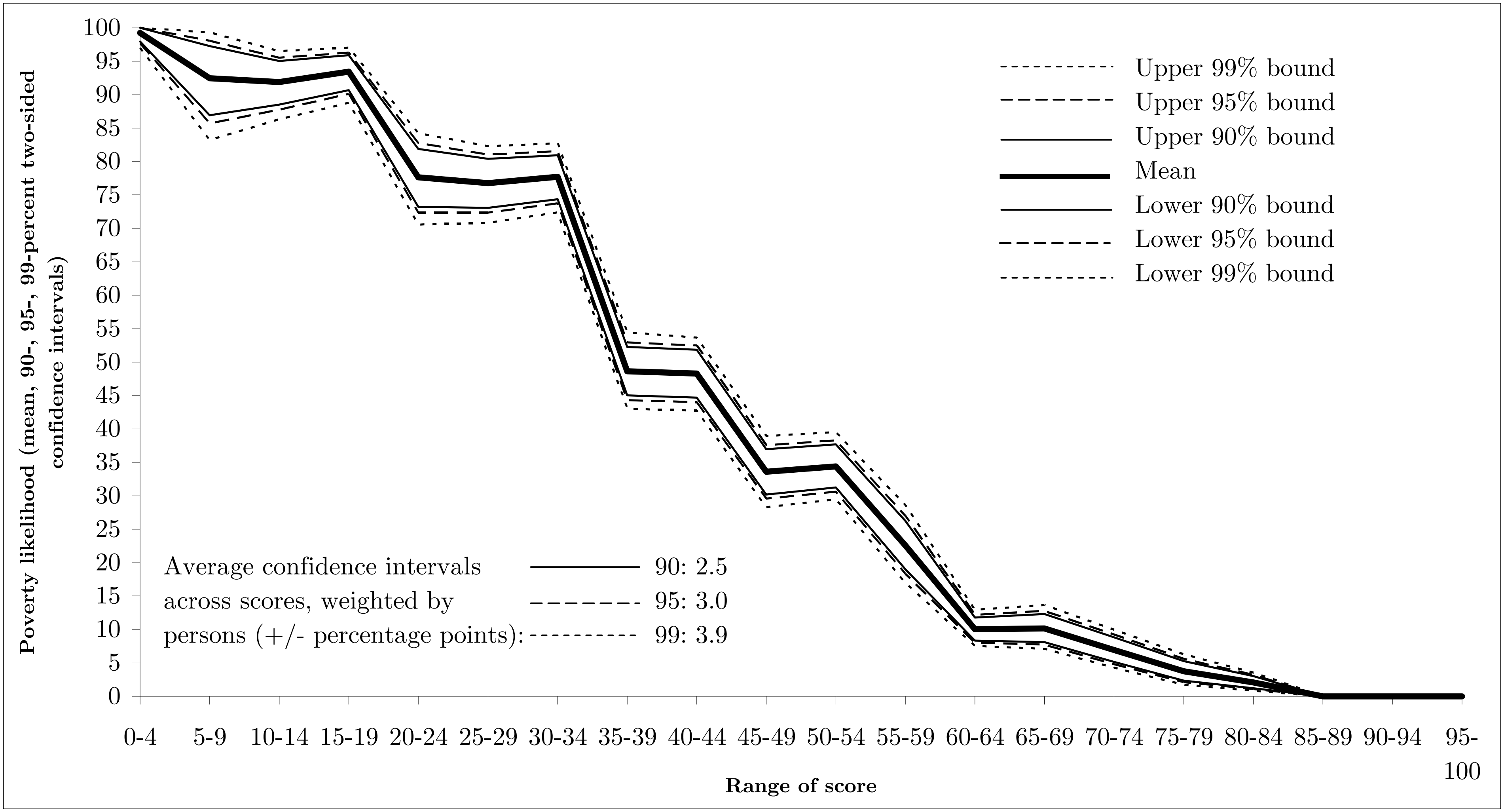

Figure 7: Differences between estimated and true poverty likelihoods

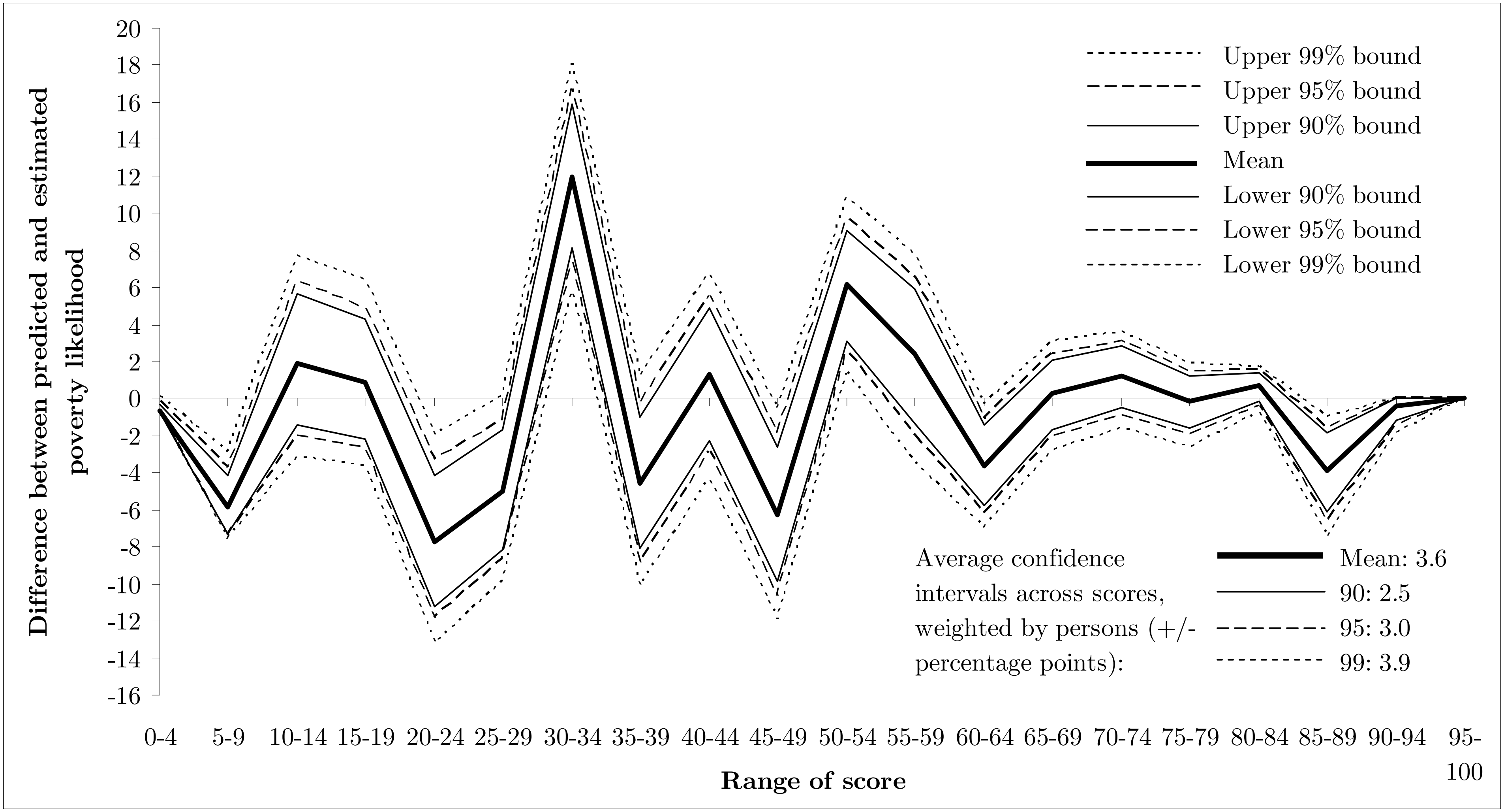

Figure 8: ROC curve of ability to rank-order households by poverty status

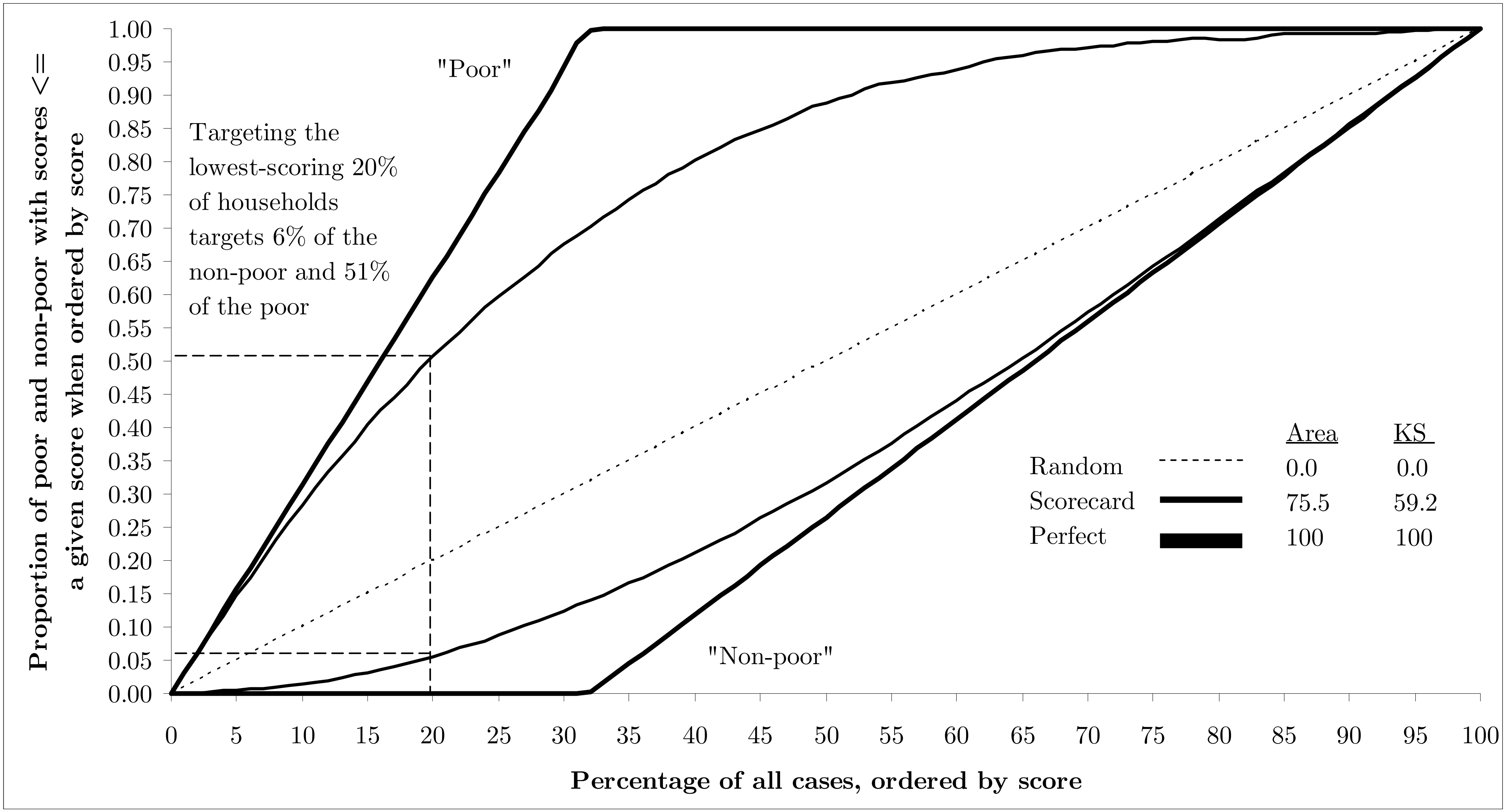

Figure 9: General classification matrix

		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 10: 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	0.7	31.4	0.0	67.9
5-9	2.1	30.0	0.1	67.8
10-14	4.3	27.8	0.3	67.6
15-19	6.4	25.6	0.5	67.5
20-24	9.0	23.1	1.2	66.7
25-29	12.4	19.7	2.2	65.7
30-34	16.6	15.5	3.4	64.5
35-39	20.0	12.1	7.0	60.9
40-44	23.4	8.7	10.6	57.3
45-49	25.6	6.5	15.0	52.9
50-54	28.3	3.8	20.2	47.8
55-59	29.2	2.8	23.4	44.5
60-64	30.1	2.0	31.3	36.7
65-69	31.1	1.0	40.1	27.8
70-74	31.6	0.4	47.2	20.7
75-79	31.9	0.2	54.0	14.0
80-84	32.1	0.0	62.0	5.9
85-89	32.1	0.0	65.5	2.5
90-94	32.1	0.0	66.6	1.3
95-100	32.1	0.0	67.9	0.0

Figures normalized to sum to 100.

Source: Based on the 2002 APIS.

Figure 11: General net-benefit matrix

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

Figure 12: "Total Accuracy" net-benefit matrix

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

Figure 13: Total net benefit for some common net-benefit matrices

	Total Accuracy	Poverty Accuracy	Non-poverty Accuracy	Undercoverage	Leakage
	(A + B)	100*A / (A+B)	100*D / (C+D)	100*B / (A+B)	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	68.6	2.2	100.0	97.8	0.8
5-9	69.9	6.6	99.8	93.4	5.4
10-14	71.9	13.4	99.5	86.6	6.8
15-19	73.9	20.1	99.3	79.9	6.7
20-24	75.7	27.9	98.3	72.1	11.7
25-29	78.1	38.6	96.7	61.4	15.2
30-34	81.1	51.7	95.0	48.3	17.1
35-39	80.9	62.3	89.7	37.7	26.0
40-44	80.7	72.8	84.3	27.2	31.3
45-49	78.5	79.7	77.9	20.3	37.0
50-54	76.0	88.2	70.3	11.8	41.6
55-59	73.7	91.1	65.5	8.9	44.5
60-64	66.8	93.9	54.0	6.1	51.0
65-69	58.9	97.0	41.0	3.0	56.3
70-74	52.3	98.6	30.5	1.4	59.9
75-79	45.9	99.5	20.5	0.5	62.9
80-84	38.0	100.0	8.7	0.0	65.9
85-89	34.5	100.0	3.6	0.0	67.1
90-94	33.4	100.0	1.9	0.0	67.5
95-100	32.1	100.0	0.0	0.0	67.9

All figures in percentage units.

Figure 14: "Poverty Accuracy" net-benefit matrix

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

Figure 15: Net-benefit matrix for BPAC

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

Figure 16: 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	85.0	14.3	0.7	85.0	14.3	0.7
5-9	79.7	12.8	7.6	81.3	13.3	5.4
10-14	61.9	30.0	8.1	71.3	21.9	6.8
15-19	70.5	22.9	6.6	71.0	22.3	6.7
20-24	53.2	24.4	22.4	65.4	22.9	11.7
25-29	42.4	34.4	23.2	58.3	26.4	15.2
30-34	35.2	42.6	22.3	52.1	30.8	17.1
35-39	23.8	24.8	51.4	44.8	29.2	26.0
40-44	22.2	26.1	51.7	40.1	28.6	31.3
45-49	16.5	17.1	66.4	36.3	26.7	37.0
50-54	12.6	21.8	65.6	32.4	25.9	41.6
55-59	8.4	14.2	77.4	30.5	25.0	44.5
60-64	4.7	5.4	90.0	26.8	22.2	51.0
65-69	2.5	7.6	89.9	23.5	20.2	56.3
70-74	1.7	5.2	93.1	21.4	18.7	59.9
75-79	1.6	2.2	96.3	19.8	17.4	62.9
80-84	0.7	1.4	97.9	18.1	16.0	65.9
85-89	0.0	0.0	100.0	17.5	15.4	67.1
90-94	0.0	0.0	100.0	17.3	15.2	67.5
95-100	0.0	0.0	100.0	17.0	15.0	67.9
Total:	17.0	15.0	67.9			

Figure 17: Confidence intervals for estimated poverty likelihoods for being very poor associated with scores

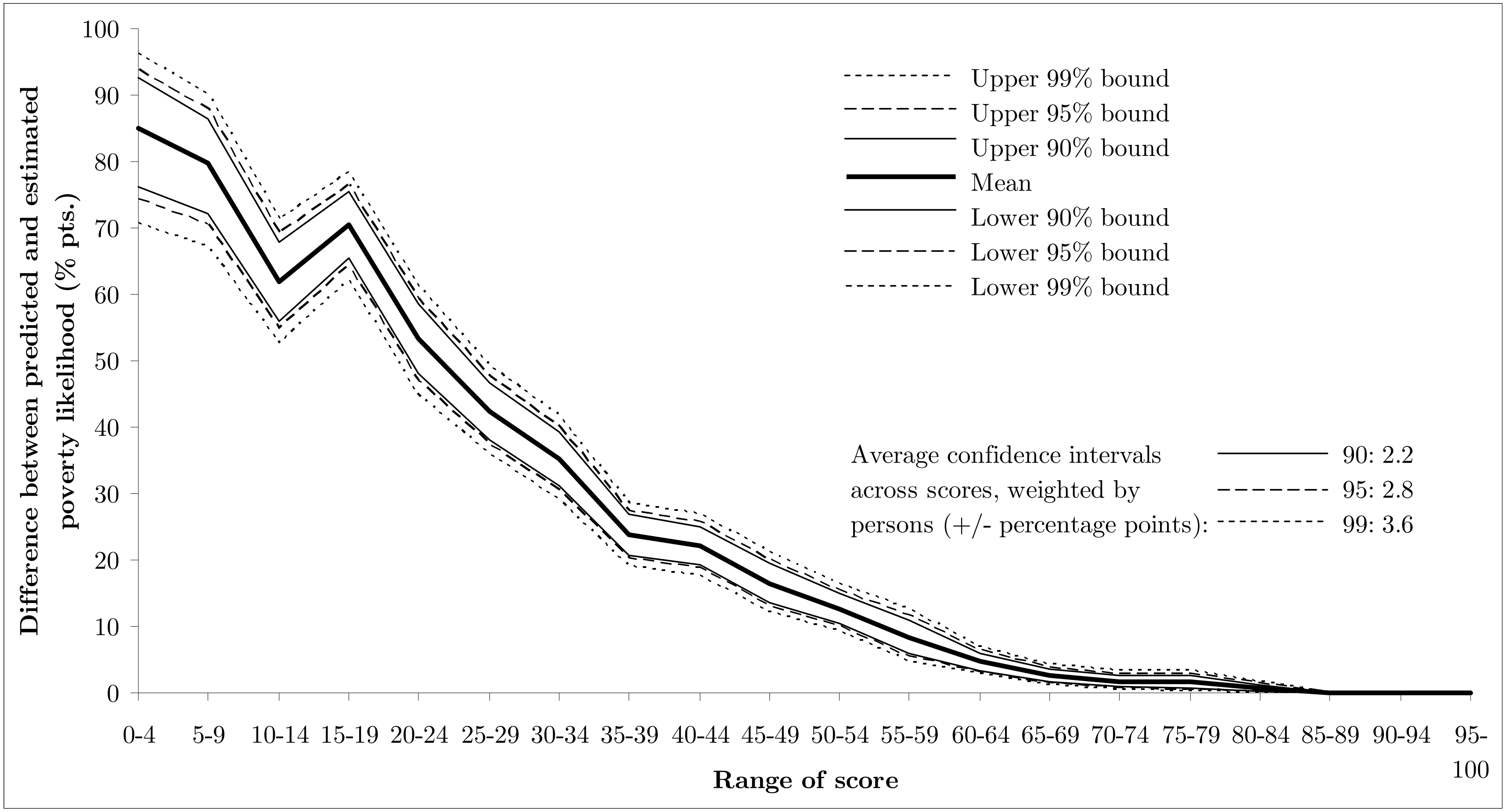

Figure 18: Differences between estimated and true poverty likelihoods for the very poor

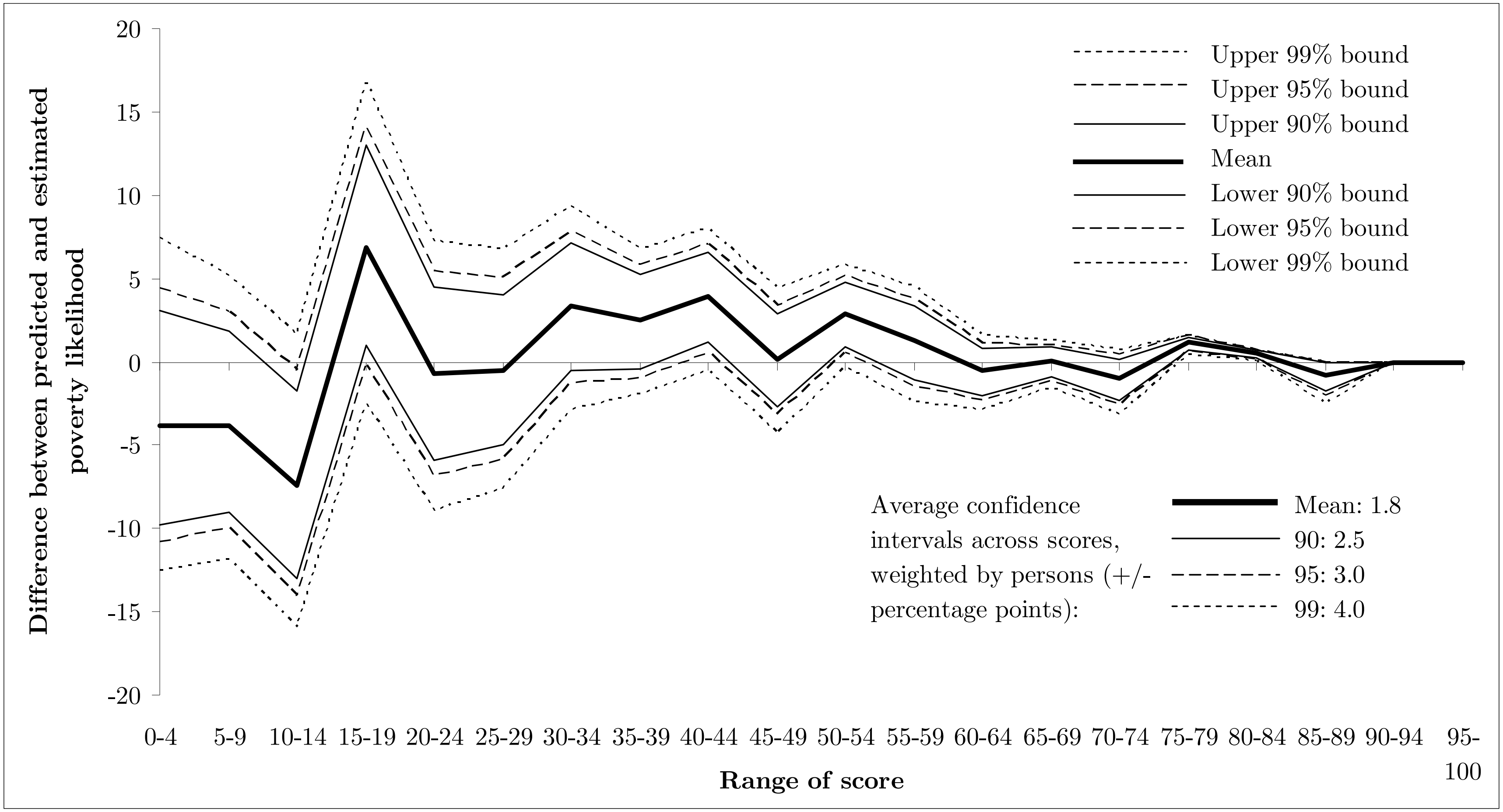

Figure 19: ROC curve of ability to rank-order households by very poor versus not very poor poverty status

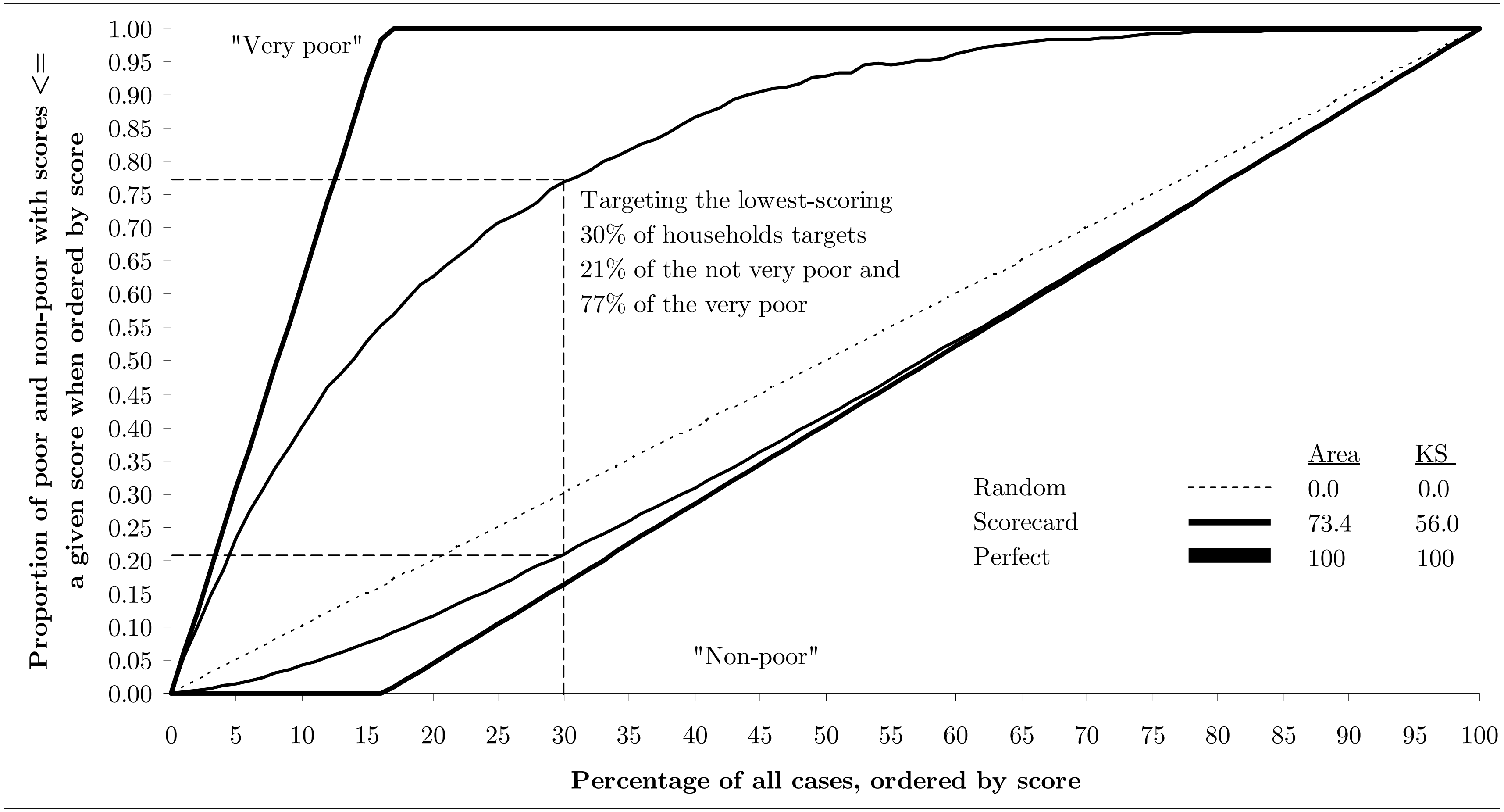

Figure 20: Classification matrix, three segments

		Targeting segment		
		Very Poor	**Poor**	**Non-poor**
True poverty status	**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 21: Net-benefit matrix, three segments

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

Figure 22: Classification results, very poor/poor cut-offs from 0 to 44 and poor/non-poor cut-offs from 5 to 49

Upper bound, very poor segment	Upper bound, poor segment																							
	5-9			10-14			15-19			20-24			25-29			30-34			35-39			40-44		
0-4	12	24	301	12	53	272	12	85	239	12	119	205	12	157	168	12	194	130	12	227	98	12	258	67
	2	4	291	2	18	277	2	28	267	2	44	251	2	74	221	2	120	175	2	154	141	2	190	105
	0	2	1,340	0	6	1,336	0	9	1,333	0	23	1,319	0	44	1,298	0	68	1,275	0	139	1,204	0	210	1,132
5-9				36	29	272	36	61	239	36	95	205	36	133	168	36	170	130	36	203	98	36	234	67
				6	14	277	6	25	267	6	40	251	6	71	221	6	116	175	6	150	141	6	186	105
				2	4	1,336	2	7	1,333	2	21	1,319	2	42	1,298	2	65	1,275	2	136	1,204	2	208	1,132
10-14							65	32	239	65	66	205	65	104	168	65	141	130	65	174	98	65	204	67
							20	10	267	20	26	251	20	56	221	20	102	175	20	136	141	20	172	105
							6	3	1,333	6	17	1,319	6	38	1,298	6	62	1,275	6	133	1,204	6	204	1,132
15-19										97	34	205	97	71	168	97	109	130	97	142	98	97	172	67
										30	16	251	30	46	221	30	91	175	30	126	141	30	162	105
										9	14	1,319	9	35	1,298	9	59	1,275	9	130	1,204	9	201	1,132
20-24													131	37	168	131	75	130	131	108	98	131	138	67
													46	30	221	46	76	175	46	110	141	46	146	105
													23	21	1,298	23	44	1,275	23	115	1,204	23	187	1,132
25-29																168	38	130	168	70	98	168	101	67
																76	45	175	76	80	141	76	116	105
																44	24	1,275	44	95	1,204	44	166	1,132
30-34																			206	33	98	206	63	67
																			122	34	141	122	70	105
																			68	71	1,204	68	142	1,132
35-39																						239	31	67
																						156	36	105
																						139	71	1,132
40-44																								
45-49																								

Figures in units of 10,000 people.

Figure 22 (cont.): Classification results, very poor/poor cut-offs from 0 to 49 and poor/non-poor cut-offs from 50 to 100

	Upper bound, poor segment																								
	50-54			55-59			60-64			65-69			70-74			75-79			80-84			85-89			
	12	299	26	12	306	19	12	314	11	12	319	6	12	321	3	12	324	1	12	325	0	12	325	0	12
0-4	2	246	49	2	258	37	2	267	28	2	282	13	2	290	5	2	293	2	2	295	0	2	295	0	2
	0	399	944	0	463	880	0	618	724	0	793	550	0	933	409	0	1,066	276	0	1,226	117	0	1,293	49	0
	36	275	26	36	282	19	36	290	11	36	295	6	36	297	3	36	300	1	36	301	0	36	301	0	36
5-9	6	243	49	6	254	37	6	263	28	6	278	13	6	286	5	6	289	2	6	291	0	6	291	0	6
	2	396	944	2	460	880	2	616	724	2	790	550	2	931	409	2	1,064	276	2	1,223	117	2	1,291	49	2
	65	246	26	65	253	19	65	261	11	65	266	6	65	268	3	65	270	1	65	272	0	65	272	0	65
10-14	20	228	49	20	240	37	20	249	28	20	264	13	20	272	5	20	275	2	20	277	0	20	277	0	20
	6	393	944	6	456	880	6	612	724	6	786	550	6	927	409	6	1,060	276	6	1,220	117	6	1,287	49	6
	97	214	26	97	220	19	97	229	11	97	233	6	97	236	3	97	238	1	97	239	0	97	239	0	97
15-19	30	218	49	30	230	37	30	239	28	30	254	13	30	262	5	30	265	2	30	267	0	30	267	0	30
	9	390	944	9	453	880	9	609	724	9	783	550	9	924	409	9	1,057	276	9	1,217	117	9	1,284	49	9
	131	180	26	131	186	19	131	195	11	131	199	6	131	202	3	131	204	1	131	205	0	131	205	0	131
20-24	46	202	49	46	214	37	46	223	28	46	238	13	46	246	5	46	249	2	46	251	0	46	251	0	46
	23	375	944	23	439	880	23	594	724	23	769	550	23	910	409	23	1,043	276	23	1,202	117	23	1,270	49	23
	168	142	26	168	149	19	168	157	11	168	162	6	168	165	3	168	167	1	168	168	0	168	168	0	168
25-29	76	172	49	76	184	37	76	193	28	76	208	13	76	216	5	76	219	2	76	221	0	76	221	0	76
	44	355	944	44	419	880	44	574	724	44	749	550	44	890	409	44	1,022	276	44	1,182	117	44	1,250	49	44
	206	105	26	206	111	19	206	120	11	206	124	6	206	127	3	206	129	1	206	130	0	206	130	0	206
30-34	122	127	49	122	138	37	122	147	28	122	162	13	122	170	5	122	173	2	122	175	0	122	175	0	122
	68	331	944	68	395	880	68	550	724	68	725	550	68	866	409	68	999	276	68	1,158	117	68	1,226	49	68
	239	72	26	239	79	19	239	87	11	239	92	6	239	94	3	239	97	1	239	98	0	239	98	0	239
35-39	156	92	49	156	104	37	156	113	28	156	128	13	156	136	5	156	139	2	156	141	0	156	141	0	156
	139	260	944	139	324	880	139	479	724	139	654	550	139	795	409	139	928	276	139	1,087	117	139	1,155	49	139
	269	41	26	269	48	19	269	56	11	269	61	6	269	64	3	269	66	1	269	67	0	269	67	0	269
40-44	192	56	49	192	68	37	192	77	28	192	92	13	192	100	5	192	103	2	192	105	0	192	105	0	192
	210	189	944	210	253	880	210	408	724	210	583	550	210	723	409	210	856	276	210	1,016	117	210	1,083	49	210
	291	20	26	291	27	19	291	35	11	291	40	6	291	42	3	291	45	1	291	46	0	291	46	0	291
45-49	214	34	49	214	46	37	214	55	28	214	70	13	214	78	5	214	81	2	214	83	0	214	83	0	214
	296	103	944	296	166	880	296	322	724	296	496	550	296	637	409	296	770	276	296	930	117	296	997	49	296

Figures in units of 10,000 people.

Figure 22 (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		55-59			60-64			65-69			70-74			75-79			80-84			85-89		
50-54		311	7	19	311	15	11	311	20	6	311	23	3	311	25	1	311	26	0	311	26	0
		248	12	37	248	21	28	248	36	13	248	44	5	248	47	2	248	49	0	248	49	0
		399	64	880	399	219	724	399	394	550	399	535	409	399	668	276	399	827	117	399	895	49
55-59					317	8	11	317	13	6	317	16	3	317	18	1	317	19	0	317	19	0
					260	9	28	260	24	13	260	32	5	260	35	2	260	37	0	260	37	0
					463	155	724	463	330	550	463	471	409	463	604	276	463	763	117	463	831	49
60-64								326	5	6	326	8	3	326	10	1	326	11	0	326	11	0
								269	15	13	269	23	5	269	26	2	269	28	0	269	28	0
								618	175	550	618	316	409	618	449	276	618	608	117	618	676	49
65-69											330	3	3	330	5	1	330	6	0	330	6	0
											284	8	5	284	11	2	284	13	0	284	13	0
											793	141	409	793	274	276	793	433	117	793	501	49
70-74														333	2	1	333	3	0	333	3	0
														292	3	2	292	5	0	292	5	0
														934	133	276	934	292	117	934	360	49
75-79																	335	1	0	335	1	0
																	295	2	0	295	2	0
																	1,066	159	117	1,066	227	49
80-84																				336	0	0
																				297	0	0
																				1,226	68	49
85-89																						
90-94																						

Figures in units of 10,000 people.

Figure 23: Classification results, very poor 0–24, poor 25–34, and non-poor 35–100

Segment	Score	Very Poor (total)	Very Poor	Poor (total)	Poor	Non-poor (total)	Non-poor
		People with score in range					
Very poor 0-24	0-4	**131** **65%**	12	**46** **23%**	2	**23** **12%**	0
	5-9		24		4		2
	10-14		29		14		4
	15-19		32		10		3
	20-24		34		16		14
Poor 25-34	25-29	**75** **38%**	37	**76** **39%**	30	**44** **23%**	21
	30-34		38		45		24
Non-poor 35-100	35-39	**130** **8%**	33	**175** **11%**	34	**1,275** **81%**	71
	40-44		31		36		71
	45-49		21		22		86
	50-54		20		34		103
	55-59		7		12		64
	60-64		8		9		155
	65-69		5		15		175
	70-74		3		8		141
	75-79		2		3		133
	80-84		1		2		159
	85-89		0		0		68
	90-94		0		0		23
	95-100		0		0		26
	Total:		336		297		1,342

Counts of people are in units of 10,000.

Figure 24: 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 25: Computation of total net benefit for a cut-off pair of 20–24 and 30–34

Cell			Persons	Net benefit/person	Net benefit
A.	Truly very poor	as very poor	131	+3	+393
B.	Truly very poor	as poor	75	–2	–150
C.	Truly very poor	as non-poor	130	–6	–780
D.	Truly poor	as very poor	46	–1	–46
E.	Truly poor	as poor	76	+2	+152
F.	Truly poor	as non-poor	175	–2	–350
G.	Truly non-poor	as very poor	23	–2	–46
H.	Truly non-poor	as poor	44	–1	–44
I.	Truly non-poor	as non-poor	1,275	+1	+1,275
				Total net benefit:	+404

Note: Persons are counted in units of 10,000.

Figure 26: Poverty likelihoods for the very poor, poor, $4/day poor, and non-poor by score

	Poverty likelihood in score range				Share of cases <= score			
Score	Very Poor	Poor	Poor $4/day	Non-poor	Very Poor	Poor	Poor $4/day	Non-poor
0-4	85.0	14.3	0.4	0.4	85.0	14.3	0.4	0.4
5-9	79.7	12.8	4.4	3.2	81.3	13.3	3.1	2.3
10-14	61.9	30.0	6.3	1.8	71.3	21.9	4.8	2.0
15-19	70.5	22.9	4.5	2.1	71.0	22.3	4.7	2.0
20-24	53.2	24.4	12.8	9.5	65.4	22.9	7.3	4.4
25-29	42.4	34.4	14.4	8.8	58.3	26.4	9.5	5.8
30-34	35.2	42.6	13.1	9.2	52.1	30.8	10.4	6.7
35-39	23.8	24.8	23.1	28.3	44.8	29.2	13.7	12.3
40-44	22.2	26.1	22.6	29.1	40.1	28.6	15.5	15.7
45-49	16.5	17.1	27.0	39.4	36.3	26.7	17.4	19.6
50-54	12.6	21.8	18.6	47.0	32.4	25.9	17.6	24.1
55-59	8.4	14.2	19.8	57.7	30.5	25.0	17.8	26.7
60-64	4.7	5.4	20.6	69.4	26.8	22.2	18.2	32.8
65-69	2.5	7.6	14.5	75.4	23.5	20.2	17.6	38.7
70-74	1.7	5.2	11.8	81.2	21.4	18.7	17.1	42.8
75-79	1.6	2.2	4.5	91.7	19.8	17.4	16.1	46.8
80-84	0.7	1.4	2.4	95.5	18.1	16.0	14.9	51.1
85-89	0.0	0.0	0.8	99.2	17.5	15.4	14.4	52.7
90-94	0.0	0.0	0.2	99.8	17.3	15.2	14.2	53.3
95-100	0.0	0.0	0.7	99.3	17.0	15.0	14.0	53.9
Total:	17.0	15.0	14.0	53.9				

Figure 27: Confidence intervals for estimated poverty likelihoods for being $4/day-or-less poor associated with scores

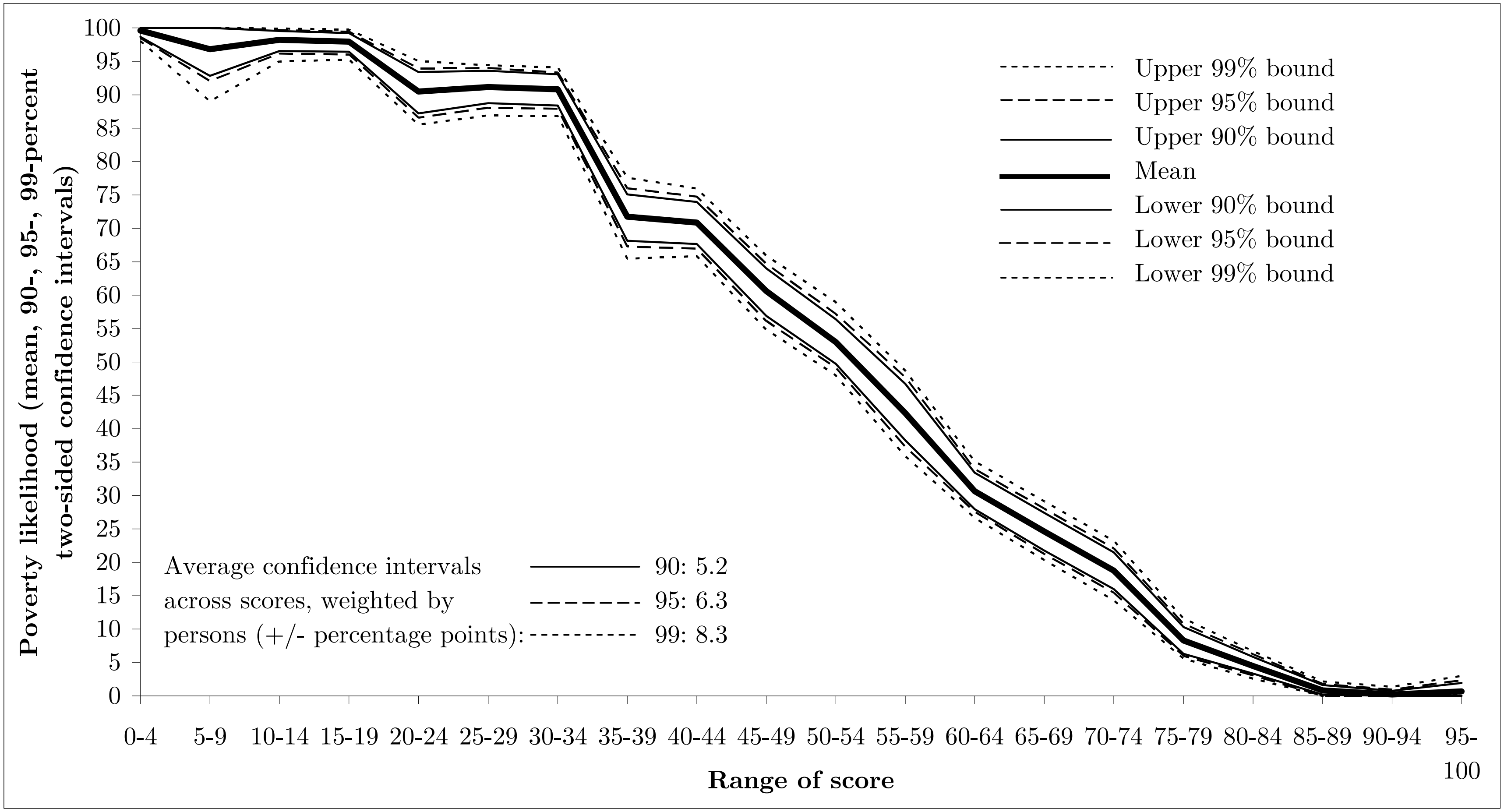

Figure 28: Differences between estimated and true poverty likelihoods for the $4/day-or-less poor

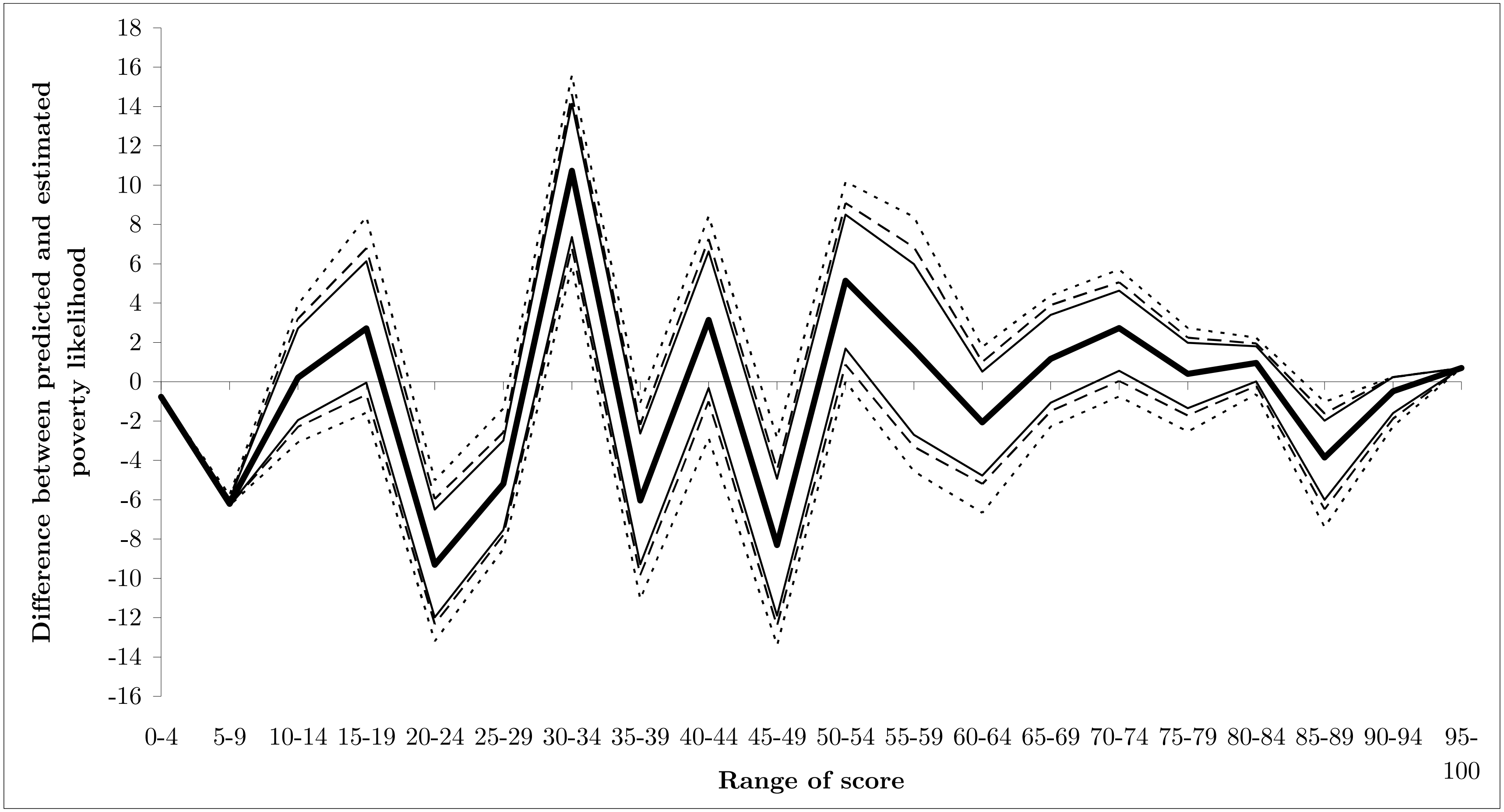

Figure 29: ROC curve of ability to rank-order households by $4/day-or-less poverty status